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Examining Tongue Movement Intentions in EEG-Based BCI with Machine and Deep Learning: An Approach for Dysphagia Rehabilitation

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Abstract
Dysphagia, a common swallowing disorder particularly prevalent among older adults and often associated with neurological conditions, significantly affects individuals' quality of life by negatively impacting their eating habits, physical health, and social interactions. This study investigates the potential of brain-computer interface (BCI) technologies in dysphagia rehabilitation, focusing specifically on motor imagery paradigms based on EEG signals and integration with machine learning and deep learning methods for tongue movement. Traditional machine learning classifiers, such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree, Naive Bayes, Random Forest, AdaBoost, Bagging, and Kernel were employed in discrimination of rest and imagination phases of EEG signals obtained from 30 healthy subjects. Scalogram images obtained using continuous wavelet transform of EEG signals corresponding to the rest and imagination phases of the experiment were used as the input images to the CNN architecture. As a result, KNN (79.4%) and SVM (63.4%) exhibited lower accuracy rates compared to ensemble methods like AdaBoost, Bagging, and Random Forest, all achieving high accuracy rates of 99.8%. These ensemble techniques proved to be highly effective in handling complex EEG datasets, particularly in distinguishing between rest and imagination phases. Furthermore, the deep learning approach, utilizing CNN and Continuous Wavelet Transform (CWT), achieved an accuracy of 83%, highlighting its potential in analyzing motor imagery data. Overall, this study demonstrates the promising role of BCI technologies and advanced machine learning techniques, especially ensemble and deep learning methods, in improving outcomes for dysphagia rehabilitation.

Keywords: BCI, dysphagia, CNN, machine learning, EEG, motor imagery

Introduction
Dysphagia is defined as a swallowing disorder that negatively affects daily life activities and impedes the feeding process [1]. This condition not only makes it difficult for individuals to eat and drink healthily but also significantly impacts their quality of life [2]. Dysphagia commonly emerges in elderly adults and is often associated with neurological diseases [3]. It can result from a combination of both neurological and non-neurological factors and is particularly linked with neurological disorders such as Parkinson's disease, stroke, or Alzheimer's [4] . Dysphagia can also arise from certain genetic sequencing problems. For instance, early-onset dysphagia has been observed in a patient with two novel variants in the NARS1 gene [5]. In this context, dysphagia poses not only a health but also a significant social and psychological problem.

The adverse effects of dysphagia on quality of life affect individuals' eating habits, physical and emotional well-being [6]. This condition can transform the eating and drinking process from a pleasurable experience to a struggle, leading to nutritional deficiencies, weight loss, and restrictions in daily activities. Additionally, it can reduce social interactions and confidence, increasing the risk of social isolation. Thus, dysphagia is not only a physical health issue but also a problem that affects individuals' mental health and social connections. Therefore, the effects of this swallowing disorder should be understood, and appropriate treatment and management strategies should be developed.

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Biotechnologies used in dysphagia rehabilitation offer a variety of innovative approaches to improve swallowing functions. Electromyography (EMG) provides noninvasive and objective strategies for swallowing assessment [7]. Robotic rehabilitation devices and kinesiology technologies simulate swallowing movements to strengthen muscles [8]. Brain-computer interfaces (BCIs) and electroencephalography (EEG) technologies analyze brain signals to support motor imagery and swallowing movements [9]. Furthermore, integrating biotechnological advancements into dysphagia research may help bridge existing gaps in our understanding and treatment of this condition. Updating the novelty and goals of ongoing research is essential to keep pace with these rapidly evolving fields.

Brain-computer interface (BCI) technologies have emerged as a rapidly developing and noteworthy field in recent years [10]. Essentially, BCI technologies facilitate interaction between individuals and their environment by detecting, analyzing, and interpreting brain activity. These technologies typically work in conjunction with non-invasive methods such as electroencephalography (EEG), which measures brain activity. Specifically, motor imagery paradigms based on EEG signals involve individuals thinking about specific motor movements, which are then analyzed through brain signals. This enables the mental movements of individuals, such as grasping with one hand or moving feet, to be detected by the machine [11].

The potential use of BCI technologies in dysphagia rehabilitation through mechanisms such as motor imagery and neuromuscular control holds promise for improving swallowing function, thus enhancing the quality of life of patients [12]. In this context, research focusing on the role of BCI technologies in dysphagia treatment presents a significant opportunity to explore advancements and potential applications in this field.

BCI systems can perceive brain activities during motor imagery and convert these mental processes into device commands. In the context of swallowing motor imagery, the literature suggests that this technique is a potential approach in post-stroke dysphagia rehabilitation [13], [14], [15], [16], [17]. Yang and colleagues suggested that motor imagery swallow and motor imagery tongue movement can be classified by the background idle state and that these techniques can be effectively used in stroke rehabilitation. However, swallowing is a complex process and requires central nervous system integration, which makes motor imagery swallow difficult to perceive [18]. Examining the effect of tongue movements in dysphagia rehabilitation will be useful for understanding the act of swallowing. The tongue plays a central role in the swallowing process and its movements are vital for effective swallowing. Therefore, focusing on tongue movements in dysphagia rehabilitation is both logical and scientifically justified. Our study aims to more accurately perceive swallowing motor imagery with EEG signals by building on these approaches.

In recent years, the increasing interest in machine learning and deep learning techniques in the medical field has triggered significant development and transformation in these areas [19]. These techniques are known for their ability to analyze large amounts of data and determine complex relationships. Particularly, machine learning and deep learning techniques associated with methods such as electroencephalography (EEG), which measures brain activity, have significant potential in medical diagnosis and treatment.

The use of machine learning and deep learning techniques in the analysis of EEG data offers several advantages [20]. Firstly, these techniques are highly effective in identifying and predicting patterns within large and complex datasets. EEG data typically consist of high-dimensional and time-series data, making manual analysis challenging and time-consuming. Machine learning and deep learning algorithms provide an ideal tool to tackle this abundance of data and discern relationships between specific brain activities and conditions such as dysphagia. These techniques, by learning patterns and relationships from EEG data collected from patients, can assist in developing personalized treatment plans. This facilitates the development of more effective and personalized treatment strategies, potentially improving the health outcomes of patients.

EEG-based motor imagery techniques are examined with machine learning for tongue movement [21]. This article examines the use of EEG-based motor imagery techniques in conjunction with machine learning and deep learning methods for tongue movement in dysphagia rehabilitation. Current dysphagia rehabilitation techniques, including swallowing therapy, physical exercises, posture modifications, and dietary adjustments, have various limitations and gaps. In this context, Brain-Computer Interfaces (BCIs) and machine learning hold transformative potential for dysphagia rehabilitation. BCIs can provide precise monitoring of swallowing muscle activity by directly interpreting brain signals, while machine learning techniques can analyze this data to develop personalized and effective rehabilitation strategies. These advancements have the potential to address the limitations of existing methods and offer a more targeted and individualized rehabilitation process. As a result, this research aims to contribute to the development of a new and effective approach to dysphagia treatment.

Materials-Methods

Data Acquisition

The EEG data was collected from 30 healthy subjects (15 males, 15 females, aged 18-56) using the g.tec Nautilus Research EEG wearable headset. The subjects were independent from one another, and healthy volunteers without neurological or psychiatric disorders that might affect EEG data were selected for this study. These data were obtained using a 16-channel EEG cap according to the international 10-20 system. The EEG signals were recorded at a sampling rate of 500 Hz. The study received approval from the Clinical Research Ethics Committee of Erciyes University on July 12, 2023, with approval number 2023/461.

To ensure the accuracy and reproducibility of EEG

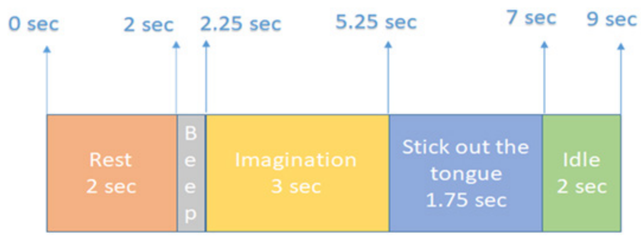

Figure 1. Experimental Paradigm

measurements, several measures were implemented. EEG devices were regularly calibrated prior to data collection to guarantee precise and reliable recordings. Standardized protocols were adhered to during data acquisition, with participants tested under consistent environmental conditions and uniform procedures. Additionally, raw EEG data were processed using specialized software for the g.tec Nautilus Research EEG wearable headset and filtering techniques to minimize artifacts and noise. Reproducibility was further evaluated through repeated measurements under identical conditions to assess the consistency of the data, thereby confirming the reliability and validity of the measurements. These measures were taken to improve the quality and reliability of the data, ensuring the validity of the study's results.

Fig. 1 illustrates the experimental paradigm, which includes a rest condition, imagining tongue protrusion, and performing the actual tongue protrusion action. Each subject undergoes 15 repeated recordings, with each trial lasting 9 seconds.

Filtering EEG Signals

Before proceeding with data analysis, the obtained EEG signals underwent various processing steps. Firstly, empirical mode decomposition (EMD) was utilized to decompose the signal into narrowband components, enabling the analysis of the temporal behavior of each component. Empirical Mode Decomposition (EMD) is a powerful method that adaptively decomposes a signal into different frequency components. Particularly, EMD is highly effective for complex signals such as EEG because it works with non-linear and non-stationary signals. In our study, we utilized EMD to more effectively separate artifacts and other noise components from the signal. Subsequently, a bandpass filter ranging from 0.5 to 40 Hz was applied to filter out unwanted noise and focus the signal within the desired frequency range. EEG signals are typically low-frequency, and the 0.5-40 Hz range encompasses the fundamental frequencies associated with brain activity. Frequencies below 0.5 Hz are often associated with movement artifacts and other slow-wave noise. Frequencies above 40 Hz typically contain high-frequency noise, such as muscle artifacts and environmental electronic interference. Therefore, the 0.5-40 Hz band was chosen to preserve the meaningful components of the EEG signal while minimizing noise. The FIR filter used in EEGLAB was applied with the default automatic filter order [22]. Finally, independent component analysis (ICA) was employed to identify and extract independent components from the dataset. ICA separates mixed signals in the dataset into independent components, helping to reduce unwanted components and reveal the true signal. It has been particularly effective in isolating artifacts such as eye blinks and muscle movements from EEG data. Independent Component Analysis (ICA) was performed using the EEGLAB MATLAB toolbox. This method was applied to separate unseen or overlapping sources in the signals, ensuring that only the neurological components remain for analysis. These processing steps resulted in relatively cleaner data, facilitating the attainment of more reliable and consistent results.

Feature Extraction

In this study, a total of 30 different features were extracted from EEG signals, encompassing characteristics from the time domain, frequency domain, non-linear domain, and autoregressive model parameters. These features have been categorized as follows:

Time-domain features include various statistical measures such as the minimum value, maximum value, median value, variance, standard deviation, and arithmetic mean. Additionally, features like the logarithm of the root sum of sequential variation, mean Teager energy, mean energy, mean curve length, normalized second difference, second difference, normalized first difference, first difference, kurtosis, skewness, Hjorth complexity, Hjorth mobility, and Hjorth activity are also included.

Frequency-domain features consist of the power in different frequency bands, including delta band power, theta band power, alpha band power, beta band power, gamma-band power, and the ratio of alpha to beta band power.

Non-linear features are represented by various entropy-based measures, such as Renyi entropy, logarithmic energy entropy, Shannon entropy, and Tsallis entropy.

Autoregressive Model Parameters involve the parameters derived from the autoregressive model used for analyzing the EEG signals.

Statistical Analysis

Each feature on each channel was examined individually. A total of 480 features (16 channels x 30 features) were subjected to a Shapiro-Wilk test to determine whether they followed a normal distribution. A t-test was applied to all features with normal distributions. For features with non-normal distributions, the Mann-Whitney U test was conducted. A significance level of 0.05 was used for statistical significance. This level is commonly accepted in the scientific community and helps balance false positives and false negatives. It's widely used in various research fields to ensure results are not due to chance. This threshold was chosen to maintain consistency and comparability with other studies in our field.

MI Classification

In the binary classification of rest and imagination of tongue protrusion, both traditional machine learning and deep learning methods were utilized to analyze motor imagery data. In the machine learning stage, the initial processing of the data involved Independent Component Analysis (ICA), Empirical Mode Decomposition(EMD), and the application of a bandpass filter. Subsequently, the data was divided into two main classes: "rest" and "imagination". At this stage, features were extracted from each class. Various classifiers were applied to the extracted features in the machine learning stage. These classifiers included K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree, Naive Bayes, Random Forest, AdaBoost, Bagging, and Kernel. KNN offers an interactive approach due to its simplicity, while SVM performs well with high-dimensional datasets and provides optimal class separation. Decision Tree enhances interpretability, whereas Naive Bayes delivers rapid results with large datasets. Random Forest improves prediction reliability by mitigating the weaknesses of individual decision trees, AdaBoost refines weak models, Bagging reduces variance, and Kernel models non-linear relationships to achieve better outcomes. This variety was employed to enhance classification performance and identify the most suitable model. In this study, the performance of different classifiers was examined in detail using the "Leave-One-Subject-Out Cross Validation" method for a more thorough analysis on the dataset. This method utilizes each data point as a test subset while using the remaining data points for training, thereby evaluating the model's generalization ability more robustly.

For the deep learning approach, preprocessing of the raw EEG data began with the application of a bandpass filter ranging from 0.5 to 40 Hz. Subsequently, the data segmented into "rest" and "imagination" classes were transformed to better capture the features of each segment in the time-frequency domain. A total of 14,400 images were obtained, representing each person and each channel, using Continuous Wavelet Transform (CWT) with “Amor” wavelet for rest and imagination signals (7200 for rest, 7200 for imagination).

The images were resized as 256x256x3 for RGB channels and used as the input to the model and were evaluated in a 12-layer classification process using Convolutional Neural Networks (CNNs) for classifying motor imagery data as rest and imagination as shown in Fig. 2. The CNN model, known for its effectiveness in image data, has the potential to handle the complexity of the dataset better. Amor wavelet is a widely used wavelet transform method in signal processing, particularly suitable for the frequency-domain representation of EEG signals and was preferred in this study.

The CNN model was trained with the Adam optimization algorithm for a maximum of 10 epochs and a mini-batch size of 20. Mini-batches were randomly shuffled each epoch, with validation occurring every 30 mini-batches. These hyperparameters aim to optimize training efficiency and reduce the risk of overfitting.

Results and Discussion

Statistical Analysis

According to the Shapiro-Wilk test results, the Log Energy Entropy feature exhibited a normal distribution in 13 channels, while the other features showed non-normal distributions. The

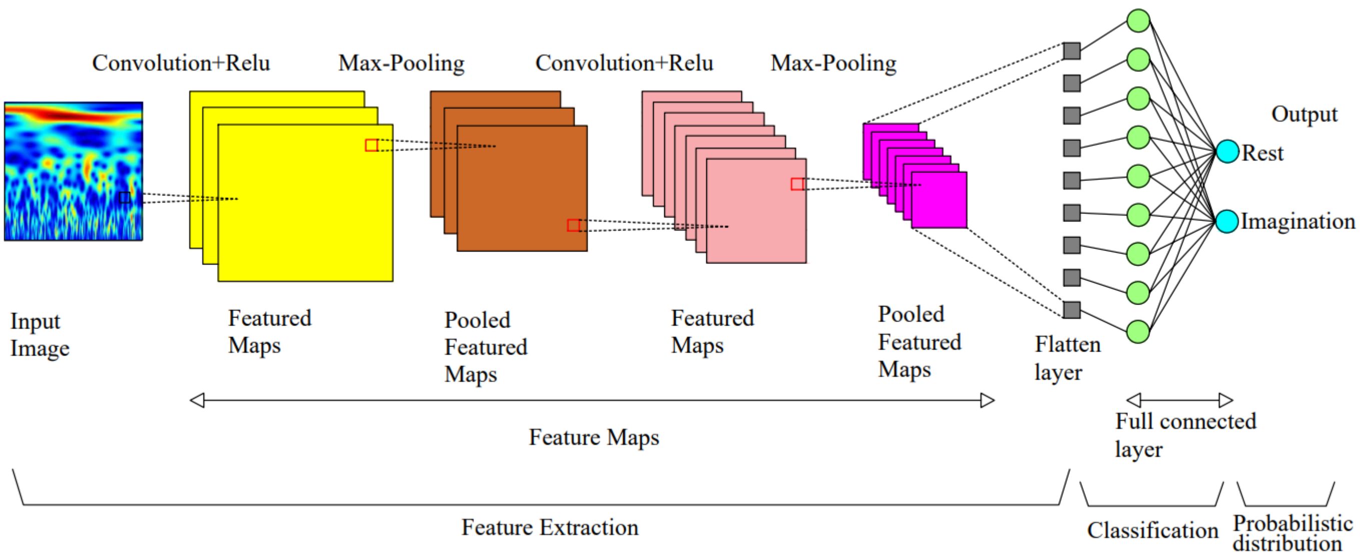

Figure 2. Convolutional Neural Networks (CNNs) for classifying scalogram images obtained from the resting and imagination EEG signals.

t-test showed statistically significant results that were obtained for these 13 features. The Mann-Whitney U test depicted that 242 out of 467 non-normal distributed features exhibited statistical significance.

Machine Learning

Various classifiers were evaluated including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naive Bayes, and Kernel methods, to understand their effectiveness in handling EEG data. Classifiers such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naive Bayes, and Kernel exhibited relatively low accuracy results in experiments conducted with this method. KNN and SVM were chosen for their well-established methods in classification tasks, but their performance was limited, likely due to high dimensionality and complex data distributions. Naive Bayes struggled with feature correlations, while Kernel methods were hampered by suboptimal parameter choices. These classifiers may have struggled to effectively address certain features and data distributions.

Conversely, classifiers employing ensemble methods such as AdaBoost, Bagging, and Random Forest achieved high accuracy rates. These ensemble methods were observed to be more effective in handling the complexity of the dataset and generally delivering stronger performance. These findings emphasize the importance of utilizing ensemble methods more widely in machine learning applications and their ability to provide better performance in more complex datasets. Future work should further explore and optimize these methods for enhanced classification accuracy. Table 1 depicts the accuracy, precision and recall results obtained using different classifiers to discriminate between rest and imagination.

Table 1. Accuracy, Precision and Recall Results Obtained using Different Classifiers to Discriminate Between Rest and Imagination.

	Classifier	Accuracy%± std%	Precision%± std%	Recall% ± std%
Machine Learning Techniques Classification Results	KNN	79.4% ± 14.0%	95.6% ± 8.1%	75.4% ± 14.8%
	SVM	63.4% ± 20.8%	53.8% ± 37.8%	51.2% ± 20.7%
	Decision Tree	99.2% ± 1.4%	99.6% ± 1.7%	99.0% ± 2.4%
	Naive Bayes	50.6% ± 5.9%	93.8% ± 11.5%	50.7% ± 5.4%
	Random Forest	99.8% ± 0.8%	100.0% ± 0.0%	99.6% ± 1.6%
	AdaBoost	99.8% ± 0.8%	100.0% ± 0.0%	99.6% ± 1.6%
	Bagging	99.8% ± 0.8%	100.0% ± 0.0%	99.6% ± 1.6%
	Kernel	51.3% ± 15.6%	56.9% ± 16.4%	51.6% ± 14.9%

Deep Learning

Utilizing CNN and CWT together, the complexity of the dataset can be effectively addressed, resulting in higher accuracy in classifying motor imagery data. Fig. 3 shows different sample scalogram images obtained from rest and imagination phases of the EEG signals from random 3 different subjects.

Several key visual differences can be observed between these two phases. In the rest phase, energy intensity is largely concentrated in the lower frequency bands, whereas in the imagination phase, a noticeable increase in energy occurs in the higher frequency bands. Furthermore, signals during the imagination phase appear to have a more irregular and complex structure, while patterns during the rest phase are more regular and homogeneous. This difference could be attributed to the interaction of various brain regions and the activation of more intense cognitive processes during the imagination phase. Additionally, the more prominent presence of high-frequency components during the imagination phase indicates a more complex neural activity structure in this state. These visual differences play a crucial role in enhancing the performance of deep learning-based models in motor imagery data classification. The achieved accuracy rate of 83% in the conducted experiments demonstrates the potential of deep learning methods in classifying motor imagery data. This high accuracy rate highlights the ability of the CNN model to successfully distinguish motor imagery data and the effectiveness of Amor wavelet in processing EEG data.

In the deep learning part of our study, we investigated on different time-frequency representations of EEG signals and observed that different wavelets may result in significantly different images to be used as inputs to the CNN model, thus different accuracy levels can be obtained. Here, we present the best accuracy level achieved when continuous wavelet transform with Amor wavelet was employed. An accuracy rate of 83% can be considered a promising result when compared to the performance of deep learning methods in motor imagery or EEG-based tasks. To better contextualize this result, it is

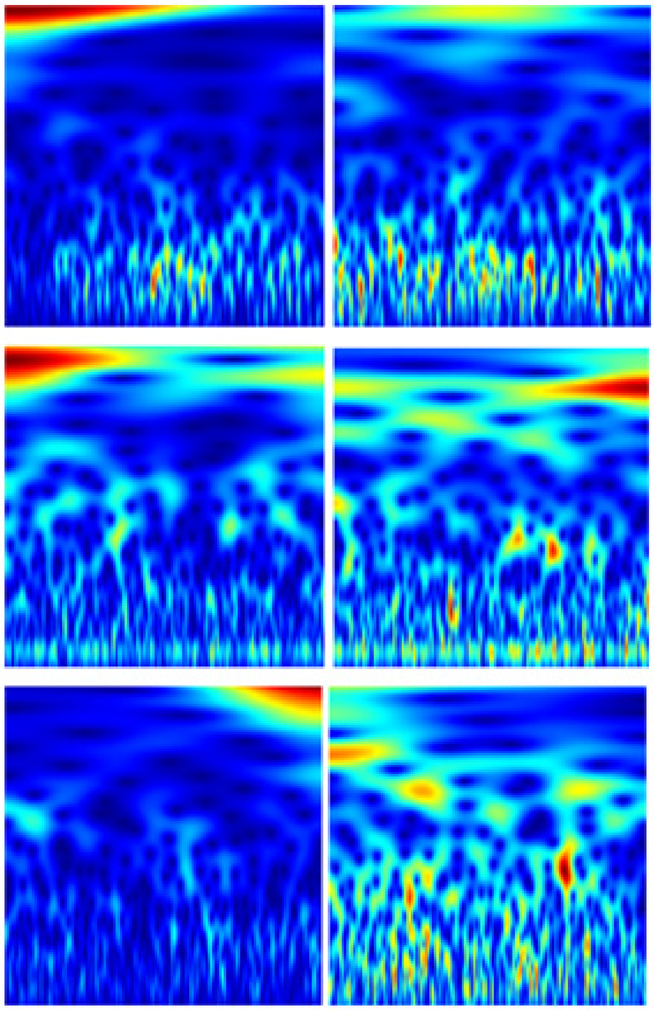

Figure 3. Scalogram images obtained from EEG signals corresponding to the rest and imagination phases of the experiment from 3 different subjects. Left and right panels show scalograms from the rest and imagination phases' respectively.

important to compare it with other studies. In the literature, accuracy rates in deep learning-based EEG studies typically range between 70% and 90%, although these figures can vary depending on factors such as the dataset used, the number of participants, signal preprocessing techniques, and model architecture [23], [24], [25]. Notably, in some studies focusing on swallow-based motor imagery, accuracy rates of 70-75% have been achieved using classical machine learning methods, but it appears that deep learning methods have not yet been extensively explored in this specific domain [26], [27], [28], [29], [30], [31], [32], [33]. In this context, the 83% accuracy rate can be considered consistent with other deep learning-based studies. It is anticipated that further improvements could be made in future work by optimizing hyperparameters, employing different network architectures, or utilizing advanced preprocessing techniques.

The results indicate that deep learning methods are effective in complex tasks such as classifying motor imagery data and may play a significant role in motor imagery research and applications. These findings provide a foundation for further exploration of the potential of deep learning methods in motor imagery-based rehabilitation processes. While CNNs are powerful in motor imagery and EEG tasks, they may struggle to capture the temporal dynamics of EEG signals, are prone to overfitting on small datasets, and are sensitive to noise. Additionally, deep CNNs require significant computational power [34]. To overcome these limitations, future studies could combine CNNs with recurrent neural networks (RNNs), utilize transfer learning to mitigate small dataset issues, and employ attention mechanisms to enhance performance.

Conclusion

This study demonstrates the effective utilization of both traditional and deep learning methods for classifying motor imagery data related to tongue protrusion. The proposed approach holds significant potential for motor imagery research and rehabilitation applications, particularly in the rehabilitation of dysphagia patients. By successfully integrating advanced machine learning and deep learning algorithms with EEG-based motor imagery data, we have showcased the ability of these technologies to accurately decode neural signals associated with specific motor tasks, such as tongue movements, which are critical for swallowing.

The combination of EEG-based motor imagery and machine learning techniques offers the potential to develop personalized and effective treatment strategies for dysphagia rehabilitation. Such approaches could improve the quality of life for dysphagia patients by enhancing their eating and daily activities. This study lays a foundation for future researchers and clinical practitioners to explore innovative and effective methods for dysphagia treatment.

Furthermore, advancements in neurotechnology can deepen our understanding of the neural mechanisms underlying swallowing and motor control in general. These insights are essential for the development of more precise interventions that not only address the physical symptoms of dysphagia but also target the underlying neurological causes of the condition. Consequently, this can lead to significant improvements in patients' quality of life by minimizing the need for invasive treatments and prolonged clinical care.

This study has several limitations. Notably, challenges in EEG data acquisition, such as individual differences and signal noise, impose constraints on the results. Since the data was collected only from healthy individuals, the applicability of the findings to dysphagia patients may be limited. EEG signals from healthy individuals may not directly reflect the neurological or physiological abnormalities observed in dysphagia patients. Therefore, this can be considered a limitation of the study. To enhance the generalizability and validity of our findings, we plan to acquire EEG data from larger and more diverse patient populations. In our study, the Leave-One-Subject-Out Cross-Validation (LOSO-CV) method was chosen to evaluate the generalization capability of the model. While we acknowledge the advantages of LOSO-CV, we also recognize its potential biases and limitations. LOSO-CV may indeed have limitations such as high variance in small datasets and systematic differences among subjects. However, we have attempted to mitigate these effects by increasing the size and diversity of our dataset. Additionally, we plan to explore alternative cross-validation strategies to comprehensively assess the model's performance. Additionally, the limited scope of existing literature complicates comprehensive comparisons of research outcomes. To address this, future studies will focus on comparing new experimental paradigms, diverse preprocessing techniques, feature extraction methods, and data augmentation strategies.

Systematically examining different preprocessing techniques and feature extraction methods could improve the accuracy and generalizability of EEG-based motor imagery applications. Moreover, developing more sophisticated analysis methods to minimize individual differences and signal noise may bridge existing knowledge gaps and provide more effective clinical solutions. In future studies, conducting similar experiments on dysphagia patients will enhance the generalizability of the method and contribute to rehabilitation applications. Future research will also aim to expand this work to include larger and more diverse populations, including individuals with varying degrees of dysphagia severity.

Incorporating multimodal data sources, such as functional MRI (fMRI) or electromyography (EMG), could further enhance classification accuracy and therapeutic effectiveness. We anticipate that integrating other neuroimaging techniques and artificial intelligence approaches will significantly advance the detection and rehabilitation processes of motor imagery swallowing. As machine learning and deep learning techniques continue to evolve, the development of more sophisticated models that generalize across different patient populations and conditions will become increasingly feasible. These advancements promise not only to benefit dysphagia rehabilitation but also to have broader implications for the treatment of other motor-related disorders. The transition of our study to clinical applications depends on overcoming technical challenges and validating with larger participant groups. Managing EEG artifacts and adapting the methodology for dysphagia patients require prototype development and safety testing. Our findings could significantly contribute to the development of motor imagery-based rehabilitation protocols. This approach has the potential to form the basis for neurorehabilitation programs aimed at improving swallowing functions in dysphagia patients and could lead to the creation of specific protocols that can be directly integrated into clinical practice. Our future research aims to contribute to the development of more effective and personalized rehabilitation strategies, both in clinical practice and fundamental research.

This study demonstrates the effective utilization of both traditional and deep learning methods for classifying motor imagery data related to tongue protrusion. The proposed approach holds significant potential for motor imagery research and rehabilitation applications, particularly in the rehabilitation of dysphagia patients. By successfully integrating advanced machine learning and deep learning algorithms with EEG-based motor imagery data, we have showcased the ability of these technologies to accurately decode neural signals associated with specific motor tasks, such as tongue movements, which are critical for swallowing.

References

1. M. Panebianco, R. Marchese-Ragona, S. Masiero, and D. A. Restivo, "Dysphagia in neurological diseases: a literature review." *Neurological sciences : official journal of the Italian Neurological Society and of the Italian Society of Clinical Neurophysiology* vol. 41,11 (2020): 3067-3073. doi:10.1007/s10072-020-04495-2.
2. P. Clavé and R. Shaker, "Dysphagia: current reality and scope of the problem." *Nature reviews. Gastroenterology & hepatology* vol. 12,5 (2015): 259-70. doi:10.1038/nrgastro.2015.49.
3. R. Martino, N. Foley, S. Bhogal, N. Diamant, M. Speechley, and R. Teasell, "Dysphagia after stroke: Incidence, diagnosis, and pulmonary complications," *Stroke*, vol. 36, no. 12, 2005, doi: 10.1161/01.STR.0000190056.76543.eb.
4. N. Bhattacharyya, "The prevalence of dysphagia among adults in the United States," *Otolaryngology - Head and Neck Surgery (United States)*, vol. 151, no. 5, 2014, doi: 10.1177/0194599814549156.
5. N. Yang *et al.*, "Novel NARS2 variants in a patient with early-onset status epilepticus: case study and literature review," *BMC Pediatr*, vol. 24, no. 1, 2024, doi: 10.1186/s12887-024-04553-0.
6. White, Gregory N et al. "Dysphagia: causes, assessment, treatment, and management." *Geriatrics* vol. 63,5 (2008): 15-20.
7. J. Garcia-Casado, G. Prats-Boluda, Y. Ye-Lin, S. Restrepo-Agudelo, E. Perez-Giraldo, and A. Orozco-Duque, "Evaluation of swallowing related muscle activity by means of concentric ring electrodes," *Sensors (Switzerland)*, vol. 20, no. 18, 2020, doi: 10.3390/s20185267.
8. H. Salfity and M. G. Hartwig, "The Robotic Method of Repairing Dysphagia." *Innovations (Philadelphia, Pa.)* vol. 15,3 (2020): 225-228. doi:10.1177/1556984520921957.
9. M. Orban, M. Elsamanty, K. Guo, S. Zhang, and H. Yang, "A Review of Brain Activity and EEG-Based Brain-Computer Interfaces for Rehabilitation Application." *Bioengineering (Basel, Switzerland)* vol. 9,12 768. 5 Dec. 2022, doi:10.3390/bioengineering9120768.
10. M. A. Lebedev and M. A. L. Nicolelis, "Brain-machine interfaces: past, present and future." *Trends in neurosciences* vol. 29,9 (2006): 536-46. doi:10.1016/j.tins.2006.07.004.

11. A. Saibene, M. Caglioni, S. Corchs, and F. Gasparini, "EEG-Based BCIs on Motor Imagery Paradigm Using Wearable Technologies: A Systematic Review." *Sensors (Basel, Switzerland)* vol. 23,5 2798. 3 Mar. 2023, doi:10.3390/s23052798.
12. C. M. Steele and A. J. Miller, "Sensory input pathways and mechanisms in swallowing: a review." *Dysphagia* vol. 25,4 (2010): 323-33. doi:10.1007/s00455-010-9301-5.
13. H. Yang, C. Guan, K. K. Ang, C. C. Wang, K. S. Phua, and J. Yu, "Dynamic initiation and dual-tree complex wavelet feature-based classification of motor imagery of swallow EEG signals," in *Proceedings of the International Joint Conference on Neural Networks*, 2012. doi: 10.1109/IJCNN.2012.6252603.
14. H. Yang *et al.*, "Detection of Motor Imagery of Swallow With Model Adaptation: Swallow or Tongue? Prognostic and Monitory EEG-Biomarkers for BCI Upper-limb Stroke Rehabilitation View project digital health View project Detection of Motor Imagery of Swallow With Model Adaptation: Swallow or Tongue?," *Proceedings of the Fifth International Brain-Computer Interface Meeting*, 2013, doi: 10.3217/978-3-85125-260-6-56.
15. H. Yang *et al.*, "Feature consistency-based model adaptation in session-to-session classification: A study using motor imagery of swallow EEG signals," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2013. doi: 10.1109/EMBC.2013.6609528.
16. H. Yang *et al.*, "Detection of motor imagery of swallow EEG signals based on the dual-tree complex wavelet transform and adaptive model selection," *J Neural Eng*, vol. 11, no. 3, 2014, doi: 10.1088/1741-2560/11/3/035016.
17. H. Yang, C. Guan, C. C. Wang, and K. K. Ang, "Detection of motor imagery of brisk walking from electroencephalogram," *J Neurosci Methods*, vol. 244, 2015, doi: 10.1016/j.jneumeth.2014.05.007.
18. H. Hashimoto *et al.*, "Swallowing-related neural oscillation: an intracranial EEG study," *Ann Clin Transl Neurol*, vol. 8, no. 6, 2021, doi: 10.1002/acn3.51344.
19. A. Esteva *et al.*, "A guide to deep learning in healthcare." *Nature medicine* vol. 25,1 (2019): 24-29. doi:10.1038/s41591-018-0316-z.
20. H. Altaheri *et al.*, "Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: a review," *Neural Comput Appl*, vol. 35, no. 20, 2023, doi: 10.1007/s00521-021-06352-5.
21. H. Yang *et al.*,"On the Correlations of Motor Imagery of Swallow with Motor Imagery of Tongue Movements and Actual Swallow," In: Wang, R., Pan, X. (eds) Advances in Cognitive Neurodynamics (V). Advances in Cognitive Neurodynamics. Springer, Singapore. https://doi.org/10.1007/978-981-10-0207-6_55.
22. A. Delorme and S. Makeig, "EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *J Neurosci Methods*, vol. 134, no. 1, 2004, doi: 10.1016/j.jneumeth.2003.10.009.
23. A. Al-Saegh, S. A. Dawwd, and J. M. Abdul-Jabbar, "Deep learning for motor imagery EEG-based classification: A review," 2021. doi: 10.1016/j.bspc.2020.102172.
24. A. Craik, Y. He, and J. L. Contreras-Vidal, "Deep learning for electroencephalogram (EEG) classification tasks: A review," 2019. doi: 10.1088/1741-2552/ab0ab5.
25. L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *J Big Data*, vol. 8, no. 1, 2021, doi: 10.1186/s40537-021-00444-8.
26. H. Yang, K. K. Ang, C. Wang, K. S. Phua, and C. Guan, "Neural and cortical analysis of swallowing and detection of motor imagery of swallow for dysphagia rehabilitation—A review," in *Progress in Brain Research*, vol. 228, 2016. doi: 10.1016/bs.pbr.2016.03.014.
27. I. Jestrović, J. L. Coyle, and E. Sejdić, "Differences in brain networks during consecutive swallows detected using an optimized vertex–frequency algorithm," *Neuroscience*, vol. 344, 2017, doi: 10.1016/j.neuroscience.2016.11.047.
28. I. Jestrović, J. L. Coyle, and E. Sejdić, "Characterizing functional connectivity patterns during saliva swallows in different head positions," *J Neuroeng Rehabil*, vol. 12, no. 1, 2015, doi: 10.1186/s12984-015-0049-x.
29. I. Jestrović, J. L. Coyle, S. Perera, and E. Sejdić, "Influence of attention and bolus volume on brain organization during swallowing," *Brain Struct Funct*, vol. 223, no. 2, 2018, doi: 10.1007/s00429-017-1535-7.
30. I. Jestrović, J. L. Coyle, S. Perera, and E. Sejdić, "Functional connectivity patterns of normal human swallowing: difference among various viscosity swallows in normal and chin-tuck head positions," *Brain Res*, vol. 1652, 2016, doi: 10.1016/j.brainres.2016.09.041.
31. I. Jestrović, J. L. Coyle, and E. Sejdić, "Decoding human swallowing via electroencephalography: A state-of-the-art review," *J Neural Eng*, vol. 12, no. 5, 2015, doi: 10.1088/1741-2560/12/5/051001.
32. I. Jestrović, J. L. Coyle, and E. Sejdić, "The effects of increased fluid viscosity on stationary characteristics of EEG signal in healthy adults," *Brain Res*, vol. 1589, 2014, doi: 10.1016/j.brainres.2014.09.035.
33. I. Jestrović, J. M. Dudik, B. Luan, J. L. Coyle, and E. Sejdić, "Baseline characteristics of cervical auscultation signals during various head maneuvers," *Comput Biol Med*, vol. 43, no. 12, 2013, doi: 10.1016/j.compbiomed.2013.10.005.
34. S. Hammi, S. M. Hammami, and L. H. Belguith, "Advancing aspect-based sentiment analysis with a novel architecture combining deep learning models CNN and bi-RNN with the machine learning model SVM," *Soc Netw Anal Min*, vol. 13, no. 1, 2023, doi: 10.1007/s13278-023-01126-4.