Elevating Neuro-Linguistic Decoding: Deepening Neural-Device Interaction with RNN-GRU for Non-Invasive Language Decoding

V Moses Jayakumar[1]*, Dr. R. Rajakumari[2], Ms. Kuppala Padmini[3], Dr. Sanjiv Rao Godla[4],
Prof. Ts. Dr. Yousef A.Baker El-Ebiary[5], Dr. Vijayalakshmi Ponnuswamy[6]
Department of English and Foreign Languages, Saveetha School of Engineering, SIMATS, Chennai, India[1]
Associate professor, Department of English and Foreign Languages, Saveetha School of Engineering, SIMATS, Chennai, India[2]
Assistant Professor, Computer Science and Science Department,
Sreenidhi Institute of Science and Technology, Hyderabad, Telangana[3]
Professor, Department of CSE (Artificial Intelligence & Machine Learning),
Aditya College of Engineering & Technology - Surampalem, Andhra Pradesh, India[4]
Faculty of Informatics and Computing, UniSZA University, Malaysia[5]
Professor, Department of Artificial Intelligence and Data Science, Koneru Lakshmiah Educational Foundation (KL Deemed to be University), Green Fields, Vaddeswaram, Guntur District, Andhra Pradesh, India[6]

Abstract*—Exploring innovative pathways for non-invasive neural communication with language interfaces, this research delves into the interdisciplinary realm of neurolinguistic learning, merging neuroscience and machine learning. It scrutinizes the intricacies of decoding neural patterns associated with language comprehension. Leveraging advanced neural network architectures, specifically Deep Recurrent Neural Networks (RNN) and Gated Recurrent Units (GRU), the study aims to amplify the landscape of neuro-device interaction. The focus of Neurolinguistic Learning lies in extracting language-related brain signals without resorting to invasive procedures. Employing cutting-edge non-invasive methods and deep learning techniques, the research aims to elevate the capabilities of neural devices such as brain-machine interfaces and neuroprosthetics. A distinctive approach involves crafting a sophisticated Deep RNN-GRU model designed to capture intricate brain patterns linked to language processing. This architectural innovation, implemented in the Python software environment, harnesses the strengths of RNNs and GRUs to enhance language decoding. The study's outcomes hold promise for advancing non-invasive brain language decoding systems, contributing to the expanding knowledge base in neurolinguistic learning. The remarkable accuracy of the proposed RNN-GRU model, boasting a 90% accuracy rate, signifies its potential application in critical real-world scenarios. This includes assistive technologies and brain-machine interfaces where precise decoding of cerebral language signals is paramount. The research underscores the efficacy of deep learning methodologies in pushing the boundaries of neurotechnology. Notably, the model outperforms established techniques, surpassing alternatives like CSP-SVM and EEGNet by an impressive 30.4% in accuracy. The model's proficiency in deciphering topic words underscores its ability to extract intricate language patterns from non-invasive brain inputs.

Keywords*—Recurrent Neural Networks (RNN); Gated Recurrent Units (GRU); neurolinguistic learning; neural devices; brain machine interfaces

I. INTRODUCTION

Within the quickly developing field of neurotechnology, the goal of creating a seamless interface between the human brain and external devices has spurred innovative research efforts [1]. Neuro technology is advancing by developing neural-device interaction, an interdisciplinary field that combines neuroscience and engineering to improve two-way communication between neural systems and external devices, aiming to create a seamless interface [2]. Addressing fundamental issues and opening up new avenues for human-machine interfaces are the driving forces behind the advancement of neural-device interaction [3]. Conventional means of communication between neural devices and the brain frequently struggle with issues of signal integrity, bandwidth of information, and procedure invasiveness [4]. It is becoming increasingly important to overcome these obstacles as technology develops in order to improve our comprehension of neural processes and to use this knowledge for useful applications that help people with neurological disorders, disabilities, or those looking to enhance their cognitive abilities.

The understanding of neural signaling’ s complexity and the need for advanced models capable of real-time signal interpretation and deciphering are at the core of this research endeavor [5]. One promising approach is the use of deep reinforcement learning networks (DNRNNs) and GRUs. The dynamic information embedded in neural signals linked to different cognitive functions can be decoded by these models, which are excellent at capturing temporal dependencies and sequential patterns [6]. Learning more about neural-device interaction is important not only for academics and researchers, but also for a wide range of applications in human-computer interaction, rehabilitation, and healthcare [7]. More innovative assistive technologies, tailored therapeutic interventions, and more successful neuroprosthetics can all be made possible by improved neural-device interfaces [8].

Furthermore, these developments pave the way for revolutionary discoveries in areas like brain-machine interfaces, neuromodulation, and cognitive augmentation by facilitating a more intuitive and natural interaction between people and machines [9]. This research explores various methods for data collection and neural network architecture creation, emphasizing non-invasiveness. It describes a workflow for deep RNN-GRU-based neurolinguistic learning to improve neural-device interaction. The goal is to advance brain functions and foster a new era of human-machine cooperation [10].

A growing field identified as neurolinguistic learning has emerged from the dynamic intersection of neuroscience and artificial intelligence in an effort to understand the neural basis of language [11]. In an effort to uncover the mysteries buried in the neural code that underpins our capacity for language comprehension and production, this research explores the complex relationship between neural activity and language processing. Neurolinguistic learning aims to directly access the neural substrate of language, in contrast to traditional linguistic analyses, which rely on external behavioral measures. This approach provides a more nuanced and direct understanding of the cognitive processes involved. The realization that language, a distinguishing feature of human cognition, is not limited to observable behaviors or linguistic outputs is what spurred researchers to explore the field of neurolinguistic learning [12]. Rather, it is firmly anchored in the intricate and dynamic neural activity patterns that emerge inside the brain.

Specifically, non-invasive neural language decoding is the emphasis of this research, which is an important application of neurolinguistic learning [13]. Using invasive techniques like brain electrode implantation, the traditional methods for deciphering neural language patterns are frequently applied. Concerns about safety, ethics, and the need to create more widely available technologies, however, drive the search for non-invasive alternatives. Understanding neural language processes can be gained without invasive procedures by using non-invasive techniques like functional magnetic resonance imaging (fMRI) and electroencephalography (EEG). This work aims to apply deep learning models, namely Deep RNN and GRU, to advance the state-of-the-art in non-invasive neural language decoding. These architectures are especially well-suited to modeling the dynamic nature of language processing because they are good at capturing sequential patterns and temporal dependencies. Through the use of these sophisticated neural network architectures, the research hopes to shed light on the complexities of neural language representation and, as a result, improve our comprehension and decoding skills for the ideas encoded in neural language [3].

Non-invasive neural language decoding has potential to revolutionize assistive technology, neurorehabilitation, and communication technology. It can help people with communication impairments, offer new perspectives on cognitive processes, and create more user-friendly interfaces. This project combines linguistics, artificial intelligence, and neuroscience, transforming our understanding of language and the human mind. [14].Improving the smooth connection between neural devices and the complex processes of language expression and comprehension is one of the main issues in this field [1]. The need to overcome the drawbacks of the invasive procedures that are typically used in neural interface development is what drives this research [15]. Even though they work well, invasive techniques like implanting electrodes directly into the brain come with risks, such as tissue damage and infections. As a result, the search for non-invasive substitutes has taken center stage in the development of neural-device interfaces [16]. This project specifically focuses on leveraging advanced neural network architectures, namely Deep RNN and GRU, to decode neural language signals without resorting to invasive interventions.

Our main focus is on the field of neurolinguistic learning, which investigates the complex connection between language processing and brain activity. The complexity of language patterns is a challenge for traditional neural interfaces because of the difficulties in decoding the rich and dynamic information contained in neural signals. In this work, the author explore the potential of deep learning—more especially, RNN-GRU models—to non-invasively decipher the complex patterns related to language. RNN-GRU models were specifically chosen because of their demonstrated ability to handle sequential data and capture temporal dependencies. These architectures offer a sophisticated understanding of how neural signals encode linguistic information over time, making them well-suited to simulate the dynamic nature of language processing. Through these advanced neural network architectures, we hope to open up new possibilities for neural devices and usher in a new era of non-invasive neural language decoding.

The practical applications of this research have transformative potential and go beyond the domain of neuroscience. A successful implementation could transform augmentative communication technologies and make it possible for people with disabilities or communication disorders to express themselves with never-before-seen ease. Furthermore, our method's non-invasiveness reduces related health risks and encourages accessibility and broad acceptance.

The key contributions of the article is,

- The work proposes a non-invasive method for neurolinguistic learning that harvests language-related brain signals without necessitating invasive procedures. This is achieved by utilizing the most advanced deep learning algorithms, specifically Deep RNN-GRU.
- The study increases the possibility of neuro-device interaction by using complex neural network architectures, notably Deep RNN and GRU. This technology has significant promise for non-invasive neuro-communication applications in both ethical and helpful situations. The incorporation of these topologies facilitates the capture of complex brain patterns associated with language processing in the creation of neurotechnological interfaces.
- The real contribution is the development and use of the Deep RNN-GRU model, which is done using the

Python programming language. This well-designed architecture plays to the strengths of RNNs and GRUs while showcasing an advanced tool for improved language decoding, encouraging transparency and reproducibility within the scientific community.

- The work offers novel and analytical techniques for deciphering language-related brain signals, which significantly advances the rapidly expanding field of neurolinguistic learning. The exceptional accuracy and performance of the suggested RNN-GRU model demonstrate its potential as a revolutionary tool in the ongoing advancement of non-invasive neural language decoding systems.

The remainder sections of the article includes related works, problem statement, methodology and results in Sections II, III, IV and V respectively. The paper is concluded in Section VI.

II. Related Works

Dash et al. [17] proposed neural interpretation of speech in amyotrophic lateral sclerosis. A motor neuron-related illness identified as ALS can result in locked-in syndrome, which is total paralysis with awareness. Through brain computer interfaces, such as EEG spellers, which have a low communication rate, these locked-in patients can converse. Neural speech decoding paradigms that could lead to normal communication rates have been the focus of recent research. However, the focus of current neural decoding research is on typical speakers, and it is unclear how far these findings can be applied to a target population (such as those with ALS). The study examined the decoding of spoken and imagined phrases from non-invasive magnetic resonance imaging signals of individuals with ALS using seven machine learning decoders and multiple spectral characteristics (band-power of neural signals: delta, theta, alpha, beta, and gamma frequency ranges). The outcomes of the experiment showed that while ALS patients' decoding performance is considerably higher than chance, it is still lower than that of healthy individuals. For five imagined phrases and five spoken phrases from ALS patients, the best scores were 75% and 88%, respectively. As far, this is the first instance of neural speech decoding for a population with speech disorders. The disadvantage is that in order to confirm the study's effectiveness, analysis involving a greater number of individuals with more severe ALS and multiple sessions are required. Moreover, improved neurolinguistic comprehension of the imagining of speech would facilitate the development of algorithms for improved imagined speech decoding performance.

Cooney et al. [13] proposed an EEG-fNIRS bimodal deep machine learning design for overt and imagining speech decoding. Research on brain-computer interfaces is increasingly utilizing various characteristics of multiple signal modalities at the same time. The bimodal gathering procedures that integrate the temporal and spatial resolutions of electroencephalography and near-infrared spectroscopy require new decoding techniques. Present an EEG-fNIRS hybrid BCI that utilizes a unique bimodal in nature deep neural network design consisting of two convolutional sub-networks to decode both overt and imagined speech. Each subnet's features are fused before being further extracted and categorized. Classification accuracy using the hybrid approach showed substantial gains on EEG used independently for imagined speech ($p = 0.02$) and a tendency towards a significance for overt speech .The classification accuracy was 46.31% and 34.29%. Bimodal decoding produced significantly better results for both speech types when compared to fNIRS .While stimulus affected overt and imagined words in significantly different ways, deeper subnets improved performance. The bimodal approach performed significantly better than the unimodal results for several tasks. The results imply that neural signal decoding could be enhanced by multi-modal deep learning. With this novel architecture, speech deciphering from bimodal in nature neural signals can be enhanced.

Llanos et al. [18] proposed peripheral stimulation of nerves without invasive procedures improves speech in adults category learning. In animal models, vagus nerve stimulation has been demonstrated to prime adult sensory-perceptual systems towards plasticity. Accurate temporal integrating with auditory stimuli can significantly improve the specificity of auditory cortical representations. Here, the study investigated whether adult speech category learning is improved by sub-perceptual thresholds transcutaneous stimulation of the vagus nerve in conjunction with non-native speech sounds. To recognize non-native Mandarin tone categories, twenty-four native English speakers received training. The tVNS was matched with the tone groups that were either easier or harder to learn for each of the two groups. While receiving no stimulation, the control group used the same thresholding process as the intervention groups. Our findings showed that tVNS significantly improved learning and retention of accurate stimulus-response associations for speech categories, but only when stimulus was combined with categories that were simpler to learn. This effect manifested quickly, generalizing to new exemplars, and differed qualitatively from the typical individual variability seen in hundreds of learners completing the same task in the absence of stimulus. Before and after training, electroencephalography recordings showed no signs of tVNS-induced modifications to the sensation representations of auditory stimuli. According to these findings, paired-tVNS selectively improves both perception and consolidation of memories of intuitively salient categories by inducing a temporally exact neuromodulatory signal.

Feng et al. [19] proposed brain and language semantic alignment: a curriculum contrastive approach for electroencephalography-to-text generation. The tremendous potential for brain-computer interfaces has led to a growing interest in Electroencephalography-to-Text creation, which attempts to produce natural text from EEG signals. But a significant obstacle to this task is the striking difference between the semantic-dependent representation of text and the subject-dependent EEG representation. In order to address this, the study develops a Curriculum Semantic-aware Contrastive Learning approach that reduces the discrepancy by effectively recalibrating the subject-dependent EEG representation to the semantic-dependent equivalent. More precisely, semantically similar EEG representations are pulled together by our C-SCL, while dissimilar ones are pushed apart. Furthermore, carefully utilize curriculum learning to both craft and make the learning progressively meaningful contrastive pairs in order to incorporate more meaningful contrastive pairs. Numerous experiments on the ZuCo benchmark, and our approach, when combined with various models and architectures, achieve the new state-of-the-art while demonstrating steady improvements through three types of metrics. Additional research demonstrates not just its advantages in low-resource and single-subject settings, but also its strong generalizability in zero-shot scenarios.

Lee et al. [20] proposed deciphering language-specific imagined speech neural correlation through EEG signals. Degenerative diseases and brain lesions can cause devastating speech impairments. For people with severe speech deficits, the use of imaginary speech in brain-computer interfaces has proven to be an urging hope for reestablishing speech production nerve impulses. However, due to low signal-to-noise ratio and high variation in both temporal and spatial information, studies in the EEG-based simulated speech domain still have some limitations. In this work, the author examined the neural signals of two native speaker groups performing two tasks in separate languages like English and Chinese. The study postulated that the tonal and ideogram-based Chinese language and the non-tonal and phonogram-based English language would differ spectrally in how their brains computed speech. The results showed that, in some frequency band groups, Chinese and English had significantly different corresponding power spectral densities. Furthermore, native Chinese speakers in the theta band demonstrated distinct spatial evaluation during the imagination task. In order to decode the brainwaves of speech, this paper will therefore propose the essential the spectral and spatial data of word creativity with specialized language. The main flaw is that while the experiment's imagination tasks were designed to categorize words using machine learning algorithms, there hasn't yet been any evaluation of the classification performance.

Jensen et al. [21] proposed MVPA analysis of intertribal phase coherence of neuromagnetic responses to words reliably classifies multiple levels of language processing in the brain. One of the least understood aspects of the human brain is language's neural processing, yet a number of circumstances call for an objective, participant-friendly, and noninvasive assessment of the language function's neurocognitive state. A brief task-free recording of MEG reactions to a series of spoken language contrasts was suggested as a basis for a solution to this problem. Spoken stimuli with differences in lexicon, semantics, were used. The multivariate pattern analysis to investigate intertribal phase coherence in five canonical bands based on beam former source reconstruction is utilized. By employing this method, effectively distinguish between the brain responses to real words and pseudo words, between proper and improper syntax, and between semantic variations. The most accurate classification results showed dispersed activity patterns that were augmented by other regions while being dominated by the core temporofrontal language circuits. The neurolinguistic properties varied across frequency bands; broad γ was used to classify lexical processes, α and β was used to classify semantic distinctions, and low γ feature patterns were used to classify syntax. Importantly, every kind of processing started almost simultaneously 100 milliseconds after the auditory data made it possible to distinguish between spoken and written input. This demonstrates that distinct neuronal networks operating at different frequency bands are involved in individual neurolinguistic processes, which occur simultaneously. This gives rise to even greater hope that neurolinguistic processes in a variety of populations can be objectively and noninvasively evaluated using brain imaging. The disadvantage is that in order to determine whether this method can be used to identify linguistic abnormalities in different populations, it is necessary to fully comprehend the relationship between time courses, frequency bands, neuronal substrates, and neurolinguistic properties.

Time courses, frequency bands, neuronal substrates, and neurolinguistic properties interact in a way that necessitates a thorough comprehension of the approach being considered for detecting linguistic abnormalities in different populations. Although this has great potential, a major limitation is that the classification performance of the word categorization tasks created with machine learning algorithms is not evaluated. Nevertheless, more recent studies demonstrate the method's strong generalizability in zero-shot scenarios in addition to its benefits in low-resource and single-subject settings. Notably, despite subnets not being specifically designed for different data types and suboptimal fNIRS data timing, the dual network enhancement in the majority of subjects' results is a promising result. However, for wider application, resolving the method's drawbacks and carrying out a comprehensive assessment of its overall performance are still essential.

III. Problem Statement

Despite considerable progress in the development of neural-device interfaces, the seamless and efficient communication between the human brain and external technologies remains a formidable challenge. The limitations of current approaches, particularly the invasive nature of many brain interfaces, pose significant risks and hinder widespread adoption. This study addresses this pressing issue by proposing an advanced methodology employing Deep Recurrent Neural Networks (RNN) and Gated Recurrent Units (GRU) for neurolinguistic learning, aiming to provide non-invasive alternatives. The primary objective is to decode cerebral language signals in a non-intrusive manner, representing a crucial initial step towards enhancing the safety and usability of neural interfaces in applications such as assistive technologies, neuroprosthetics, and brain-machine communication. The existing landscape of non-invasive neural language decoding struggles to capture the intricate sequential patterns inherent in language processing. The complexity and dynamism of language-related brain signals pose challenges for conventional techniques. Consequently, the research advocates for the integration of deep RNN-GRU architectures, renowned for their proficiency in capturing sequential dependencies, into the neurolinguistic learning framework. The central challenge lies in designing and optimizing deep learning models to advance our understanding of non-invasive neural language decoding, thereby facilitating more effective and user-friendly neuro-device interactions [21].

IV. Proposed Deep RNN-GRU based Neurolinguistic Learning

The methodology advances non-invasive communication between brain devices and language interfaces by utilizing a multidisciplinary approach based in neurolinguistic learning. The study explores the complexities of deciphering language-related brain patterns, with a focus on the interface between neuroscience and machine learning. By utilizing cutting-edge neural network topologies, particularly Deep RNN and GRU, the study seeks to improve the capabilities of neuro-device interaction. Because the process is non-invasive, there is no need for intrusive procedures, which ensures both practical and ethical viability. A Deep RNN-GRU model is painstakingly built in Python to capture intricate brain patterns related to language processing. The model's ability to decipher complex language patterns, particularly for subject words, indicates its potential for practical uses such as brain-machine interfaces and assistive technologies. This represents a major advancement in the integration of neurolinguistic learning and neurotechnology. The proposed methodology is shown in Fig. 1.

A. Data Collection

Eleven healthy volunteers within the ages of 20 and 34 were recruited for this study, six of them were male and five of them were female. Respondents were made aware of the methods, frameworks, and goals before to the study. Every participant provided written permission in accordance with the Declaration of Helsinki, and all research methods were approved by Korea University's Institutional Review Board. Eight terms that represent the subject, verb, and object parts of the sentence were selected for the experimental setting based on their applicability to natural human-machine interaction, particularly with neural mechanical arm control. The fundamental language was made up of these words, which included subjects like "I" and "partner," verbs like "move," "have," and "drink," and object terms like "box," "cup," and "phone." Every phrase was said by those taking part 25 times, and their audio cues were captured. Respondents wore 64-channel EEG actiCaps during the EEG monitoring session, and MATLAB 2020a software's BrainVision Recorder was used to record EEG signals. Respondents in the study completed speech imaging tasks for every single one of the three sub sessions that focused on subject, verb, and object terms, correspondingly. High signal quality was maintained during the entire trial by providing students with pauses to preserve their physical and mental health and by displaying illustrations on a monitor [22].

One method for transforming EEG signals into a format that is easier to analyze and understand is called spectrogram embedding. EEG data, which show the brain's electrical activity over time, are frequently intricate and provide important insights into cognitive functions. By converting the EEG signal into a spectrogram—a graphic depiction of the signal's frequency content across time spectrogram embedding is achieved. The first step in the procedure is to divide the EEG signal into smaller temporal chunks, or epochs. By doing this, the EEG signal is converted from the time domain to the frequency domain, displaying the various frequency components that are present. Following that, the data is usually shown as a two-dimensional picture with time on one axis and frequency on the other. The shading or color intensity of the image indicates the amplitude of each frequency at a certain moment in time.

B. Preprocessing using Bandpass Filter

The role of a Bandpass Filter is paramount in signal processing, serving to selectively permit a specified range of frequencies while attenuating frequencies outside this designated band. This filter is instrumental in various applications where isolating specific frequency components from a signal is crucial. In fields such as telecommunications, audio processing, and biomedical signal analysis, Bandpass Filters help extract relevant information by allowing only the desired frequency range to pass through. In the context of communication systems, Bandpass Filters aid in frequency division multiplexing, enabling multiple signals to coexist without interference. Moreover, in biomedical applications, Bandpass Filters are essential for isolating physiological signals of interest, such as detecting heartbeats in an ECG. Their versatility in isolating and enhancing specific frequency components makes Bandpass Filters indispensable tools in signal processing, facilitating accurate and targeted analysis across diverse domains.

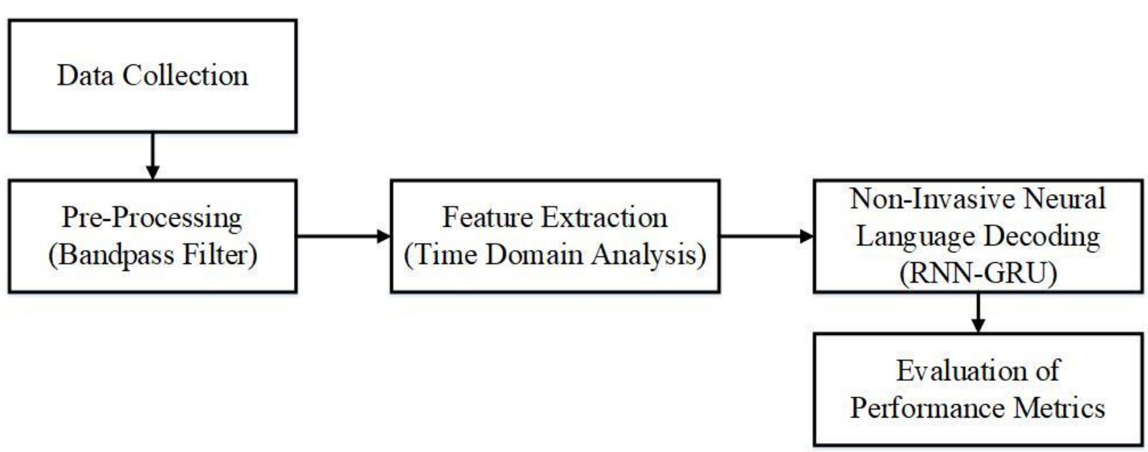

Fig. 1. Proposed methodology.

Applying a Bandpass filter to EEG signals during preprocessing is a crucial step in improving the specificity and quality of brain information derived from the raw data. By selectively allowing some frequencies and attenuating others, the bandpass filter helps to separate the brain oscillations of interest from possible noise and artefacts. One common option for EEG data linked to language activities is to apply a bandpass filter in a certain frequency range, this range has been deliberately selected to include the brain frequencies associated with cognitive functions such as language comprehension and speaking. Unwanted elements, including muscular artefacts or outside interference, are reduced by using the bandpass filter, which makes it possible to analyze the brain activity related to the experimental task more narrowly. Bandpass filtering is important for EEG preprocessing because it can increase the signal-to-noise ratio, which guarantees that the underlying brain signals are more accurately represented in the studies that follow. This specific stage is critical for reliably extracting features for applications requiring nuanced brain patterns, such as language decoding. By helping to improve the overall quality of the EEG data, bandpass filtering advances our knowledge of the brain mechanisms underlying language and communication by enabling more precise interpretations and insights into the neural dynamics linked to cognitive activities.

C. Feature Extraction using Time Domain Analysis

Feature Extraction using Time Domain Analysis serves a crucial role in the neuro-linguistic decoding framework presented in this article. It involves the identification and extraction of relevant features from temporal data patterns associated with neural language signals. By delving into the time domain, this technique enables the model to capture subtle variations and temporal nuances inherent in the non-invasive brain signals. This process enhances the discriminative power of the features fed into the subsequent RNN-GRU model, contributing to the accurate decoding of complex linguistic patterns. Essentially, Feature Extraction using Time Domain Analysis acts as a critical pre-processing step, facilitating the comprehensive representation of temporal information and thereby augmenting the overall effectiveness of the neuro-linguistic decoding system proposed in the study.

Time-domain analysis feature extraction turns out to be a crucial step in deciphering the temporal complexities of EEG signals related to language processing, which is important in the quest to advance neural-device interaction through deep RNN-GRU based neurolinguistic learning for non-invasive neural language decoding. Time-domain features provide a way to describe the dynamic interaction between language components and brain activity throughout the experimental tasks. These features are produced directly from the timing and amplitude information of EEG data. An important temporal aspect of this research is the examination of Event-Related Potentials (ERPs). ERPs are the mean brain responses that are time-locked to certain events, such words being presented in speech-imaging tasks. Researchers can learn more about how the brain responds to language inputs over time by extracting ERPs. The characteristics of ERP components, such as their peak amplitudes, latencies, and durations, offer a thorough description of the brain dynamics connected to various language components. The Mean Absolute Value (MAV) is given below,

$$\text{MAV} = \frac{1}{M}\sum_{j=1}^{M}|y_j| \tag{1}$$

The length of the sample is denoted by M.

When analyzing EEG data, zero crossing is an essential time-domain feature extraction technique, especially when trying to comprehend the temporal dynamics of brain activity. Finding the locations in the EEG signal where the amplitude crosses the zero axis is the goal of this approach. Zero crossing analysis offers important insights into the frequency and pattern of oscillatory variations in the EEG signal, providing information about the underlying brain processes connected to language-related activities in the context of neurolinguistic learning. Researchers can extract features that describe the frequency of transitions between positive and negative voltage values by measuring the number of times the EEG waveform crosses zero within a certain time interval. This characteristic is particularly relevant for identifying rhythmic neural patterns and can enhance the effectiveness of non-invasive neural language decoding techniques by providing a thorough grasp of the temporal dynamics of brain activity during language processing tasks.

$$\{y_j < 0 \text{ and } y_{j+1} > 0\} \text{ or } \{y_j > 0 \text{ and } y_{j+1} < 0\} \tag{2}$$

The consecutive samples are denoted as y_j and y_{j+1}.

To better clarify the timing elements of brain responses during language activities, the study may also concentrate on temporal features including signal length, rise time, and fall time. These behavioral characteristics add to our sophisticated knowledge of the brain's real-time processing of language data. Time-domain analysis is applied to both neural language pattern decoding and deep RNN-GRU model training, where it captures the sequential dependencies present in EEG data related to non-invasive language decoding. This methodological approach is in line with the overall objective of improving neural-device interaction, which will aid in the creation of more efficient and user-friendly brain-machine interfaces for a range of applications in assistive technologies, rehabilitation, and communication.

D. Deep RNN-GRU-based Neurolinguistic Learning for Non-Invasive Neural Language Decoding

RNN-GRU plays an important role in sequential data processing tasks, exhibiting distinct advantages in capturing and understanding temporal dependencies within input sequences. The GRU architecture, a variant of traditional RNNs, introduces gating mechanisms that enable more effective handling of long-range dependencies and mitigate issues like vanishing gradients. This makes RNN-GRU particularly well-suited for applications such as natural language processing, time series analysis, and speech recognition, where contextual information across different time steps is crucial. The inherent ability of RNN-GRU to selectively update and forget information, combined with its parallel processing capabilities, enhances its efficiency in modeling complex temporal patterns. These networks have proven instrumental in tasks requiring nuanced understanding of sequential data, making them a valuable asset in advancing various fields.

The development of deep RNNs and GRUs has led to major breakthroughs in neurolinguistic learning, a cutting-edge discipline at the nexus of neuroscience and linguistics. By non-invasively decoding cerebral language patterns, this novel method seeks to open up new avenues for comprehension of the complex interplay between language processing and brain activity. Deep RNN-GRU models are an advanced type of neural networks that are very useful for language decoding tasks since they are made to collect and analyze temporal connections in sequential input. Because of the GRU's capacity to store and update information selectively across long periods, the design makes it possible to represent language-related brain signals' fluctuations in time in a sophisticated manner.

The ability of deep RNN-GRU models to handle variable-length sequences present in natural language is a significant benefit in neurolinguistic learning. The network can learn hierarchical characteristics of language representation, from intricate syntactic patterns to subtle phonetic variations, thanks to its hierarchical structure. It is ideally suited for deciphering brain signals linked to different language processes because of its versatility. These models are very useful for non-invasive neural language decoding. Conventional approaches frequently entail intrusive techniques like brain electrode implantation, which restricts their application and raises ethical questions. However, non-invasive neuroimaging data, like electroencephalography (EEG), may be used to train deep RNN-GRU models, making this method more generally applicable and morally sound.

During the training phase, the model is exposed to language stimuli while brain activity is being recorded. The deep RNN-GRU continuously improves its capacity to decipher language-related information from brain signals by learning to associate particular patterns in the input data with matching linguistic qualities. The model will get more and more adept at capturing the complex links between brain activity and language representation thanks to this iterative learning process. Deep RNN-GRU-based neurolinguistic learning has a wide range of significant applications. In addition to basic studies on the neurological underpinnings of language, this method has applications in therapeutic situations. It may, for example, aid in the creation of assistive technology for people with communication impairments or function as a tool for tracking alterations in language-related brain activity in response to treatment measures.

Even with the advancements, deep neurolinguistic learning still faces several obstacles. Further work is needed to address ethical issues with permission and privacy, interpretability of learnt representations, and generalization of models across different populations. Interdisciplinary cooperation among neuroscientists, linguists, and machine learning specialists is becoming more and more important as the field develops in order to overcome these obstacles and realize the full potential of deep RNN-GRU-based neurolinguistic learning.

Eq. (3) represents the hidden state update h_t at time t in the RNN. Here, y_t is the input at time h_{t-1} is the hidden state from the previous time step, V^h is the weight matrix associated with the hidden state, and tanh is the hyperbolic tangent activation function. The tanh function introduces non-linearity, allowing the network to capture complex relationships and patterns in the data.

$$h_t = \tanh\left(V^h y_t + V^h h_{t-1}\right) \tag{3}$$

$$x_t = V^h h_t \tag{4}$$

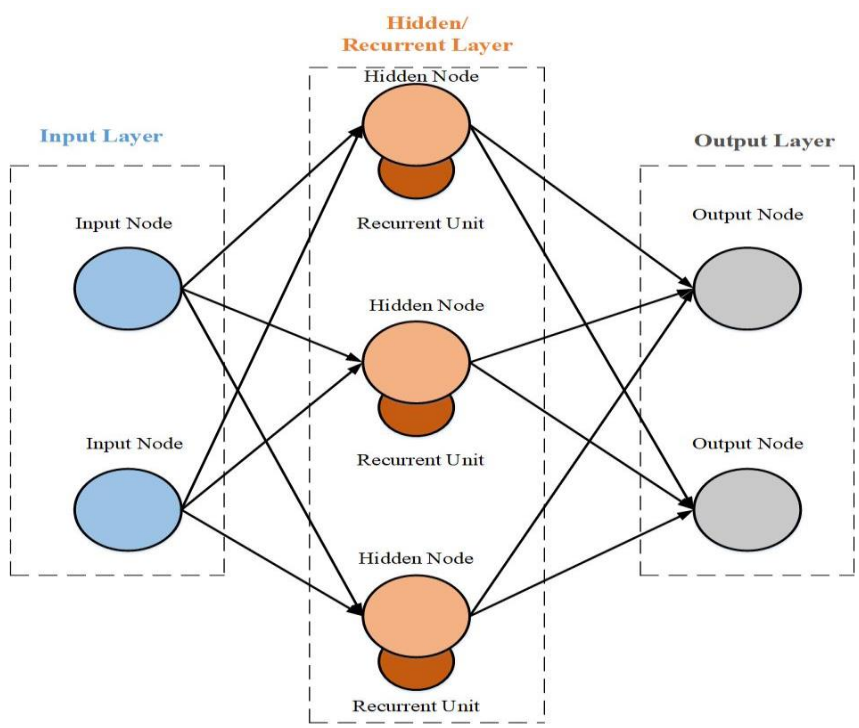

Fig. 2. RNN-GRU architecture.

Fig. 2 shows the architectural diagram of the RNN-GRU model. The above equations form the basis of a GRU, a kind of RNN architecture intended to effectively capture and handle sequential data. The update gate z_t and reset gate r_t, which are both triggered by the sigmoid function σ, are defined by Eq. (3). By deciding what to keep from the prior hidden state h_{t-1} and the current input y_t, these gates control the flow of information. Eq. (4) uses the tanh function to generate the candidate hidden state $\widetilde{h_t}$ and integrates the reset gate r_t to update the hidden state selectively. To provide a seamless transition between the past and current states, Eq. (5) finally combines the update gate z_t with the former hidden state and the candidate hidden state. All together, these formulas describe the complex dynamics of a GRU, which allows it to efficiently recognize and learn sequential patterns in a variety of contexts, including natural language processing and maybe neurolinguistic learning.

$$z_t = \sigma\,(y_t W^z + h_{t-1} V^z) \tag{5}$$

$$r_t = \sigma\,(y_t W^r + h_{t-1} V^r) \tag{6}$$

$$\widetilde{h_t} = \tanh\,(y_t W^h + (r_t * h_{t-1}) V^h) \tag{7}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * h_t \tag{8}$$

RNN-GRU Algorithm

```
Load and preprocess data      // Bandpass filter
Feature Extraction            // Time Domain Analysis
Define RNN-GRU model architecture
    Split data into training and testing sets
Train the RNN-GRU model
Evaluate the model on the test set
Make predictions on new data
Visualize results
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V. Results and Discussion

With a foundation in neurolinguistic learning, the methodology advances non-invasive communication between language interfaces and brain devices through a multidisciplinary approach. Situated at the nexus of neuroscience and machine learning, the research delves into the complexities involved in deciphering brain patterns linked to language. The goal of the project is to improve neuro-device interface capabilities by utilizing cutting-edge neural network topologies, including Deep RNN and GRU. Because the approach is non-invasive, it ensures both ethical and practical feasibility by removing the need for intrusive operations. A Deep RNN-GRU model that is carefully designed to capture intricate brain patterns related to language processing is created using Python. The model represents a major advancement in the fusion of neurolinguistic learning and neurotechnology because of its ability to decode complex language patterns, particularly for subject words. This shows the model's potential for use in assistive technologies and brain-machine interfaces.

A. Model Loss

The model loss is a key metric of the model's performance during training. It is commonly expressed as a mathematical measure of the dissimilarity between expected and real neural language patterns. When the loss trend is trending downward, the model is doing a good job of reducing mistakes and modifying its parameters to better suit the training set. A steady decline in loss values across epochs indicates that the non-invasive brain signals have been successfully learned to recognize and adjust to. On the other hand, variations or plateaus in the loss trajectory call for further examination and may indicate that the model needs its hyper parameters adjusted or that overfitting or underfitting occurred. Moreover, comprehending the relationship between decoding accuracy and loss offers a thorough grasp of the model's generalization capabilities and clarifies how resilient it is when decoding a variety of neural language patterns. It is depicted in Fig. 3.

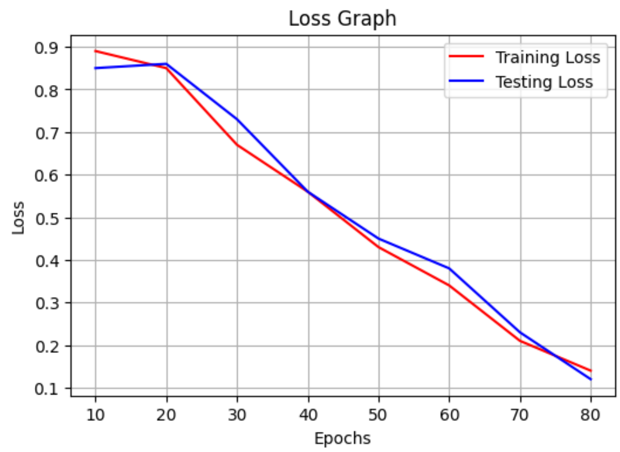

Fig. 3. Model loss.

B. PVC Performance

A statistic called Percent Valid Correct (PVC) performance is employed, especially in cognitive or behavioral studies, to measure the precision and dependability of a classification or prediction system. It shows the proportion of accurate answers or forecasts among all valid cases that were taken into account for a task or experiment. This statistic only looks at how well the system performs when a legitimate answer or forecast can be made; it ignores incorrect or ambiguous data items. This statistic offers a more focused evaluation of the system's effectiveness by highlighting its accomplishments particularly in situations where a significant answer or forecast is anticipated.

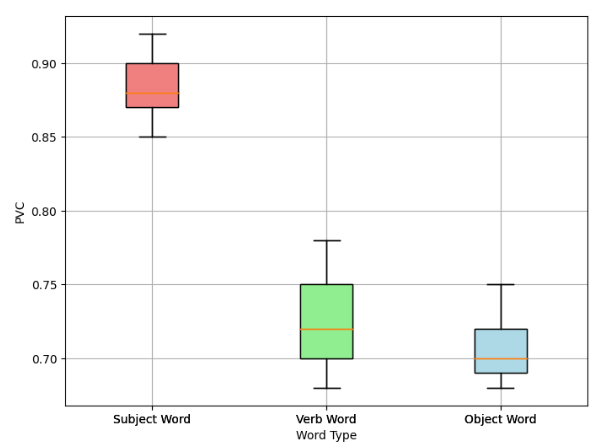

Fig. 4. PVC performance.

A thorough assessment of the model's capacity to decipher brain language patterns is provided by Fig. 4, which shows PVC Performance across many linguistic aspects, namely subject words, verb words, and object words on the x-axis. The way that PVC performance is distributed among various linguistic components provides information on how well the model can identify and anticipate different sentence structure components. Differences in the PVC performance of subject, verb, and object words might be a sign of various brain representations for these linguistic components or of varying degrees of complexity. Understanding the model's complex reactions to many aspects of language requires analyzing the PVC performance across these categories. Doing so may reveal brain activity patterns that alter according to grammatical functions. Furthermore, it offers useful data for adjusting the architecture and training strategies of the model to improve decoding accuracy across various linguistic components, which helps to improve neurolinguistic learning techniques in non-invasive neural language decoding paradigms.

C. Decoding Accuracy over Time

A statistic called decoding accuracy over time is used to evaluate how well a neural decoding model performs and changes over the course of an experiment or activity. This statistic assesses how well the model can predict and understand neural patterns linked to certain cognitive processes or stimuli throughout time. The decoding accuracy's dynamic nature over time offers valuable insights into the model's flexibility and learning dynamics, demonstrating its ability to grasp temporal variations in brain activity. Researchers can identify patterns, trends, or fluctuations in the model's performance by analyzing decoding accuracy at various time intervals. This provides a thorough knowledge of the model's ability to detect and adapt to temporal variations in cognitive or language processing. This measure is especially useful for research using time-series data, such as EEG signals, since it offers a detailed assessment of the model's performance in real-time and its possible applications, such as brain-machine interfaces and neurolinguistic learning.

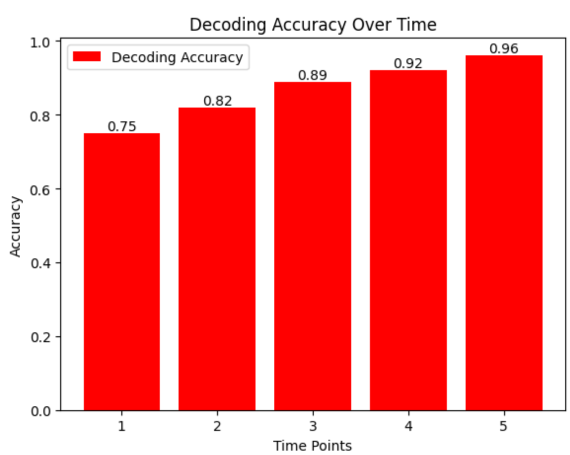

Fig. 5. Decoding accuracy over time.

A more comprehensive illustration of how the model's accuracy changes throughout the course of the task or experiment is given in Fig. 5. Decoding accuracy trajectory tracking over time can show learning, adaptation, or stabilization tendencies in response to changing cognitive demands. Accuracy peaks or troughs at particular times might be related to different stages of the experiment, such when stimuli are presented or when language tasks are performed. Determining the model's sensitivity to temporal changes in brain activity and maybe identifying crucial intervals for optimal performance require an understanding of the oscillations in decoding accuracy. Furthermore, this temporal analysis provides useful insights for improving the model, helping scientists adjust parameters or add adaptive techniques to improve accuracy at critical times. In the end, this helps develop more efficient and temporally-aware neural decoding systems for use in neuroscience and brain-machine interfaces.

D. PVC Distribution across Different Word Types for Various Methods

The pattern or spread of PVC performance across several categories or classes of words within a given dataset is referred to as the PVC distribution across various word kinds. This metric measures the precision of a classification or decoding system and evaluates its performance over a range of linguistic aspects, especially in the context of neurolinguistic learning or non-invasive brain language decoding. The distribution analysis seeks to identify any differences in the model's ability to decode various word kinds, including verb, object, and subject terms. Gaining an understanding of the PVC distribution allows one to assess the model's performance in a more complex way by gaining insight into how sensitive and flexible it is to different linguistic elements.

TABLE I. PVC DISTRIBUTION ACROSS DIFFERENT WORD TYPES FOR VARIOUS METHODS

Methods	Subject Word	Verb Word	Object Word
CSP-SVM [23]	0.60	0.52	0.48
EEGNet [24]	0.78	0.56	0.53
Proposed RNN-GRU	0.90	0.72	0.70

Table I presents the decoding accuracy ratings for the various techniques (CSP-SVM [23], EEGNet [24], and the suggested RNN-GRU model) for various linguistic components (verb, object, and subject words). Prominently, the suggested RNN-GRU model outperforms the other techniques in every category, with exceptional accuracy of 0.90 for subject words, 0.72 for verb words, and 0.70 for object words. This shows that in terms of collecting and interpreting neural patterns associated with various linguistic components, the RNN-GRU architecture—which was created for neurolinguistic learning in non-invasive neural language decoding performs better than more conventional techniques like CSP-SVM and EEGNet. The suggested RNN-GRU model's effectiveness in comprehending and decoding complex linguistic representations from non-invasive neural signals is highlighted by the notable accuracy improvement, especially in the decoding of subject words. This highlights the model's potential to advance the fields of neural-device interaction and neurolinguistic learning. It is depicted in Fig. 6.

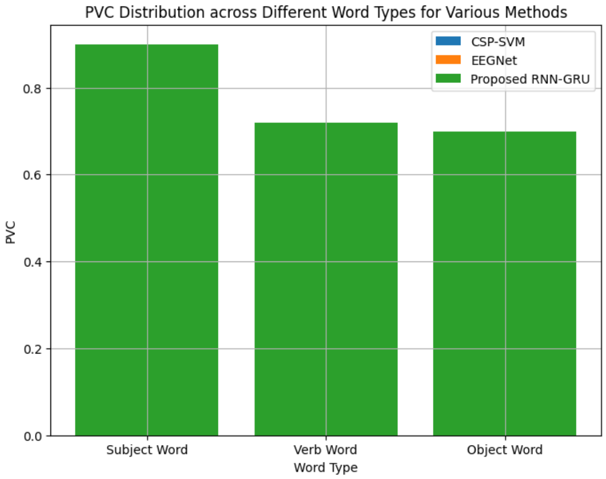

Fig. 6. PVC distribution across different word types for various methods.

E. Discussion

The study's findings, which are represented in the decoding accuracy scores for various techniques across subject, verb, and object words, offer important new information on the effectiveness of applied neurolinguistic learning strategies for non-invasive brain language decoding. Remarkably, the suggested RNN-GRU model demonstrates significant accuracy gains over conventional techniques like CSP-SVM [23] and EEGNet [24], especially in the decoding of topic words. This indicates how well the model is able to represent and decipher intricate brain patterns linked to various language components. The observed distribution of PVC performance over various word kinds clarifies the model's subtle competency and provides a thorough grasp of its flexibility to various language processing components. The area of neuro-device interaction has benefited greatly from these discoveries, which highlight the promise of deep learning techniques more especially, the suggested RNN-GRU model in improving the precision and usability of non-invasive neural language decoding systems.

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VI. CONCLUSION AND FUTURE SCOPE

This research underscores the advancement possibilities in non-invasive neural language decoding through the application of a deep RNN-GRU-based neurolinguistic learning technique, thereby augmenting the capabilities of brain-device interfaces. The findings presented illustrate the superior aptitude of the proposed RNN-GRU model in capturing intricate linguistic nuances from non-invasive brain signals, outperforming traditional methods like CSP-SVM and EEGNet, particularly in decoding topic terms. The model's adaptability to diverse linguistic components is evident in the nuanced distribution of PVC performance across different word types, emphasizing its potential to enhance the accuracy and robustness of non-invasive neural language decoding systems. The flexibility of the model to various linguistic elements highlights its potential to improve the precision and resilience of non-invasive neural language decoding systems. For responsible implementation, it is imperative to handle constraints including generalizability, interpretability, and ethical issues. Neural patterns associated with language comprehension can vary across individuals, languages, and contexts. Thus, the model's performance might differ when applied to different populations or languages.

In order to further increase decoding performance, future research could concentrate on optimizing hyper parameters and fine-tuning the model for the proposed RNN-GRU architecture. Expanding the dataset to include more real-world scenarios and language components might improve the model's applicability and generalizability. Enhancing the model for real-time decoding and dynamic language processing tasks could increase its usefulness in applications like assistive technology and brain-machine interfaces. Furthermore, examining the interpretability of the model's learnt representations may yield further insights into the neurological underpinnings of language processing. It is still essential for responsible implementation to address ethical issues, such as participant privacy and the moral use of brain data.

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