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AI Techniques for Decoding Language Representation from EEG-Based Brain Activity: A Comprehensive Review

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Abstract

This study presents a thorough description of artificial intelligence techniques that use EEG signals to extract language from brain activity. EEG is a non-invasive technology that uses high temporal precision to monitor brain activity during language processing. The study looked at both classical models like Support Vector Machine (SVM) and Random Forest (RF) as well as deep learning methods like Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Transformers. It was discovered that these models are particularly effective in decoding language representations from brain signals. This research also considers the primary applications of these technologies, such as providing communication tools for people with disabilities, medical diagnosis and treatment, and understanding linguistic perception, as well as the challenges associated with data quality, cost, complexity, and ethical concerns.

1. Introduction

Reading human brain activity provides an understanding of the complex cognitive function involved language processing. The process of converting neural activity into visual representations by computer models marks a breakthrough in human-computer interaction and plays a vital role in restoring functions for patients with speech loss. [1, 2] . To record brain activity from individuals correctly and comfortably, the common EEG technique is used, which is characterized by its high temporal resolution in capturing neural activity from the brain and its ease of use. However, this signal is often filled with noise due to the experiment or from the electrodes during recording. This requires precise and logical signal processing, especially when it comes to language, which is more complex. It is essential to benefit from the artificial intelligence and to employ it correctly in this field[3-5]. Artificial intelligence (AI) technologies have advanced significantly in recent years, making them a powerful tool for analyzing complex neural data and decoding hidden linguistic patterns within brain signals. These technologies are essential for overcoming the challenges associated with understanding and processing neural activity, especially regarding linguistic representation [6-9] . Below are the most prominent contributions made by AI technologies in this field:

- Improving the treatment of speech and language disorders: Artificial intelligence technologies have contributed significantly to the diagnosis and treatment of speech and language disorders, such as aphasia [10].
- Developing communication systems for patients with paralysis: AI-powered brain-computer interfaces (BCIs) provide an effective means of communication for people with paralysis or locked-in syndrome. These systems decode neural signals and convert them into text or voice commands, enhancing independence and improving patients' quality of life[11-13].
- Accelerating neural signal processing: AI technologies contribute to Instant signal processing, enabling rapid interpretation of neural responses, Advanced pattern recognition, and identifying complex neural patterns associated with language processing[14,15]
- Improve the accuracy of neural translation.

Language decoding is one of the promising areas, and there is still a gap in unifying knowledge about the most commonly used technologies. In this comprehensive review, we present a compilation and evaluation of the latest technologies contributing to this field, particularly the handling of EEG signals related to language and their classifications. We also review the promising applications in clinical and research fields and provide future insights for researchers in this growing area.

2. Methodology of the Literature Review

In this comprehensive scientific review, scientific literature was collected from reliable databases **including** IEEE Explore, Science Direct, arXiv, PubMed, Springer-Link, and MDPI, using Google Scholar as an auxiliary search tool. This was based on recent studies from 2020 to 2025 to ensure clarity on the latest developments in this future scientific field. Keywords such as EEG, Transformers, Deep Learning, Machine Learning, BCI, and Decoding language were used. Studies from older years, unpublished and unpreserved studies, and unpublished research in English were excluded. The studies were organized using citation tools like Mendeley. These studies were selected based on their relevance to the topic and their application in decoding linguistic representations from EEG signals and the associated challenges.

3. Background

3.1. EEG in Brain-Language Decoding

Electroencephalography has existed for over a century. Hans Berger, a German psychiatrist, released his research article on the electroencephalogram (EEG) in 1929 and developed the technology for recording electrical activity from the human brain. Electroencephalography captures electrical signals, i.e., EEG, inside the subject's brain with sensors/electrodes mounted in a cap-like structure [16] .EEG signals are non-invasive, low-cost, compatible, portable, and have a high temporal resolution, this explains why EEG is the most widely used tool to measure brain activity, Furthermore, it is reasonably priced and has an excellent temporal resolution (1 ms). However, it has a poor signal, is prone to artifacts, and has a low spatial signal resolution [17-19] . The synchronized activity of neurons in the brain produces electrical currents. The resulting voltage fluctuations can be recorded with external electrodes on the scalp. This allows for more fine-grained language understanding experiments on the word-level, which is crucial for applications in NLP [20-22] . To isolate certain cognitive functions, EEG signals can be split into frequency bands. Different signal patterns are produced inside the human brain by the multiple-thinking process [18]. EEG signals can provide characteristics in the time domain, frequency domain, or time-frequency domain during the feature extraction step; the time-frequency technique is the most used [5,23]. During the acquisition of data, the signal could be noisy and contain artifacts due to either electrical interference, incorrect placement of electrodes, or due to the participant's eye and muscle movements, or clenching of the jaw. These artifacts could mess up the readings if left uncorrected, and therefore, it is necessary to get them removed for data analysis. The methods to remove these artifacts could be filtering, noise removal, or correction of the data. Standardized, automated processing pipelines in Figure 1 provide a lot of advantages that would help in the uniform removal of artifacts and efficiency with larger data[15].

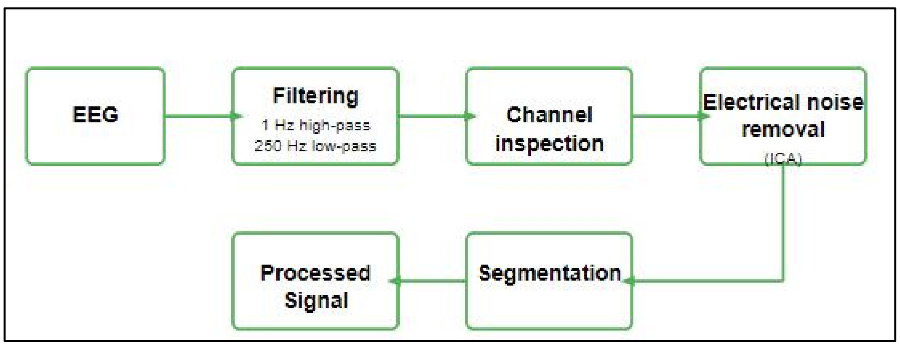

Figure (1): The pipelines for processing EEG signals.

The diagram illustrates the basic steps for preparing EEG signals for analysis in brain language processing. These are sequential flow steps that begin with

1. obtaining raw EEG signals, which contain noise and electrical interferences.
2. Frequency filters should be applied to remove noise, such as a high-pass filter starting at 1 Hz to eliminate low-frequency drifts and a low-pass filter at 250 Hz to preserve important frequencies and remove noise.
3. Channel inspection: Unrelated channels, such as eye, sound, or muscle channels, which have high frequencies, are removed.
4. One of the most important steps is the analysis of the independent components of the signal to separate noise from important components and frequencies. This is done by applying ICA.
5. To handle the signal in computational models, it must be divided into time segments based on stimuli or events, which facilitates the analysis of neural activity related to specific tasks.

These steps are considered essential when using EEG signals to ensure data quality and reliable analysis results.

4. The Brain and Language Processing in Neuroscience

To discover how the brain interacts with linguistic information, it is necessary to understand the neural basis of language processing, as this process depends on a complex network of neural regions and pathways that work together to process sounds, meanings, and grammatical structures [24]. Traditionally, language processing was believed to be primarily dependent on Broca's area (responsible for language production) and Wernicke's area (responsible for language comprehension), connected via the arcuate fasciculus. This pathway, known as the classical language processing model, plays a crucial role in integrating linguistic information [25] as illustrated in Figure (2 a). The study of the neurobiology of language is entering a new era with advanced methodologies that go beyond traditional localizations views. Research shows that language processing is not confined to a single brain region but relies on dynamic interactions across widespread neural networks, including cortical areas, subcortical structures, and white matter pathways. Which contribute to phonological (sounds), syntactic (grammar), and semantic (meaning) processing, figure (2 b) [26- 28]. This network highlights the distributed nature of language processing, with different brain regions connected through dorsal and ventral pathways, which facilitate the integration of sensory, motor, and cognitive aspects of language, as shown in Figure (2b).

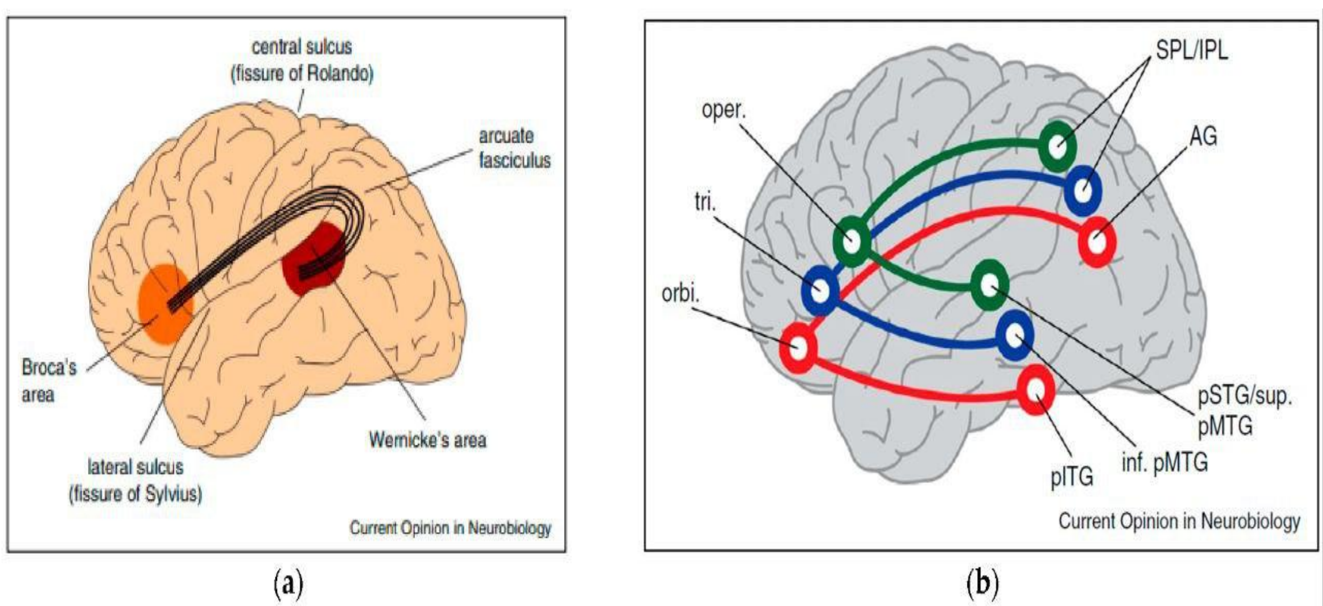

Figure (2): Neural models for language processing.

This figure illustrates the difference between traditional processing (a), which relies on Broca's area and Wernick's area, and modern processing (b), which shows that language processing is a series of interactions between different brain regions.

Moreover, the brain uses syntactic analysis to interpret language. This method combines sensory inputs and stored linguistic knowledge to infer meanings and grammatical structures [28] . The brain can distinguish between grammatically similar and phonetically similar structures, which means that it is difficult to process language using traditional pathways [1,30] . Understanding the basic neural structure of the brain's language processing significantly facilitates how this language is decoded from the brain, and this is what we will learn in the next section.

5. AI Techniques for Decoding EEG Data

5.1. Machine Learning Techniques

EEG signal analysis techniques have significantly advanced recently due to the increasing use of EEG signals in various fields, with the presence of two main approaches. Traditional machine learning techniques and deep learning techniques conducted a comprehensive survey of studies addressing these technologies in recent years, 2020-2025 .Traditional studies rely on extracting specific features from EEG signals, followed by the application of classification and regression algorithms. They are characterized by their effectiveness with relatively small datasets and the interpretation of results. According to recent studies, machine learning techniques for analyzing EEG signals related to language processing vary significantly and include direct classification machines such as SVM, random forests, and the XG-Boost algorithm, as well as ANN, which have proven effective and highly capable in classifying neural patterns from EEG signals[4-8, 23, 31-36]. The traditional approach does not rely solely on classification but also uses techniques like PCA, ICA, and Wavelet Transformer to analyze and process EEG signals into their basic components, breaking down the signal into its frequency and temporal components, which are later used in the classification stage. Advanced methodologies benefit from feature selection techniques like GA and PSO[37], which greatly help reduce data complexity and dimensionality, obtaining only the important features, thereby significantly improving model performance. All these techniques benefit from limited data. Recently, there has been a significant reliance on hybrid approaches that combine different methods, such as ICA-SVM and adaptive filtering with ensemble learning, achieving promising results in improving the accuracy of language decoding from EEG signals in real applications like brain-computer interfaces.

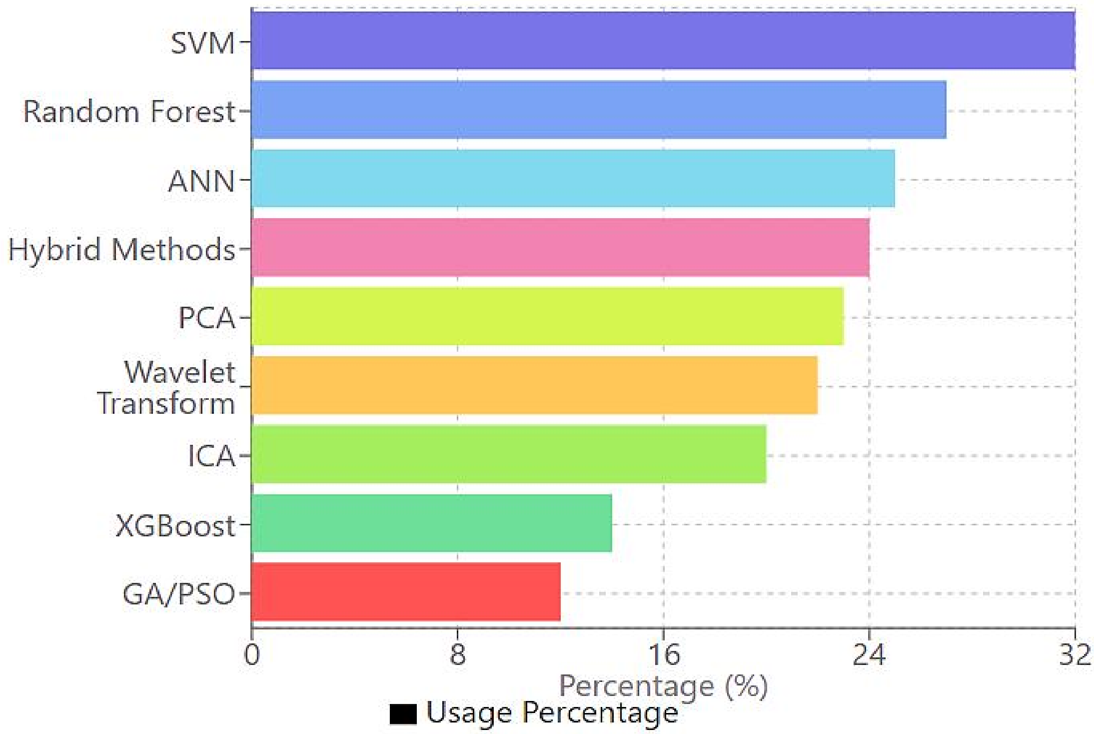

Figure (3): Distribution of machine learning techniques in analyzing EEG signals related to language processing.

This figure illustrates the traditional techniques used in language decoding, showing that SVM, RF, and ANN are the most frequently used according to the percentage of studies counted.

5.2. Deep Learning Techniques

With the rapid development of artificial intelligence technologies, deep learning techniques have become powerful tools for analyzing complex neural data and deciphering the linguistic patterns present in brain signals. This section provides a comprehensive review of the modern deep learning techniques used to analyze EEG signals related to language processing.

Deep learning techniques are characterized by their ability to automatically extract features from raw data, which reduces the complexity of manual feature extraction as in traditional learning, providing a more flexible approach to analyzing EEG signals.

According to recent studies[13-18, 38-63], the use of CNN, LSTM, transformers, RNN, Constructive Learning, and DNN has been significant and has proven their real effectiveness in signal analysis and reliable, good results. figure 4.

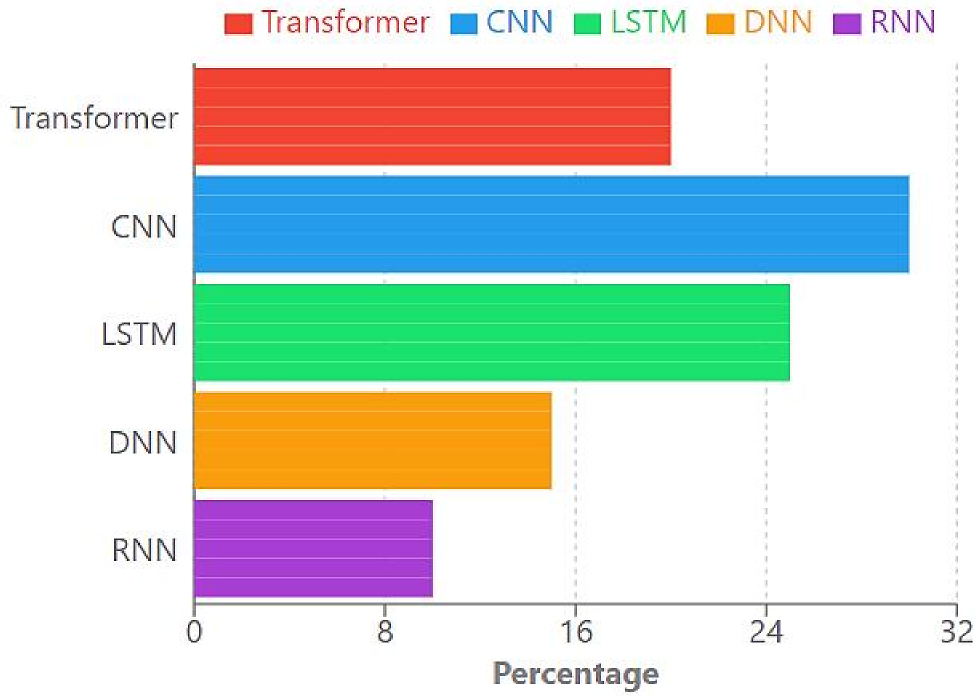

Figure (4): Distribution of Deep Learning Techniques in EEG Signals Analysis.
This figure illustrates the deep learning techniques used in language decoding, showing that CNN, LSTM, and Transformer are the most frequently used according to the percentage of studies counted.

These technologies are characterized by their unique ability to extract complex features from EEG signals using neural networks automatically. The main challenge lies in processing the immense complexity of neural signals. Despite the challenges of data quality and high computational cost, the integration of deep learning with neuroscience and generative artificial intelligence opens entirely new horizons in understanding human brain functions and language processing mechanisms.
due to the efficiency of CNN in extracting spatial features, it has become a suitable choice in many EEG studies, where multiple filters are used to process the hierarchical sequences of EEG signals and capture spatial patterns of brain activity[60].
CNNs consist of a series of specialized layers for data processing, starting with the input layer, followed by convolutional layers that use filters to extract features, then reducing dimensions while preserving important information through pooling layers [41] . Transformers can encode long sequences that have demonstrated exceptional performance, surpassing machine learning methods, particularly in EEG signal analysis [40]. It has hundreds of millions of parameters and can capture long-term data sequences while efficiently handling underlying relationships within the data. Since EEG data is a time series, it presents a valuable opportunity for the increased use of transformers[46]. (Figure 2.8) Illustrates the mechanism of the transformer.
A connected decoder and encoder are the two primary components of the transform. The encoder processes inputs using multiple layers of multi-head attention and neural networks. At the same time, the decoder utilizes

the encoder's outputs to generate the final results through the attention mechanism—a crucial component for understanding the relationships between the sequence's elements[61]. Researchers created a specialized recurrent neural network called LSTM, which improves the RNN after it fails to preserve temporal information. The RNN is vulnerable to gradient explosion and gradient disappearance[62].

LSTM is essentially similar to RNN, a time-series neural network designed to solve the long-term dependence of RNNs. A mechanism called gating is used to identify long-term sequences. Just like in our problem in this paper, where we deal with EEG signals that are long-term time series[63].

LSTM can store the previous unit cell information in data containing long-distance information and update the node information with the current cell value. It can also determine which information to output by discarding irrelevant information. Data is added or removed through the gate structure, which contains three types of gates: input, output, and forget.

To compare deep learning and machine learning techniques, let's refer to Table 1.

Criterion	**Machine Learning**	**Deep Learning**
Dataset Size	Small to medium (Works well with limited data)	Very big (to achieve optimal performance)
Accuracy	Medium to high (depending on the extracted data)	Very high (especially with large data)
Feature Extraction	Manual	Automatic (models extract features based on their functional structure)
Training Time	Relatively good (depends on local device resources)	Requires a long training time that needs GPU and TPU resources
Interpretability	Hight	Low (Black box)
Challenges	Sensitive to noise	Requires strong infrastructure and high computing resources

Table (1): compare deep learning and machine learning techniques.

This table generally illustrates the difference between techniques in analyzing EEG signals for language decoding. The results showed a significant superiority of deep learning techniques, especially with large datasets, while machine learning was limited to resource-constrained systems.

6. **Application**

AI applications in analyzing electroencephalogram signals open entirely new horizons for understanding the human brain to improve people's lives, providing innovative solutions in various fields.

1. Communication for people with disabilities

Brain signal analysis techniques are primarily used for communication for individuals with motor or speech disabilities. These techniques convert neural signals directly into text or speech, helping these individuals express their thoughts and communicate with the outside world. For example, the EEG2TEXT project [13] allows individuals with complete paralysis to communicate simply by thinking, using advanced decoding techniques to interpret brain signals.

2. Medical and therapeutic diagnosis

In language and speech disorders, EEG signal analysis techniques have enabled doctors to detect neurological imbalances early and with high precision, such as diagnosing cases of aphasia or tracking language disorders[56]. These techniques allow for the accurate analysis of neural patterns to identify subtle changes in language processing, which aids in developing early therapeutic plans.

3. Scientific research and understanding of linguistic perception

This field of understanding EEG signal analysis in the realm of neuro-linguistic sciences opens a wide avenue for researchers to comprehend how the brain processes language and how information is transmitted between different regions of the brain during comprehension and communication, such as the study[60] by showed the ability to predict semantic understanding directly from brain activity, revealing complex mechanisms of linguistic perception, and the study[57] by on decoding speech perception from non-invasive brain recordings and precise analysis of neural signals.

4. Advanced and future applications

Go beyond the medical field to include innovative areas such as brain-computer interfaces. Project Brain2Word [42]. How can language be generated directly from brain activity, opening up amazing possibilities for interaction between humans and machines? These fields represent the visual analysis of neural signals and the recognition of psychological and cognitive states. With the advancement of artificial intelligence, we are approaching a new era of technological progress.

5. Challenges and limitations

Decoding language from EEG signals is a highly complex task that involves numerous technical, cognitive, and ethical challenges. Despite the significant advancements in artificial intelligence and neuroscience, many obstacles still limit the accuracy and generalizability of current approaches. This section highlights the most critical challenges and limitations that researchers face in this field.

1. Data quality

Data quality is considered one of the biggest fundamental challenges in EEG signal analysis due to its high complexity and susceptibility to electrical interference. Researchers face difficulties in obtaining pure signals as they are affected by simple movements such as eye blinks and muscle movements during recording. This requires precise and complex preprocessing, which is a technical challenge that demands high skill in signal processing.

2. Cost and Complexity

The cost and complexity of advanced deep learning models require very large computational resources and consume high energy and time during the analysis of EEG signals. Balancing the model's accuracy and computational cost poses a significant challenge for researchers, creating a large gap between computational complexity and scientific interpretation.

3. Limited Understanding

Our understanding of the human brain is still very limited. Despite significant scientific advancements, understanding how the brain converts neural signals into thoughts and concepts remains a challenge, especially with the considerable individual differences that make it difficult to generalize models.

4. Ethical challenges

One of the main challenges is the ethical challenges, particularly concerning individuals' privacy and the fear of reading others' thoughts.

6. Future direction

We are approaching an unprecedented understanding of the human brain and a tremendous potential for analyzing EEG signals in the future:

1. The future is heading towards integrating multiple technologies for a deeper understanding of the human brain, such as EEG signals with fMRI, to build comprehensive models capable of analyzing brain activity in an integrated manner.
2. Predicting neurological and cognitive conditions with the development of advanced systems for early prediction and monitoring of neurological changes before symptoms appear.
3. Advanced brain-computer interfaces, which are now the beginning of a new era of direct communication, allow individuals with speech impairments to communicate smoothly by integrating technology with human neural capabilities.
4. Establishing strict ethical frameworks to maintain individuals' privacy to ensure the humane use of technology.
5. Integrating data from multiple sources—text, audio, images, video, and others—provides a more comprehensive understanding of cognitive processes.
6. The integration of quantum computing with EEG signal analysis techniques is a field that keeps pace with the development of artificial intelligence and is very promising, especially in such a complex domain.

7. Conclusion

This research is a direct and comprehensive scientific contribution to the field of decoding language from human brain activity. It revealed a radical development in data handling, moving from traditional techniques to more modern ones, by collecting recent studies from 2020-2025. These studies effectively contribute to achieving the best results in this complex field of understanding the mechanisms of language processing in the human brain. Despite the immense challenges in terms of data quality, quantity, and ethical issues, this field, although relatively new, offers communication systems for individuals with communication disabilities. This paper also revealed a new era for this field by integrating quantum computing with multiple technologies and artificial intelligence, which opens up unlimited horizons for developing advanced brain-computer interfaces that serve humanity and enhance the quality of life. It also establishes a deeper understanding of the nature of human consciousness and the mechanisms of linguistic thought.

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