Engineered Science
DOI: https://dx.doi.org/10.30919/es1507

Artificial Intelligence-Driven Advancements in Non-Invasive Neural Communication: A Deep Learning Approach to Neurolinguistic Learning

Suresh Palarimath,[1,*] Fatima Ali Amer Jid Almahri[1] and Wilfred Blessing N.R[2]

Abstract

This study investigates innovative, non-invasive methods for neural communication in the context of language by combining neuroscience, machine learning, and artificial intelligence in the realm of neurolinguistic learning. Our study aims to decipher neural patterns associated with language comprehension using deep recurrent neural networks (RNNs) and gated recurrent units (GRUs). The primary objective is to enhance interactions between neuro-devices and artificial intelligence (AI) through non-intrusive means, thereby improving brain-machine interfaces and neuroprosthetics. The project entails developing an advanced deep RNN-GRU model in Python, utilizing AI to accurately capture intricate neural patterns for language processing. The results indicate the significant potential of non-invasive brain language decoding systems for assistive technologies and brain-machine interfaces. Our AI-enhanced model achieved a notable accuracy rate of 91%, which represents a substantial improvement of 31.4% compared to traditional approaches. This substantial improvement illustrates AI's superior capacity for extracting complex language patterns from non-invasive brain signals, emphasizing its crucial role in advancing neural communication. Moreover, the research underscores the broader implications of integrating AI with neuro-devices, laying the groundwork for future innovations in cognitive enhancement and rehabilitation, and ultimately contributing to the development of more effective and user-friendly assistive technologies.

Keywords: Artificial intelligence; Recurrent neural networks; Brain-machine interfaces; Neurolinguistic learning; Neural devices.
Received: 16 June 2024; Revised: 20 November 2024; Accepted: 21 November 2024.
Article type: Research article.

1. Introduction

In the rapidly advancing field of neurotechnology, there is a critical need to create a strong connection between humans and other technologies, leading to a wave of innovative research projects. Leading this effort is the goal to develop neural-device interaction, a cross-disciplinary field combining knowledge from neuroscience with advanced engineering skills. This project is focused on advancing this area by introducing new methods and technology to enhance the interaction between brain systems and other devices. This endeavor is driven by the determination to address fundamental difficulties and create new avenues for human-machine interactions.[1] The use of traditional methods to communicate between neural devices and the brain often presents difficulties concerning the precision of signals, the capacity for data storage, and the invasive nature of the procedures. In light of technological advancements, it is essential to address these challenges in order to advance our understanding of brain progression and apply this knowledge to benefit individuals with neurological syndromes, incapacities, or those seeking to enhance their mental capabilities.

Understanding the complex process of brain signaling that can understand and decode signals in real-time are crucial to current research efforts. One interesting approach involves using deep reinforcement learning networks (DNRNNs) and gated recurrent units.[2] These models are highly skilled at capturing temporal dependencies and sequential patterns in brain signals related to cognitive operations, allowing them to extract dynamic information effectively. Studying how the

[1] *College of Computing and Information Sciences, University of Technology and Applied Sciences, Salalah, 211, Sultanate of Oman*
[2] *College of Computing and Information Sciences, University of Technology and Applied Sciences, Ibri, 511, Sultanate of Oman*
**Email:* suresh.palarimath@utas.edu.om (S. Palarimath)

brain interacts with devices is important for academic studies and has various implications.[1] Advanced neural-device interfaces enable the development of cutting-edge technologies, modified medicinal treatments, and highly efficient neuroprosthetics. Moreover, these advancements are resulting in fields such as “brain-machine” interfaces, neuromodulation, and mental enhancement by enhancing the connection between humans and machines to be more instinctive and seamless.

This research involves a thorough investigation of many approaches, including gathering and organizing data, as well as designing and improving complex neural network structures. This endeavor is guided by a careful evaluation of the ethical and practical implications of interacting with the human brain, with a focus on non-invasiveness. Main goal of this project is to further scientific knowledge of brain activities and to initiate a new era of collaboration between humans and machines, where the distinction between the two becomes less clear and more interwoven.

Neurolinguistic learning is a rapidly evolving field that brings together neuroscience and AI to explore the neural mechanisms underlying language comprehension and production.[3] By focusing on the neurological basis of language, this approach diverges from conventional linguistic research, which typically relies on behavioral observations.

The acknowledgment that language, a key aspect of human awareness, goes beyond just visible behaviors or verbal expressions has motivated the investigation of neurolinguistic learning.[4] The origin is in the complex and ever-changing patterns of neuronal activity in the brain.

Conventional approaches to interpreting cerebral language patterns frequently include intrusive methods like implanting brain electrodes. The hunt for non-invasive methods is driven by concerns over protection, integrity, and the necessity to produce more accessible technologies. The objective is to employ deep learning models, namely, DRNN and GRU architectures, to enhance “non-invasive neural language decoding”.[5] These structures have outstanding effectiveness in capturing sequential patterns and temporal interdependence, making them ideal for modelling the dynamic aspect of language processing.

The successful interpretation of non-invasive brain language has significant ramifications. Aside from its scientific importance in understanding the human brain, it is ready to transform areas like assistive technology, neurorehabilitation, and communication technology.[6] Non-invasive neural language decoding can benefit individuals with communication problems, provide new understanding of cognitive processes, and enhance the creation of user-friendly human-machine interfaces.

In recent years, augmented reality (AR) and virtual reality (VR) have emerged as significant facilitators of communication that integrates real and digital experiences. This convergence of technologies coincides with advancements in neural interface systems, particularly non-invasive brain-machine interfaces (BMIs) that enable direct brain-device communication. By leveraging these technological innovations, methodologies such as neurolinguistic learning and neural language decoding can enhance the interactions between humans and devices. Consequently, this leads to more immersive and naturalistic communication environments that reduce the gap between human cognitive processes and machine computations.[7,8]

In the past few years, significant advancements have been made in brain language decoding systems, with an increasing interest in non-invasive methods for interpreting cerebral signals.[9] presented a neural speech decoding technique for individuals with amyotrophic lateral sclerosis (ALS), attaining significant outcomes in interpreting imagined speech from Electroencephalogram (EEG) data.[10] investigated non-invasive nerve stimulation to improve speech learning in adults, demonstrating the efficacy of these techniques in neurorehabilitation. Nonetheless, current methodologies continue to face challenges related to data quality and noise, especially in non-invasive technologies. Our research aims to overcome these constraints by employing DRNNs and GRUs, which have demonstrated efficacy in capturing the intricate temporal dynamics of brain signals. This study aims to improve the accuracy and efficacy of non-invasive neural language decoding systems by employing deep learning architectures that can extract meaningful patterns from EEG data. The proposed method seeks to enhance neural-device connection, hence optimizing applications in brain-machine interfaces (BMIs) and aided technology.

One of the major challenges in this field is the need to improve the seamless integration of neural strategies with intricate methods of language production and understanding. This is motivated by the need to overcome the limitations of invasive approaches that are often employed in the creation of brain interfaces. Although invasive methods like direct brain electrode implantation can yield positive results, it is crucial to explore non-invasive alternatives in order to advance the improvement of neural-device interfaces.

This study's implications extend beyond the realm of neurology and possess the potential to significantly impact a wide range of areas. If successfully implemented, this technology has the power to transform augmentative communication technologies, enabling individuals with disabilities or communication challenges to more effectively express themselves. Furthermore, the use of non-invasive techniques reduces health risks and enhances accessibility, making it a widely acceptable solution in diverse socioeconomic contexts.

This study provides multiple significant contributions.

• The suggested research presents a new method for studying language-related brain signals in a non-invasive way, without the need for intrusive treatments.

• The objective of this study is to enhance the practicality of Neurodevice interaction by utilizing advanced "neural network topologies", such as DRNN and GRU models.

• The main contribution of our study is the creation and execution of a deep RNN-GRU model, which was coded via the Python programming language.

• Introduction of Innovative Analytical Methods: This study introduces new analytical methods for interpreting brain signals connected to language, which helps progress the growing subject of neurolinguistic learning.

1.1 Relevant literature

The study of Dash *et al*.[11] presents an innovative method for analyzing brain responses to speech in persons with ALS, a condition affecting motor neurons that may result in locked-in syndrome, characterized by complete paralysis while maintaining consciousness. By using "brain-computer" interfaces like EEG, which have previously shown low interaction rates, locked-in individuals can participate in conversations. Recent research has concentrated on neural speech decoding methods to attain regular communication speeds, although it is unclear how relevant these results are for some groups such individuals with ALS. The study utilizes seven machine-learning decoders and evaluates various spectral properties, including beta, delta, alpha, theta and gamma frequency ranges of neural signals. The results show that ALS patients do better than chance in decoding tasks, but their performance is still inferior to that of healthy individuals. The study successfully accomplished brain speech decoding for a group with speech difficulties, achieving top scores of 75% for imagined sentences and 88% for spoken phrases from ALS patients. Improving the understanding of how the brain processes speech imaging could help in creating algorithms to enhance the decoding of imagined speech. This innovative study provides valuable insights into the use of neural decoding methods to tackle communication difficulties related to ALS and other speech problems, with room for improvement and further exploration in future research.

Llanos *et al*.[10] conducted a study suggesting that peripheral nerve stimulation can improve speech classification acquisition in grown person without invasive procedures. The study investigates the potential benefits of combining threshold percutaneous stimulus of the vagus nerve with non-native speech sounds. It draws on research conducted on animal models, which has shown that vagus nerve stimulation can improve the adaptability of adult sensory-perceptual systems. Twenty-four native English speakers participated in a study in which they were trained to recognize non-native Mandarin tones. During training, transcutaneous vagus nerve stimulation (tVNS) was applied simultaneously, with the stimulation tailored to tone groups classified as either easier or more difficult to learn. These findings indicate that (tVNSsignificantly enhances the response. Electroencephalography recordings before and after training show no noticeable differences in the perception of audio stimuli caused by tVNS. The results indicate that paired tVNS increases the experience and retention of remembrances associated with subconsciously significant by producing a precisely timed neuromodulatory signal.[12] This study emphasizes the potential of peripheral nerve stimulation, particularly tVNS, as a non-invasive method to enhance speech category learning in adults. It provides insights into the mechanisms involved in neuroplasticity and memory consolidation.

Cooney *et al*.[13] presented a novel EEG-fNIRS bimodal deep machine learning approach to decode both spoken and thought speech. Brain-computer interface (BCI) research is utilizing features from different signals at the same time. The integration of EEG and fNIRS (functional Near-Infrared Spectroscopy) data collecting technologies, which combine temporal and spatial resolutions, requires innovative decoding approaches. Features from each subnet are combined and then analyzed for classification. The hybrid technique significantly improves classification accuracy compared to using EEG alone for imagined speech ($p = 0.02$) and shows a trend towards significance for overt speech, with accuracies of 46.31% and 34.29%, respectively. Bimodal decoding produces much superior outcomes for both speech types compared to using fNIRS alone. The study shows that the stimulus has distinct effects on overt and imagined words, with deeper subnets improving performance significantly.

The study of Jensen *et al*.[14] employed multivariate pattern analysis (MVPA) to examine the intertribal phase coherence of neuromagnetic responses to words, efficiently differentiating several levels of language managing in the brain. Understanding how the brain processes language is still a challenge, so there is a need for a method that is unbiased, user-friendly, and non-intrusive to assess the cognitive state of language function. This study suggests using a short task-free magnetoencephalography (MEG) recording to capture reactions to different spoken language contrasts. Verbal cues with changes in vocabulary and meaning are used. Investigating intertribal phase coherence in five canonical frequency bands using multivariate pattern analysis and beamformer source reconstruction. The results show the capability to differentiate brain reactions to actual words and made-up words, correct and incorrect grammar, and semantic changes. The classification results show scattered activity patterns, influenced by various regions, but mostly controlled by core "temporofrontal" language circuits. Neurolinguistic features differ depending on the frequency bands, with broad gamma used for categorizing lexical processes, alpha and beta for semantic differences, and low gamma for syntax classification.

Crucially, the commencement of both processing modalities occurs precisely one hundred milliseconds after the receipt of auditory data, thereby allowing for the discernment of voiced and transcribed input. The findings imply that neural networks functioning at various frequency ranges are engaged in concurrent neuro-linguistic processes.

Feng *et al*.[15] presented a new method called Brain and Language Semantic Alignment, designed for generating text using EEG data. Due to the increasing interest in brain-computer interfaces, there is a rising demand for techniques that can convert EEG data into readable text. The paper introduces a Curriculum Semantic-aware Contrastive Learning (C-SCL) technique to address the difficulty by aligning subject-dependent EEG representations with their semantic-dependent equivalents. The C-SCL technique does this by aggregating semantically comparable EEG representations and separating different ones. The study utilizes curriculum learning to methodically design and improve the learning process by including more significant contrastive pairs over time. The proposed approach, when integrated with different models and architectures, achieves top performance, demonstrating consistent enhancements across three evaluation parameters. Moreover, further research emphasizes the benefits of this approach in situations with limited resources and individual subjects, as well as its strong potential to be applied in instances where no training data is available. This new approach is a significant improvement in EEG-to-Text generation, bridging the semantic gap between EEG signals and natural language to enhance brain-computer interactions in text generating applications.

It is essential to comprehend the connection between the progression of time, different frequency ranges, specific parts of the brain, and linguistic characteristics in order to effectively identify language difficulties in various populations. Recent research has emphasized the approach's impressive capacity to generalize in zero-shot settings and its benefits. Although the fNIRS data was not timed optimally and there was no specific design for distinct data kinds, the improvement in dual network performance in most participants is a promising result. To expand its use and overcome current restrictions, it is essential to acknowledge and evaluate the shortcomings of the method thoroughly to assess its overall effectiveness. Addressing these problems is crucial for fully maximizing the promise of this strategy in identifying linguistic anomalies in various populations.

1.2 Problem statement

The advancements made in the field of neural-device interfaces have been truly remarkable, however, establishing effective communication between "brain-machine" remains a challenging endeavor. Despite the potential demonstrated by current methods, their invasiveness poses substantial hazards and restricts their general use. However, current non-invasive methods for capturing cerebral language signals often struggle to capture complex successive samples that are associated with language processing. The complex and nuanced characteristics of brain impulses connected to language present substantial challenges for conventional approaches.

Architectures of this nature are particularly adept at detecting sequential relationships, making them well-suited for the purpose of deciphering intricate patterns present in neural language inputs. The main goal is to enhance human comprehension of non-invasive brain language decoding by developing and perfecting deep learning models. This would enable more efficient and user-friendly interactions with neurodevices. This breakthrough represents a significant milestone in the utilization of deep learning to revolutionize non-invasive neural language decoding, ultimately resulting in safer, more accessible, and user-friendly neural-device interfaces.[14]

2. Proposed neural linguistic learning model based on deep RNN-GRU

The following text presents a system that aims to enhance communication between brain and computer interfaces and language-processing devices without the need for invasive procedures. This approach is grounded in a multidisciplinary framework that incorporates neurolinguistic principles. The research examines the complex problem of interpreting brain signals related to language, bridging the gap between neuroscience and machine learning. The research aims to enhance the neural device interface through the utilization of advanced neural network architectures, particularly deep RNN and GRU.[16]

The current approach has the advantage of being non-invasive, so avoiding the use of intrusive methods and ensuring both practicality and adherence to ethical ideals. A Python implementation of a complex deep RNN-GRU model is constructed to precisely represent the various brain processes associated with language comprehension. The model's aptitude for dissecting complex linguistic structures, particularly those involving subject-related terms, exemplifies its potential for real-world applications, including brain-machine interfaces and supportive technologies.

This signifies notable progress in combining neurolinguistic learning and neurotechnology, providing a possible route to enhance communication between the human brain and external equipment. The methodology outlined in Fig. 1, is a complete framework designed to advance non-invasive brain communication. It has the potential to significantly impact the field of neuro-device interfaces.

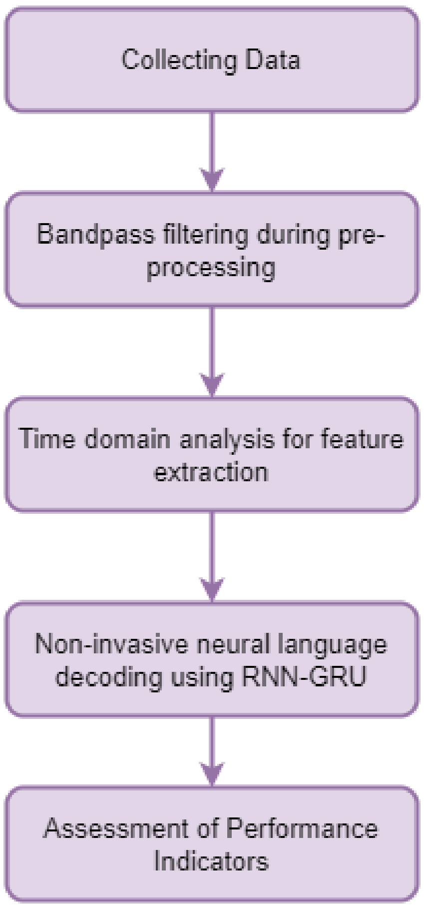

Fig. 1: Proposed methodology framework for advanced non-invasive brain communication.

2.1 Collecting data

Eleven healthy volunteers aged between 20 and 34 years, consisting of six males and five females, were recruited for the study. Before taking part, participants were extensively informed about the study's methodologies, theories, and goals. Every participant gave written consent following the guidelines of the Declaration of Helsinki.[17] When creating the experimental setup, eight terms representing the verb, subject, and object components of the sentences were meticulously chosen. The terms were selected for their significance in natural human-machine interaction, namely in the realm of neural mechanical arm control. The selection method intended to guarantee that the chosen concepts were relevant and feasible within the experimental context.

The study relied on a predetermined set of words, which integrated subjects such as I and partner, as well as verbs like move, have, and drink, and object terms like box, cup, and phone. The participants were instructed to say each word 30 times, and their audio cues were carefully recorded. To capture EEG signals, participants wore 64-channel EEG actiCaps during the EEG monitoring sessions. The EEG signals were accurately and precisely recorded using BrainVision Recorder software, specifically MATLAB 2024a version. High signal quality was carefully maintained throughout the whole testing. Additionally, visual stimuli were displayed on a monitor to help with understanding and involvement in the activity.[18]

Spectrogram embedding is a method used to convert EEG signals into a more accessible format for analysis and interpretation. EEG data, which depicts the electrical activity of the brain over time, is complex and can provide valuable insights into cognitive processes. The technique begins by dividing the EEG signal into minor sequential segments called epochs. The information is commonly presented as a two-dimensional visual, where time is shown on one side and frequency is shown on the other side. The visual representation allows researchers to view and analyze the frequency features of the EEG signal over time, aiding in a more profound comprehension of the underlying brain activity and cognitive processes.

2.2 Bandpass filtering during pre-processing

The bandpass filter in signal processing is crucial, as it selectively permits a designated range of frequencies while attenuating frequencies beyond this range. The utilization of this filter is of utmost importance in situations where the isolation of particular frequency components from a signal is necessary for meticulous investigation and interpretation.[19]

Bandpass filters play a crucial role in biomedical applications by selectively separating certain physiological signals, such as recognizing heartbeats in an electrocardiogram (ECG). This Filters enhance the accuracy of diagnosing and monitoring cardiac activity by enhancing the heartbeat signal frequency range and suppressing extraneous frequencies and noise. When analyzing EEG data for language performances, it is typical to use a "bandpass filter" set to a certain frequency scale that includes brain frequencies linked to cognitive functions like language comprehension and speech output. By doing this, undesired aspects like muscle artefacts or external interference are significantly reduced, enabling a more concentrated study of brain activity associated with the experimental task.[20]

This level is vital for extracting features for applications that demand a thorough analysis of brain patterns, including language decoding. This improves EEG data quality, aiding in the study of brain systems related to language and communication. It allows for a more accurate analysis and understanding of the neurological processes linked to cognitive tasks, which helps in creating new methods for investigating and interpreting brain function during language-related activities.

2.3 Time domain analysis for feature extraction

This technique involves the extraction and segregation of prominent characteristics from data patterns correlated with cerebral linguistic signals.

This approach greatly improves the ability of the features input into the next RNN-GRU model to distinguish between different elements, therefore aiding in the precise interpretation of intricate language structures. Feature extraction through time domain analysis is a vital preprocessing step that improves the neuro-linguistic decoding system's efficacy by capturing temporal information comprehensively.[21]

The model attains a more comprehensive and precise interpretation by employing time-domain analysis to identify features and examining the temporal dynamics of brain language signals. Extracting features using time-domain analysis is an essential step in understanding the temporal intricacies seen in EEG data associated with language processing. The following passage is crucial for enhancing the interaction between neurons and devices, particularly in the context of DRNN with GRU for non-invasive decoding of neural language. Examining time-domain aspects enables researchers to understand the interaction between linguistic components and brain activity during investigational tasks.

The distinct characteristics of the components of the ERP (Event-Related Potential), including their most significant levels of intensity, the time delays they exhibit, and their durations, offer a comprehensive portrayal of the intricate neural mechanisms that are associated with the various components of language. As shown in Eq. (1), the Mean Absolute Value (MAV) is a crucial metric in this area of study.

$$MAV = \frac{1}{L}\sum_{i=1}^{L}|y_i| \tag{1}$$

where the sample length is represented by L.

Zero crossing analysis is an essential method in EEG data processing, particularly for investigating the time-related patterns of brain activity. The approach aims to identify the specific points in the EEG data when the amplitude crosses the zero axis.[22] Zero crossings research offers useful insights into the frequency and nature of the rhythmic variations found in the EEG signal.

This method is super useful for researchers trying to figure out how the brain works when it comes to language processing. By looking at the EEG waveforms, they can tell how often the voltage goes from positive to negative and back again. This is important for understanding rhythmic patterns in the brain, which are key to language processing. It gives them a better understanding of how brain activity changes over time during language processing tasks, which helps them interpret EEG data more accurately in neurolinguistic research.

$$\{y_i < 0 \ and \ y_{i+1} > 0\} \ or \ \{y_i > 0 \ and \ y_{i+1} < 0\} \tag{2}$$

The successive samples are denoted as y_i and y_{i+1}.

Eq. (2) indicates the sign change condition between consecutive values y_i and y_{i+1} indicating a zero-crossing point. Examining temporal variables, such as signal duration, rise time, and fall time, could provide valuable insights into the timing aspects of brain responses during language tasks. By analyzing these temporal aspects, researchers can gain a better understanding of how the brain immediately processes language signals. Integrating time-domain analysis into the decoding of neural language patterns and training of deep RNN-GRU models is a wise strategy. This technique allows for the detection of sequential patterns in EEG data that are linked to the non-invasive interpretation of language. This comprehensive technique is designed to improve the connection between the brain and technology. These interfaces are versatile and can be utilized in assistive technology, rehabilitation, and communication.

2.4 Decoding neural networks using RNN-GRU: a non-invasive approach

Because of its exceptional ability to capture and understand temporal correlations within input sequences, RNN-GRUs are crucial for processing sequential data. GRUs are an adaptation of traditional RNNs that use gating techniques to solve problems like vanishing gradients and improve long-range dependency management.

Applications that require contextual information across different time steps, including speech recognition and natural language processing, are well-suited to the design of RNN-GRUs. With its parallel processing capabilities and the capacity to selectively update and forget information, RNN-GRUs are able to capture complex temporal patterns more effectively. RNN-GRU networks have demonstrated effectiveness in tasks requiring a detailed understanding of sequential input. Their adaptability and superior performance make them essential assets in industries that primarily rely on sequential data analysis and processing.

Training the deep RNN-GRU model involves feeding its language inputs while keeping tabs on its neural activity. The model enhances its proficiency in deciphering language-related data from brain signals by repeatedly executing the same code. As the model discovers patterns in the input data and associates them with linguistic features, it gains a deeper understanding of neural activity and language representation.

Neurolinguistic learning based on deep RNN-GRU has many important and practical uses. Outside of fundamental studies on the brain reinforcements of language, this paradigm shows promise for use in therapeutic settings. People who have trouble communicating may benefit from this information when designing assistive equipment. In addition, it has the potential to be a useful tool for monitoring how various forms of therapy affect brain activity associated with language.

There have been advancements, but deep neurolinguistic learning still faces a number of obstacles. Questions of privacy and permission, the understandability of data representations obtained, and the generalizability of models to other populations need more investigation. The advancement of deep RNN-GRU-based neurolinguistic learning is becoming more and more dependent on collaboration among linguists, neuroscientists, and machine learning specialists. Eq. (3) for the hidden state h_t at time t in the RNN is represented as follows.

$$h_t = tanh(y_t.V_h + h_{t-1}) \tag{3}$$

where y_t is symbolic of the input at instant t, h_{t-1} represents a condition that was hidden in a prior time step, V_h is the hidden state's weight matrix, and $tanh$ the activation function of hyperbolic tangent.

The utilization of the tangent hyperbolic function ($tanh$) on the individual elements of the sum of the input at time t and the weighted sum of the previous hidden state is a vital component of the GRU, a specific type of RNN engineered to efficiently handle sequential data. The tangent function performs a vital role in stabilizing gradients during backpropagation, thereby enhancing the model's capacity to learn and represent intricate temporal correlations in sequential data. The equations mentioned above constitute the fundamental components of the GRU.

The gates are essential for regulating the information flow by selecting which information to keep from the past hidden state h_{t-1} and the present input y_t. The update gate z_t controls the balance between retaining the prior hidden state and integrating the present input, while the reset gate r_t identifies the components of the prior hidden state to disregard.

Eq. (4) integrates the update gate z_t with the prior hidden state h_{t-1} and the candidate hidden state state h_t in Eq. (5). This combination enables a seamless shift from previous to present conditions, enabling the GRU to adeptly grasp and understand sequential patterns as they evolve over time. Eqs. (4)-(6) elucidate the intricate dynamics of a GRU, enabling it to proficiently discern and comprehend sequential patterns in several domains, including natural language processing and perhaps neurolinguistic learning. The GRU's capacity to maintain long-term connections while addressing the issue of the vanishing gradient problem makes it an effective tool for handling sequential data.

$$z_t = \sigma(y_t W^z + h_{t-1} V^z) \tag{4}$$

$$r_t = \sigma(y_t W^r + h_{t-1} V^r) \tag{5}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * h_t \tag{6}$$

The RNN-GRU algorithm consists of various essential stages in handling and examining sequential input. Here is an overview of the algorithm.[23]

- Load and preprocess data by applying “bandpass filter”.
- Characteristic Extraction: Time Domain Analysis.
- Describe the architecture of an “RNN-GRU” model.
- Partition of the data into training and testing sets.
- Implement training for the “RNN-GRU” model.
- Assess the model using the test set.
- Generate forecasts for fresh data.
- Visualize outcomes.

3. Results and discussion

The research utilizes an interdisciplinary method combining neuroscience and machine learning to interpret language-related brain signals. The goal is to improve neurodevice interfaces without using intrusive techniques by utilizing sophisticated neural network designs, such as deep RNN and GRU. The development of a specialized deep RNN-GRU language processing model represents a significant breakthrough in integrating neurolinguistic learning with neurotechnology, and it holds promising applications in

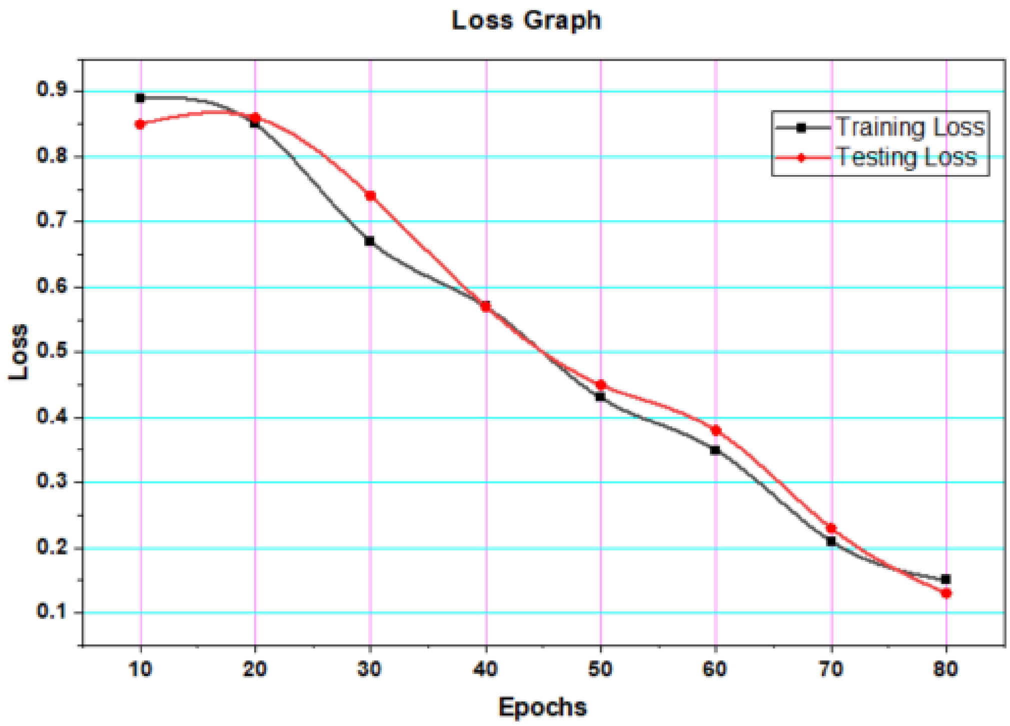

Fig. 2: Analysis of loss fluctuations and decoding accuracy, identifying key phases of learning and generalization.

assistive technologies and brain-machine interfaces.

3.1 Loss function

The model's loss is a crucial element in assessing the effectiveness of training by quantifying the disparity between predicted and actual neural linguistic patterns. An observed reduction in losses indicates successful parameter modifications and knowledge acquisition from the training dataset.[24] Fluctuations or plateaus in loss might indicate problems such as overfitting or underfitting, requiring modifications to hyperparameters. Analyzing how decoding accuracy and loss interact offers valuable information regarding the model's capacity to generalize and interpret various brain language patterns, as seen in Fig. 2.

3.2 Percent vlid crrect (PVC) prformance

To evaluate the accuracy and reliability of a predictive system, researchers often employ a statistical metric termed PVC n behavioral or cognitive investigations. PVC is the percentage of accurate responses or predictions among all valid cases considered for a task or experiment. This measure is calculated by ignoring inaccurate or unclear data items and focusing solely on the system's performance when valid replies or forecasts are possible. PVC offers a concentrated assessment of the system's performance, emphasizing its achievements, particularly in scenarios when the system is anticipated to give significant responses or predictions.

Examining how PVC performance varies across different linguistic components can offer valuable information about the model's capacity to identify and predict distinct aspects of sentence structure. Variations in PVC performance for verb, subject, and object words may imply differences in brain representations or levels of complexity associated with these language elements. This analysis guides modifications to the model's structure and training methods to improve decoding accuracy for various linguistic elements and to progress non-invasive brain language decoding procedures in neurolinguistic learning scenarios.

3.3 Accuracy of decoding over time

Evaluating decoding accuracy over time is an essential metric utilized to gauge the performance and progress of a neural decoding model during experimentation. This assesses the model's ability to decipher and comprehend neural patterns associated with specific cognitive processes or inputs at various intervals.[25] The assessment offers a comprehensive examination of the model's real-time operation and its potential applications, including brain-machine interfaces and neurolinguistic learning.

Fig. 3 illustrates a detailed depiction of the model's accuracy at various points in time during the experiment or task. Variations in precision at various time intervals may align with distinct phases of the experiment, such as the presentation of the stimulus or the execution of the linguistic task. Another critical component of evaluating the model's capacity to respond to fluctuations in brain activity over extended periods and pinpointing key moments for optimal performance is to examine these shifts in decoding accuracy. Moreover, conducting a temporal analysis of the model offers invaluable information for refining it, enabling researchers to adjust parameters or implement adaptive techniques to increase accuracy during crucial periods.

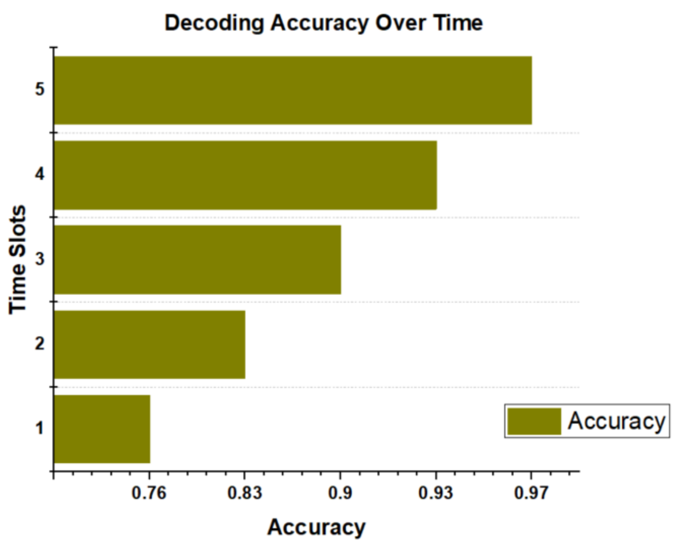

Fig. 3: Accuracy decoding over time.

3.4 PVC distribution among a variety of word types for several methods

The assessment of the effectiveness of principal component analysis (PCA) across different types of words in a dataset is stated as the distribution of PCA across word classes. This measure evaluates the precision of a system that categorizes or decodes linguistic information. Examining the PCA distribution offers a comprehensive evaluation of the model's capability, revealing its ability to respond and adapt to different linguistic components.

Table 1 displays the decoding accuracy scores of CSP-SVM (Common Spatial Pattern – Support Vector Machine pipeline),[26] EEGNet (Electroencephalography Neural Network),[27] and the proposed RNN-GRU model for various language components such as verbs, objects, and subjects. The outcomes indicate that the RNN-GRU model demonstrates greater performance compared to other approaches in all categories, achieving accuracies of 0.91 for subject words, 0.75 for verb words, and 0.72 for object words. The results suggest that the RNN-GRU architecture, which is specifically designed for neurolinguistic learning, surpasses conventional methods such as CSP-SVM and EEGNet.

Table 1: PVC distribution exploring diverse word categories for different methods.

Methods	Subject	Object	Verb
EEGNet[23]	0.78	0.56	0.53
CSP-SVM[22]	0.60	0.52	0.48
Proposed RNN-GRU	0.91	0.75	0.72

The notable enhancement in precision, especially in deciphering subject words, highlights the model's capacity to progress in both the neural-device interface and neurolinguistic learning domains. Refer to Fig. 4, for a graphical depiction of these findings.

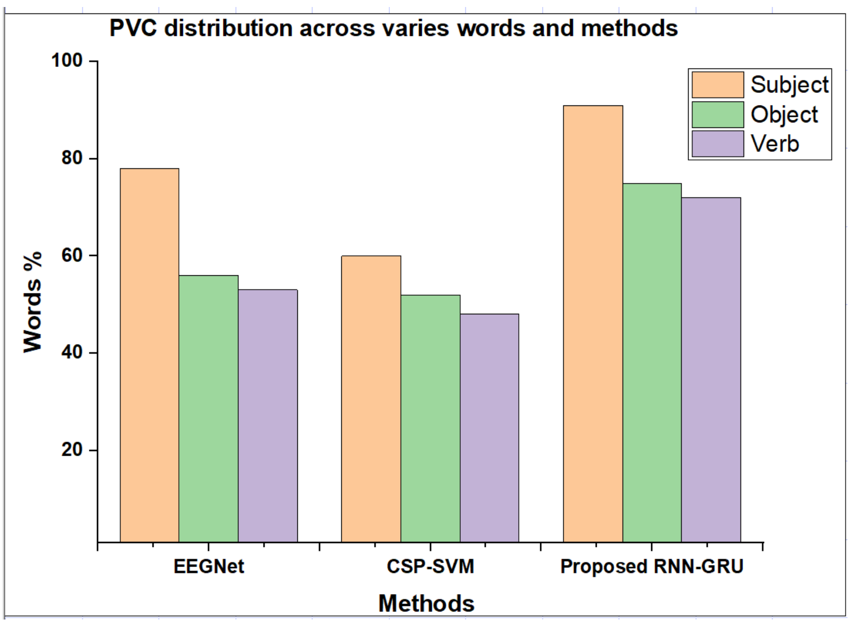

Fig. 4: PVC Distribution across varies words and methods.

3.5 Evaluation of the RNN-GRU model

The results indicate the model's proficiency in accurately interpreting various language elements, achieving accuracy rates of 91% for subject words, 75% for verbs, and 72% for objects. The findings demonstrate the efficacy of the RNN-GRU model in enhancing the accuracy of non-invasive neural language decoding systems compared to conventional models such as CSP-SVM and EEGNet.[28,29] The model's capacity to capture both short-term and long-term dependencies in EEG data enhances its ability to interpret dynamic brain activity associated with language processing.

The RNN-GRU model addresses significant limitations of conventional NNs,[30] including the vanishing gradient problem, through the implementation of GRUs. GRUs incorporate gating mechanisms that enable the model to retain significant temporal information throughout extended sequences, enhancing the decoding of complex brain signals. This architecture substantially improves the model's capacity to analyze the sequential data present in EEG signals, thereby enhancing its overall efficacy in decoding brain language patterns.[31]

The model's exceptional precision in interpreting neural signals demonstrates significant potential for practical applications in brain-machine interfaces (BMIs) and neural prosthetics. This technique may be employed in assistive communication devices for patients with conditions such as locked-in syndrome or amyotrophic lateral sclerosis (ALS), facilitating communication through brain-computer interfaces (BCIs) by converting neural patterns into speech or text.[32] Moreover, the model can be integrated into neuroprosthetic devices, enabling users to operate robotic limbs or other external apparatuses. Although empirical assessments have not been conducted, prospective collaborations with medical institutions are anticipated to evaluate the model's efficacy in clinical environments, specifically in enhancing motor control and communication in individuals with neurological disabilities.

The RNN-GRU model represents a significant advancement in neuro-device interfaces, offering improved accuracy and feasibility in non-invasive neural language decoding.[33] This development creates new opportunities for applications in neurotechnology, human-computer interfaces, and neurolinguistic learning, thereby enhancing the field of non-invasive brain language decoding.

3.6 Performance assessment of RNN-GRU in neural language decoding

The results of this study provide valuable insights into neurolinguistic learning techniques for deciphering non-intrusive brain language. The RNN-GRU model demonstrated a notable increase in accuracy compared to conventional techniques such as CSP-SVM and EEGNet, highlighting its ability to accurately capture and comprehend intricate brain patterns associated with various language elements. The variation in PVC performance across different types of words underscores the model's versatility in handling a range of language processing components. These findings have significant implications for the field of neuro-device interaction, showing that deep learning approaches, specifically the RNN-GRU model, can improve the accuracy and usefulness of non-invasive neural language decoding systems.

The findings acquired from the PVC performance of several word types illustrate the model's superior capabilities and capacity to adjust to a diverse set of language processing properties. The discovery has greatly progressed the field of neuro-device interface by highlighting the efficacy of deep learning methods, namely the RNN-GRU model, in improving the precision and feasibility of "non-invasive neural language decoding systems".[34] The results indicate possible uses in neurotechnology, human-computer interfaces, and neurolinguistic learning approaches, creating opportunities for upcoming developments in the non-invasive decoding of brain language.

This study evaluated the model's accuracy of 91% using the Percent Valid Correct (PVC) measure, which quantifies the proportion of accurate predictions across various language elements, including subjects, verbs, and objects. The dataset consisted of EEG signals obtained from 11 participants, each repeating the specified verbal components multiple times. Cross-validation was utilized to guarantee robust model performance by dividing the data into training and testing sets. Supplementary metrics, including accuracy, recall, and the F1-score, were computed for each linguistic component to evaluate the equilibrium between true positives and false positives.[35] Furthermore, the Mean Squared Error (MSE)[36] loss function was utilized to quantify the discrepancy between the predicted and actual outputs during training, providing insights into the model's learning efficiency over time. By incorporating these indicators, we ensured the model's predictive reliability and accuracy.[37]

4. Conclusion and future work

This study demonstrates the significant potential of an RNN-GRU-based neurolinguistic learning model in advancing non-invasive cerebral language decoding and enhancing the functionality of brain-device interfaces. The model achieved an accuracy of 91% in decoding subject words, 75% for verbs, and 72% for object words, indicating its efficacy in managing various linguistic components. These results surpass those of traditional approaches, such as CSP-SVM and EEGNet, in accurately interpreting complex brain signals associated with language processing. The RNN-GRU model exhibited proficiency in capturing both short-term and long-term relationships in EEG data, rendering it a robust solution for non-invasive neural language decoding.

The results demonstrate the model's robustness to diverse linguistic elements, as evidenced by the Percent Valid Correct (PVC) performance across distinct word categories. This finding underscores the model's potential applicability in practical scenarios, particularly in brain-machine interfaces and assistive communication technology for patients with conditions such as amyotrophic lateral sclerosis (ALS) or locked-in syndrome. Subsequent research will focus on expanding the dataset to include additional participants and a broader range of language inputs, thereby enhancing the model's scalability and robustness. Moreover, improving the model's real-time decoding capabilities and its resilience to noise in EEG signals would be crucial for practical implementation. Ethical considerations, including data protection and secure management of brain data, will be prioritized to ensure the responsible implementation of this technology. This investigation elucidates the potential of neurolinguistic learning and non-invasive brain language decoding, establishing a foundation for the development of advanced, ethically sound neuron-device interfaces that are both precise and applicable in real-world contexts.

Numerous avenues for future research exist to expand upon the findings of this study. A primary challenge is the model's scalability. Expanding the dataset to incorporate additional participants and a wider array of linguistic inputs will be essential for ensuring the model's robustness and practical applicability. Another crucial objective is enhancing the model's real-time decoding capabilities, allowing it to process neural signals with minimal latency, which is vital for applications in brain-machine interfaces (BMIs) and neuroprosthetic control systems. Evaluating the model's efficacy in real-time applications will be an essential phase. The RNN-GRU model is adept at managing sequential data, enabling it to interpret neural impulses in real time. Subsequent assessments will involve the integration of the model with current real-time EEG equipment to assess its proficiency in accurately decoding brain signals as they are generated. Critical metrics, including reaction time, latency, and accuracy, will be evaluated in practical applications, such as brain-computer interfaces (BCIs) and assistive communication devices.

Furthermore, enhancing the model's resilience to noise is essential, particularly in scenarios where brain data may be compromised by muscular artifacts or external disturbances. Future research endeavors will focus on incorporating advanced noise-filtering methodologies to ensure optimal performance in less controlled environments. Additionally, ethical considerations, such as data privacy, participant consent, and secure management of brain data, are critical for the implementation of this technology in practical settings. Addressing these ethical issues will be a primary objective in the subsequent phase of research, ensuring that the model's real-world applications are secure and ethically responsible.

Acknowledgements

This work is supported by Ministry of Higher Education, Research and Innovation (MoHERI) Sultanate of Oman, under the Block Funding Program of Research Grant #BFP/RGP/ICT/23/420.

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

References

[1] W. Xiong, H. Fan, L. Ma, C. Wang, Challenges of human: machine collaboration in risky decision-making, *Frontiers of Engineering Management*, 2022, **9**, 89-103, doi: 10.1007/s42524-021-0182-0.

[2] K. E. ArunKumar, D. V. Kalaga, C. Mohan Sai Kumar, M. Kawaji, T. M. Brenza, Comparative analysis of Gated Recurrent Units (GRU), long Short-Term memory (LSTM) cells, autoregressive Integrated moving average (ARIMA), seasonal autoregressive Integrated moving average (SARIMA) for forecasting COVID-19 trends, *Alexandria Engineering Journal*, 2022, **61**, 7585-7603, doi: 10.1016/j.aej.2022.01.011.

[3] C. Surianarayanan, J. J. Lawrence, P. R. Chelliah, E. Prakash, C. Hewage, Convergence of artificial intelligence and neuroscience towards the diagnosis of neurological disorders: a scoping review, *Sensors*, 2023, **23**, 3062, doi: 10.3390/s23063062.

[4] E. Rossi, M. Diaz, How aging and bilingualism influence language processing, *Linguistic Approaches to Bilingualism*, 2016, **6**, 9-42, doi: 10.1075/lab.14029.ros.

[5] S. Palarimath, H. Gunasekaran, Advancing brain image segmentation: a comprehensive exploration of enhanced VGG16 architecture for precise neuroanatomical mapping, *2024 2nd International Conference on Computing and Data Analytics (ICCDA)*, November 12-13, Shinas, Oman, IEEE, 2024, 1-6, doi

10.1109/ICCDA64887.2024.10867393.
[6] M. Semprini, M. Laffranchi, V. Sanguineti, L. Avanzino, R. De Icco, L. De Michieli, M. Chiappalone, Technological approaches for neurorehabilitation: from robotic devices to brain stimulation and beyond, *Frontiers in Neurology*, 2018, **9**, 212, doi: 10.3389/fneur.2018.00212.
[7] T. Hilken, M. Chylinski, K. de Ruyter, J. Heller, D. I. Keeling, Exploring the frontiers in reality-enhanced service communication: from augmented and virtual reality to neuro-enhanced reality, *Journal of Service Management*, 2022, **33**, 657-674, doi: 10.1108/josm-11-2021-0439.
[8] J. S. G. Al Balushi, M. I. A. Al Jabri, S. Palarimath, P. Maran, K. Thenmozhi, C. Balakumar, Incorporating artificial intelligence powered immersive realities to improve learning using virtual reality (VR) and augmented reality (AR) technology, *2024 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, June 5-7, 2024, Salem, India,I EEE, 2024, 760-765, doi: 10.1109/ICAAIC60222.2024.10575046.
[9] N. R. Dash, S. Y. Guraya, M. T. Al Bataineh, M. E. Abdalla, M. S. B. Yusoff, M. F. Al-Qahtani, W. N. K. A. van Mook, M. S. Shafi, H. H. Almaramhy, W. N. O. Mukhtar, Preferred teaching styles of medical faculty: an international multi-center study, *BMC Medical Education*, 2020, **20**, 480, doi: 10.1186/s12909-020-02358-0.
[10] F. Llanos, J. R. McHaney, W. L. Schuerman, H. G. Yi, M. K. Leonard, B. Chandrasekaran, Non-invasive peripheral nerve stimulation selectively enhances speech category learning in adults, *NPJ Science of Learning*, 2020, **5**, 12, doi: 10.1038/s41539-020-0070-0.
[11] D. Dash, P. Ferrari, A. Hernandez, D. Heitzman, S. G. Austin, J. Wang, Neural speech decoding for amyotrophic lateral sclerosis, *Interspeech*, 2020, 2782, doi: 10.21437/interspeech.2020-3071.
[12] T. C. Zhao, F. Llanos, B. Chandrasekaran, P. K. Kuhl, Language experience during the sensitive period narrows infants' sensory encoding of lexical tones: Music intervention reverses it, *Frontiers in Human Neuroscience*, 2022, **16**, 941853, doi: 10.3389/fnhum.2022.941853.
[13] C. Cooney, R. Folli, D. Coyle, A bimodal deep learning architecture for EEG-fNIRS decoding of overt and imagined speech, *IEEE Transactions on Biomedical Engineering*, 2022, **69**, 1983-1994, doi: 10.1109/TBME.2021.3132861.
[14] M. Jensen, R. Hyder, Y. Shtyrov, MVPA analysis of intertrial phase coherence of neuromagnetic responses to words reliably classifies multiple levels of language processing in the brain, *Eneuro*, 2019, **6**, 16, doi: 10.1523/eneuro.0444-18.2019.
[15] X. Feng, X. Feng, B. Qin, T. Liu, Aligning semantic in brain and language: a curriculum contrastive method for electroencephalography-to-text generation, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2023, **31**, 3874-3883, doi: 10.1109/TNSRE.2023.3314642.
[16] F. Badrulhisham, E. Pogatzki-Zahn, D. Segelcke, T. Spisak, J. Vollert, Machine learning and artificial intelligence in neuroscience: a primer for researchers, *Brain, Behavior, and Immunity*, 2024, **115**, 470-479, doi: 10.1016/j.bbi.2023.11.005.
[17] M. D. E. Goodyear, K. Krleza-Jeric, T. Lemmens, The declaration of Helsinki, *BMJ*, 2007, **335**, 624-625, doi: 10.1136/bmj.39339.610000.be.
[18] J. Jeong, J. Cho, K. Shim, B. Kwon, B. Lee, D. Lee, D. Lee, S. Lee, Multimodal signal dataset for 11 intuitive movement tasks from single upper extremity during multiple recording sessions, *GigaScience*, 2020, **9**, 1-15, doi: 10.1093/gigascience/giaa098.
[19] M. Witteveen, H. J. C. M. Sterenborg, T. G. van Leeuwen, M. C. G. Aalders, T. J. M. Ruers, A. L. Post, Comparison of preprocessing techniques to reduce nontissue-related variations in hyperspectral reflectance imaging, *Journal of Biomedical Optics*, 2022, **27**, 106003, doi: 10.1117/1.jbo.27.10.106003.
[20] E. Bedoyan, J. W. Reddy, A. Kalmykov, T. Cohen-Karni, M. Chamanzar, Adaptive frequency-domain filtering for neural signal preprocessing, *NeuroImage*, 2023, **284**, 120429, doi: 10.1016/j.neuroimage.2023.120429.
[21] M. S. Keezhatta, The impact of neuro-linguistic programming on English language teaching: perceptions of NLP-trained English teachers, *International Journal of English Linguistics*, 2019, **9**, 454, doi: 10.5539/ijel.v9n6p454.
[22] J. Pyrzowski, J. E. Le Douget, A. Fouad, M. Siemiński, J. Jędrzejczak, M. Le Van Quyen, Zero-crossing patterns reveal subtle epileptiform discharges in the scalp EEG, *Scientific Reports*, 2021, **11**, 4128, doi: 10.1038/s41598-021-83337-3.
[23] Z. Zainuddin, Predicting machine failure using recurrent neural network-gated recurrent unit (RNN-GRU) through time series data, *Bulletin of Electrical Engineering and Informatics*, 2021, **10**, 870-878, doi: 10.11591/eei.v10i2.2036.
[24] L. Ciampiconi, A. Elwood, M. Leonardi, A. Mohamed, A. Rozza, A survey and taxonomy of loss functions in machine learning, *arxiv preprint arxiv:2301.05579*, 2023, doi: 10.48550/arXiv.2301.05579.
[25] D. Walther, J. Viehweg, J. Haueisen, P. Mäder, A systematic comparison of deep learning methods for EEG time series analysis, *Frontiers in Neuroinformatics*, 2023, **17**, 1067095, doi: 10.3389/fninf.2023.1067095.
[26] R. Chatterjee, T. Bandyopadhyay, EEG based motor imagery classification using SVM and MLP, *2016 2nd International Conference on Computational Intelligence and Networks (CINE)*, January 11, Bhubaneswar, India, IEEE, 2016, 84-89, doi: 10.1109/CINE.2016.22.
[27] T. Schneider, X. Wang, M. Hersche, L. Cavigelli, L. Benini, Q-EEGNet: an energy-efficient 8-bit quantized parallel EEGNet

implementation for edge motor-imagery brain-machine interfaces, *2020 IEEE International Conference on Smart Computing (SMARTCOMP)*, September 14-17, Bologna, Italy, IEEE, 2020, 284-289, doi: 10.1109/smartcomp50058.2020.00065.

[28] P. B. Júnior, D. P. Campos, A. E. Lazzaretti, P. Nohama, A. A. Carvalho, E. Krueger, M. C. M. Teixeira, Influence of EEG channel reduction on lower limb motor imagery during electrical stimulation in healthy and paraplegic subjects, *Research on Biomedical Engineering*, 2022, **38**, 689-699, doi: 10.1007/s42600-021-00189-6.

[29] P. Saideepthi, A. Chowdhury, P. Gaur, R. B. Pachori, Sliding window along with EEGNet-based prediction of EEG motor imagery, *IEEE Sensors Journal*, 2023, **23**, 17703-17713, doi: 10.1109/JSEN.2023.3270281.

[30] B. Musunuri, S. Shetty, D. K. Shetty, M. K. Vanahalli, A. Pradhan, N. Naik, R. Paul, Acute-on-chronic liver failure mortality prediction using an artificial neural network, *Engineered Science*, 2021, **15**, 187-196, doi: 10.30919/es8d515.

[31] S. A. Murad, I. Member, N. Rahimi, I. Member, Unveiling thoughts: a review of advancements in EEG brain signal decoding into text, *IEEE Transactions on Cognitive and Developmental Systems*, 2025, **17**, 1-15, doi: 10.1109/tcds.2024.3462452.

[32] R. D. Prasad, N. R. Prasad, R. S. Prasad, N. Prasad, S. R. Prasad, M. Shrivastav, M. Gour, V. B. Kale, Z. Guo, C. B. Desai, G. M. Nazeruddin, Y. I. Shaikh, S. Banga, P. Sane, M. Saxena, J. Kamble, A review on nanotechnology from prehistoric to modern age, *ES General*, 2024, **4**, 1117, doi: 10.30919/esg1117.

[33] A. Balakrishnan, J. Medikonda, P. K. Namboothiri, M. Natarajan, Role of wearable sensors with machine learning approaches in gait analysis for Parkinson’s disease assessment: a review, *Engineered Science*, 2022, **19**, 5-19 doi: 10.30919/es8e622.

[34] S. Palarimath, N. R. Wilfred Blessing, T. Sujatha, M. Pyingkodi, B. H. Ugalde, R. D. Palarimath, A robust authentication and authorization system powered by deep learning and incorporating hand signals, *Intelligent Data Communication Technologies and Internet of Things, Lecture Notes on Data Engineering and Communications Technologies*, Springer Nature, Singapore, 2022, 1061-1071, doi: 10.1007/978-981-16-7610-9_77.

[35] S. Palarimath, P. Maran, K. V. Shiny, T. Sujatha, W. B. NR, Empowering breast cancer detection with AI: a modified support vector machine approach for improved classification accuracy, *2024 International Conference on Expert Clouds and Applications (ICOECA)*, April 18-19, Bengaluru, India, IEEE, 2024, 897-903, doi: 10.1109/ICOECA62351.2024.00159.

[36] C. J. Willmott, K. Matsuura, Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance, *Climate Research*, 2005, **30**, 79-82, doi: 10.3354/cr030079.

[37] S. Ali, T. Abuhmed, S. El-Sappagh, K. Muhammad, J. M. Alonso-Moral, R. Confalonieri, R. Guidotti, J. Del Ser, N. Díaz-Rodríguez, F. Herrera, Explainable Artificial Intelligence (XAI): What we know and what is left to attain Trustworthy Artificial Intelligence, *Information Fusion*, 2023, **99**, 101805, doi: 10.1016/j.inffus.2023.101805.