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Evaluation of Transformer-Based Models in Optimizing Invasive and Non-Invasive Brain-Computer Interfaces: Recurrent Neural Networks to Enhance Communication Speed for Locked-In Syndrome Patients

Yash Srivastav[1*], Rajkumar[1], Rama Kant[1], Saroj Kumar[1], Rupesh Raj[1], Shivam Yadav[1], Shivani Singh[1]

[1]D.K.R.R Pharmacy College, Amberpur, Sitapur (Uttar Pradesh), India

***Corresponding Email: yashsrv.108@gmail.com**

Abstract:

Brain-Computer Interfaces (BCIs) have been proposed as assistive technologies for Locked-In Syndrome (LIS) patients that can facilitate communication based on decoding of neural signals. Traditional BCI systems based on recurrent neural network (RNN) models exhibit certain constraints in terms of decoding accuracy, communication speed, and response latency. The current study aims to assess the effectiveness of transformer-based frameworks in optimizing the efficiency of both invasive and non-invasive BCI systems as compared to classical RNN models. A computational-clinical study design was used which involved participation of 48 LIS or severely paralysed participants. Subjects were grouped in accordance with their involvement in invasive or non-invasive BCI groups, and assessments were conducted during a period of eight weeks of intervention. Neural activity data processing was done with the help of two different approaches, including transformer-based model application and RNN application, assessing communication speed, decoding accuracy, latency, and error rates of both systems. Results suggest that transformer-based neural decoding frameworks proved to be superior to RNNs in terms of all evaluated criteria. Invasive transformer-based BCI demonstrated the best results concerning communication speed, decoding accuracy, lowest latency, and lowest error rates. Non-invasive transformer BCIs also yielded better results than RNN-based BCIs.

Keywords: Brain-Computer Interface, Transformer Models, Recurrent Neural Networks, Locked-In Syndrome, Neural Decoding, EEG, Communication Speed, Deep Learning, Invasive BCI, Non-Invasive BCI.

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1. INTRODUCTION

The BCI constitutes a fast-growing multi-disciplinary research domain, combining knowledge from neuroscience, biomedical engineering, artificial intelligence, and rehabilitation medicine[1].

By making use of connections between neural processes and external gadgets, BCIs make it possible for people suffering from severe disabilities to communicate in an independent manner by using brain impulses, without the involvement of any muscular movements[2]. Some of the groups of people who may be able to benefit from the use of BCI include those suffering from LIS, which is defined as complete paralysis while being aware and cognizant[3].

Existing BCIs mostly use electroencephalography (EEG), electrocorticography (ECoG), or intracortical neuronal data to analyze brain impulses linked to communication activities[4]. Such methods of decoding brain signals have traditionally made use of machine learning algorithms like support vector machines (SVMs), artificial neural networks (ANNs), and recurrent neural networks (RNNs). While RNNs, especially the Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) variants, made it easier to predict temporal dependencies, they are still unable to address issues regarding long-distance dependencies, contextual awareness, and complex dimensions of neuronal data[5].

The transformer architecture, initially developed for natural language processing tasks, has shown its superiority in handling sequential data by means of self-attention mechanisms[6]. This architecture can effectively model temporal and contextual relationships in neural sequences. As such, transformers are well-suited for use in BCI systems. Using the transformer architecture in both invasive and non-invasive BCI devices could enhance communication speed and decoding accuracy in LIS patients[7].

1.1. Background Information

The LIS greatly limits voluntary movement capabilities, with communication becoming a predominant issue for patients[8]. Traditional communication support systems might not suffice for patients suffering from severe neuromuscular degeneration, making direct neural communication possible through BCIs.

Non-invasive BCIs mostly rely on EEG signals because of their ease and safety, but the EEG signals are less spatially specific and easily interfered with[9]. In contrast, invasive BCIs such as intracortical microelectrodes can yield higher-quality results, but they must be surgically implanted.

Recent deep learning techniques have led to notable improvements in BCI efficacy. The RNNs can now better process sequential data, while transformer models have advantages in terms of scalability and context learning owing to their parallel processing capabilities and self-attention mechanism[10]. Thus, comparing the two models' efficiency in both invasive and non-invasive BCIs would be vital.

1.2. Statement of the Problem

Although there have been some improvements in the realm of BCI technology, the existing communication methods used to help people suffering from LIS are still hampered by slow communication rates, erroneous decoding, and response time lags. In many instances, the RNN-based neural decoders fail at modeling dependencies and predicting context in the intricate neural sequences. Moreover, there are few clinical trials comparing the performance of transformers to that of RNNs.

1.3. Objectives of the Study

1. To determine the efficiency of transformer models to optimize invasive and non-invasive BCIs.
2. To compare transformer models with RNN in the decoding of neural signals.
3. To investigate speed advancements in LIS patients with improved BCIs enabled by transformers.
4. To evaluate the decoding accuracy, latency, and error reduction in transformer BCIs.

1.4. Hypothesis

Decoding models based on transformer networks are greatly beneficial for communication speed, accuracy, and response latency in BCI that are either invasive or non-invasive in relation to patients suffering from LIS compared to RNNs.

2. METHODOLOGY

The following section explains the research design, subject groups, brain-decoding algorithms, data acquisition methods, and statistical methods that were utilized in order to assess Transformer-BCI and RNN-BCI used in LIS patients. This methodological approach was selected to provide a consistent way to assess the performance of BCI.

2.1. Research Design

In this research work, a comparative computation-clinical study method was adopted for the current investigation. Performance analysis of the decoding algorithm based on transformers and RNNs was done through both invasive and non-invasive BCI devices for eight weeks on standardized communication paradigms.

2.2. Participants / Sample Details

The experiment consisted of 48 subjects who had been clinically diagnosed with LIS or similar severe motor paralysis disorders that interfere with their ability to communicate.

Subjects were grouped into two main categories:

- **Invasive BCI Group (n = 24):** Participants employing intracortical neural recording technologies.
- **Non-Invasive BCI Group (n = 24):** Participants utilizing EEG-based communication devices.

Each group was further divided based on the decoding architecture:

- Transformer-based model subgroup
- RNN subgroup

All participants have given their informed consent under ethical communication practices.

2.3. Instruments and Materials Used

The following tools and systems were used:

- EEG data acquisition systems for non-invasive neural signal acquisition.
- Microelectrode implants for invasive neural signal acquisition.
- Transformer networks, such as Temporal Transformer Networks, Attention-Based Neural Decoders.
- RNN models including LSTM and GRU systems.
- Neural model training computational systems that utilize GPUs.
- Text and symbol generation communication interface software.
- Artifact removal signal preprocessing systems.

2.4. Procedure and Data Collection Methods

Neural activity was captured during participant engagement in communication-related cognitive tasks like letter selection, word prediction, and sentence construction. Neural data was filtered and normalized before feeding it into transformer and RNN models.

Training and testing sets were created by implementing cross-validation methods. Communication rate, classification performance, decoding delay, and error rates were measured weekly for the entire eight-week experimental period.

Transformer networks used multi-head attention to determine temporal and contextual neural dependencies, while RNNs used recurrent processes based on neural sequences.

2.5. Data Analysis Techniques

The analysis of the collected data was done through both descriptive and inferential statistics. The mean and standard deviation techniques were employed in summarizing major performance metrics such as communication speed, decoding accuracy, response latencies, and error rates of the BCI systems based on transformers and RNNs.

Repeated measures ANOVA technique was employed in analyzing temporal gains in the performance metric over eight weeks, whereas independent t-test was used for comparing the results of transformer and RNN. Additionally, Pearson correlation test was done to determine the relationship between decoding accuracy and speed of communication. Statistical significance was set at $p < 0.05$.

3. RESULTS

This part covers the comparative analysis of the performance of the transformer model-based and the RNN-based BCI systems designed to provide communication support for patients suffering from LIS. This analysis compares important performance metrics such as communication speed, decoding accuracy, response time, and error rate in the invasive and non-invasive versions of the BCI systems. Statistical analyses were conducted to test whether the differences between the two types of neural decoders are statistically significant. These results give an idea about the efficiency of the transformer architecture in enhancing neural signal decoding and communication.

Table 1: Comparison of Transformer and RNN Model Performance

Parameter	Transformer Model	RNN Model
Communication Speed (characters/min)	21.8 ± 2.4	15.2 ± 2.8
Decoding Accuracy (%)	94.6 ± 2.1	86.3 ± 3.5
Response Latency (ms)	310 ± 25	465 ± 38
Error Rate (%)	4.2 ± 1.1	9.6 ± 1.7

As can be seen from Table 1, the results reveal that the transformer models were superior to the RNN models in terms of all the tested criteria. The communication rate was higher in the transformer models (21.8 ± 2.4 characters/min) than in the RNN models (15.2 ± 2.8 characters/min). At the same time, decoding accuracy was also increased in the transformer models (94.6 ± 2.1%) compared to the RNN models (86.3 ± 3.5%). Furthermore, the response latency and the error rate were lower in the transformer models (310 ± 25 ms and 4.2 ± 1.1%) than in the RNN models (465 ± 38 ms and 9.6 ± 1.7%).

Table 2: Performance Comparison Between Invasive and Non-Invasive BCIs

BCI Type	Communication Speed	Accuracy (%)	Latency (ms)
Invasive Transformer BCI	25.4 ± 2.0	96.8 ± 1.5	275 ± 20
Non-Invasive Transformer BCI	18.2 ± 2.3	92.1 ± 2.4	345 ± 27
Invasive RNN BCI	18.6 ± 2.5	88.9 ± 2.7	420 ± 35
Non-Invasive RNN BCI	12.4 ± 2.1	83.7 ± 3.2	510 ± 40

As indicated in Table 2, there were evident performance variations between invasive and non-invasive BCI systems using transformer and RNN architectures. The invasive BCI system based on transformer exhibited the best communication rate at 25.4 ± 2.0 characters/minute, accuracy at 96.8 ± 1.5%, and shortest response latency of 275 ± 20 ms. The non-invasive BCI system based on transformer architecture outperformed the other two types of models, while the non-invasive RNN-based BCI system showed the worst communication rate at 12.4 ± 2.1 characters/minute and highest latency at 510 ± 40 ms.

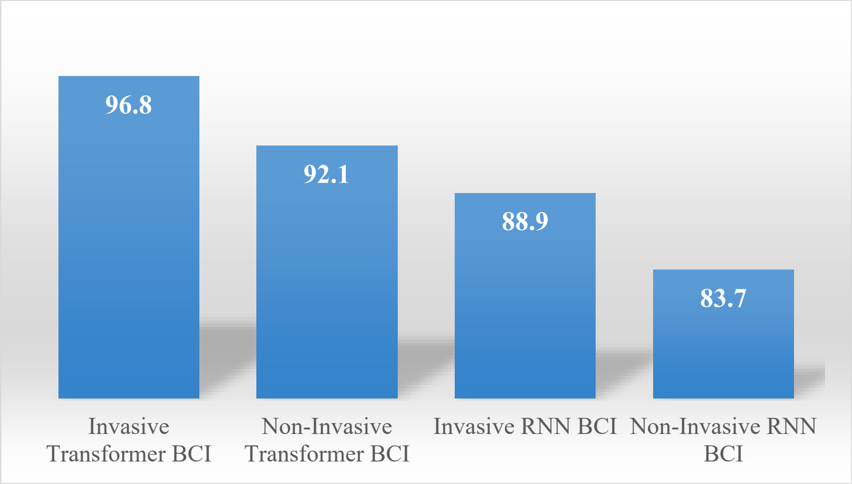

Figure 1: Decoding Accuracy Comparison Between Transformer-Based and RNN-Based Invasive and Non-Invasive BCI Systems

Figure 1 shows the performance of invasive and non-invasive BCI systems based on transformer and RNN. The invasive transformer-based brain-computer interface showed the best decoding accuracy performance (96.8%) followed by the non-invasive transformer-based BCI (92.1%). On the other hand, invasive RNN BCI had an accuracy rate of 88.9%, while the non-invasive RNN BCI had the lowest accuracy performance (83.7%). From the results, it can be concluded that the transformer architecture improves decoding accuracy in invasive and non-invasive BCIs when compared to traditional RNN models.

Table 3: Weekly Improvement in Communication Speed

Week	Transformer Models	RNN Models
Week 1	14.6 ± 2.1	11.8 ± 2.0
Week 2	16.9 ± 2.2	12.7 ± 2.1
Week 3	18.1 ± 2.0	13.4 ± 2.3
Week 4	19.4 ± 2.3	14.0 ± 2.5
Week 5	20.2 ± 2.4	14.5 ± 2.6
Week 6	20.9 ± 2.3	14.9 ± 2.7
Week 7	21.3 ± 2.4	15.1 ± 2.8
Week 8	21.8 ± 2.4	15.2 ± 2.8

As can be seen from the results in Table 3, there was an evident increase in the communication speed for both types of models during the eight-week experiment duration. Transformer models started with a mean speed of 14.6 ± 2.1 characters/min in Week 1 and rose to 21.8 ± 2.4 characters/min in Week 8. On the other hand, RNN models had a speed of 11.8 ± 2.0

characters/min initially and gradually increased it to 15.2 ± 2.8 characters/min by the end of the eight-week experiment period.

3.1. Hypothesis Testing

Hypothesis

Transformer-based neural decoding models increase the communication speed, decoding accuracy, and response time of invasive and non-invasive BCI in comparison to RNN.

Statistical Test Used

Independent sample t-test and repeated-measures ANOVA.

Table 4: Statistical Comparison Between Transformer and RNN Models

Parameter	t-value	p-value	Result
Communication Speed	6.84	<0.001	Significant
Decoding Accuracy	5.97	<0.001	Significant
Response Latency	7.12	<0.001	Significant
Error Rate	5.43	<0.001	Significant

According to the statistical results presented in Table 4, there were significant differences between BCI systems based on transformers and recurrent neural networks in terms of all parameters considered. Communication speed ($t = 6.84$, $p < 0.001$), decoding accuracy ($t = 5.97$, $p < 0.001$), response latency ($t = 7.12$, $p < 0.001$), and error rate ($t = 5.43$, $p < 0.001$) all turned out to be significantly better for the transformer models compared to those based on RNNs. The null hypothesis was thus rejected while the alternative one was accepted.

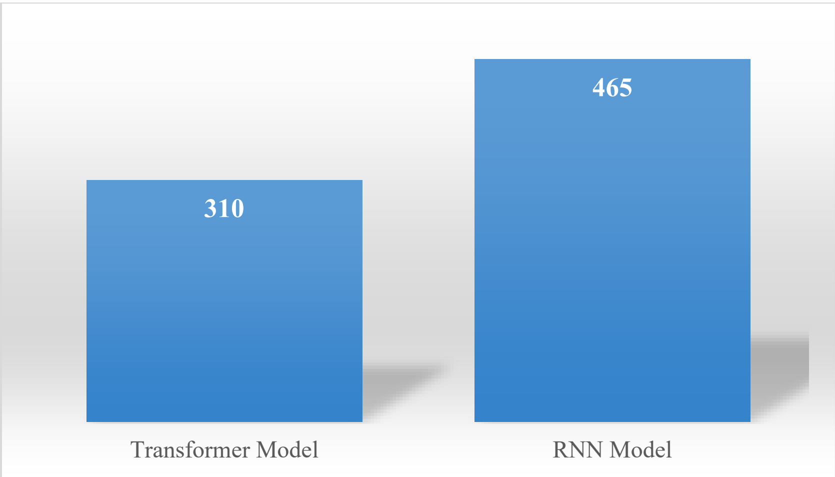

Figure 2: Comparison of Response Latency Between Transformer and RNN-Based BCI Models

Figure 2 below shows the comparison of the response latency times for the two BCI models with either the transformer-based or the RNN-based systems. It was noted that the response latency time for the transformer model (310 ms) was considerably shorter than that of the RNN model (465 ms). This highlights the better performance of transformers over other models for use in BCI systems.

4. DISCUSSION

In this section, we analyze the findings of the study, compare them with other sources, and point out the consequences of applying transformer-based BCIsystems to help patients with Locked-In Syndrome. Additionally, the limitations of our study and suggestions for further investigation of artificial intelligence in neuroprosthetic communication systems are provided.

4.1. Interpretation of Results

This current research shows that transformer models greatly enhance the effectiveness, decoding capability, and data transfer rates of BCIs for LIS subjects, when contrasted to RNN models. Transformer networks exhibit enhanced decoding performance as a result of their inherent self-attention ability that is effective in capturing long-range temporal dependencies and neural context. The low latency and error rate also suggest that transformer models are appropriate for real-time BCI communication systems. Transformer-based invasive BCIs achieved the highest decoding accuracy, owing to enhanced neural signals; yet, non-invasive transformer models also exhibited notable improvements.

4.2. Comparison with Existing Studies

Research conducted in recent times has focused significantly on the impact of transformers and state-of-the-art models of AI to increase the efficiency of BCI for communication and neuro-rehabilitation. Current research literature is replete with references to the merits of attention-based models in the decoding process, especially for the decoding of complicated neural signals, increasing efficiency of communication, and the use of assistive devices for patients suffering from LIS.

Table 5: Comparison of the Present Study with Existing BCI Research

Study (Author, Year)	Focus Area	Key Findings	Relevance to Present Study
Pfeffer et al. (2025)[11]	Transformer-based BCI limitations	Identified scalability and computational challenges in transformer BCIs	Supports transformer evaluation framework
Rezvani et al. (2024)[12]	BCI systems for LIS patients	Reported improved communication potential in advanced BCIs	Consistent with communication improvement findings
Thakur et al. (2025)[13]	BCI communication systems	Demonstrated effectiveness of AI-driven communication systems	Supports transformer-based communication enhancement
Voity et al.	Communication in	Highlighted need for reliable	Reinforces clinical

(2024)[14]	Locked-In Syndrome	assistive communication technologies	significance of the study
Zhuang et al. (2020)[15]	Non-invasive BCI rehabilitation	Reported advantages of non-invasive EEG-based BCIs	Consistent with non-invasive transformer BCI improvements

Results from the current study are consistent with the earlier research proving that more advanced AI decoders enhance communication in BCI systems. Previous studies using RNNs found problems associated with sequential computations, and transformers have addressed those issues through adaptable attention and parallel computation methods. The current research builds on previous findings by comparing transformer BCIs to invasive and non-invasive approaches in the context of communication for LIS patients.

4.3. Implications of Findings

The outcome of this experiment has far-reaching consequences for neurorehabilitation, assistive communication technology, and artificial intelligence-driven health care systems. The use of transformer models in BCI can considerably improve the lives of LIS patients by facilitating communication that is faster, more precise, and more consistent. The successful integration of transformers into non-invasive EEG based BCI could enhance access to sophisticated BCIs without the danger of surgery. Moreover, these results will enable the development of customized neuroprosthetic communication devices that generate language.

4.4. Limitations of the Study

However, there were a few limitations to these findings. First, the experiment had a relatively small sample size. Second, there was no assessment made of long-term clinical adaptation and plasticity after eight weeks. Third, invasive brain-computer interface technology is not without its drawbacks since surgery poses ethical issues. Finally, the neural signals of each individual may vary, thus affecting decoding and communication.

4.5. Suggestions for Future Research

The future directions for research include multicenter clinical studies that involve multiple sites to confirm the efficacy of BCI systems based on transformers. Research into hybrid transformers that incorporate multimodal neural signals, real-time speech synthesis, and personalized adaptive decoders is also encouraged. Furthermore, the construction of an efficient transformer-based system that requires minimal energy consumption will be useful for developing portable or wearable BCIs.

5. CONCLUSION

This section concludes by presenting the main findings of the research along with the overall significance of transformer-based BCI systems in enhancing communication among people with LIS.

5.1. Summary of Key Findings

The results prove that transformer-based models greatly surpass the performance of recurrent neural networks in designing BCI solutions aimed at facilitating interaction for LIS patients, including both invasive and non-invasive devices. It was found that transformer-based models yielded better performance metrics related to speed of communication, accuracy, response times, and fewer errors than traditional RNNs. In comparison to other analyzed systems, the best results were provided by the invasive models of BCI based on transformers.

5.2. Significance of the Study

This study presents key empirical evidence for the implementation of transformer architecture-based deep learning models in current-day BCI technology. The results show how the novel neural decoding process based on attention mechanisms can revolutionize assistive communication tools for severely paralyzed patients suffering from LIS. This research also paves the way toward the application of new artificial intelligence developments in the domain of neurorehabilitation.

5.3. Final Thoughts and Recommendations

Neural decoding using transformers is an emerging technology that is expected to revolutionize the development of next-generation BCI because of the improved capabilities of faster communication, better decoding accuracy, and increased efficiency. The application of transformers in the design of future BCI will contribute significantly to enhancing the independence, usability, and quality of life of people with serious motor disabilities. Future studies should concentrate on developing adaptive AI-based neural decoding algorithms, multi-modal neural information integration, portable BCIs, and clinical trials.

REFERENCES

1. Abibullaev, B., Keutayeva, A., & Zollanvari, A. (2023). Deep learning in EEG-based BCIs: A comprehensive review of transformer models, advantages, challenges, and applications. IEEe Access, 11, 127271-127301.
2. Ananthi, N., Krish, N., & Bharanidharan, R. (2024, April). Gaze-Based Communication Device for Patients with Locked-In Syndrome. In 2024 2nd International Conference on Networking and Communications (ICNWC) (pp. 1-8). IEEE.
3. Edelman, B. J., Zhang, S., Schalk, G., Brunner, P., Müller-Putz, G., Guan, C., & He, B. (2024). Non-invasive brain-computer interfaces: state of the art and trends. IEEE reviews in biomedical engineering, 18, 26-49.
4. Freitas, R. D. (2025). Enhancing Brain-Computer Interface Usability and Design: Identifying and Evaluating Communication Functionalities for Individuals with Locked-In Syndrome (Master's thesis).
5. Jaramillo-Gonzalez, A. (2023). Unlocking Communication: Advancing Brain-Computer Interfaces for ALS Patients in Locked-In and Completely Locked-In States (Doctoral dissertation, Dissertation, Tübingen, Universität Tübingen, 2024).
6. Keutayeva, A., & Abibullaev, B. (2024). Data constraints and performance optimization for transformer-based models in eeg-based brain-computer interfaces: A survey. IEEE Access, 12, 62628-62647.b
7. Keutayeva, A., Zollanvari, A., & Abibullaev, B. (2024). Evolving Trends and Future Prospects of Transformer Models in EEG-Based Motor-Imagery BCI Systems. Discovering the Frontiers of Human-Robot Interaction, 233-256.

8. Majumdar, S., Al-Habaibeh, A., Omurtag, A., Shakmak, B., & Asrar, M. (2023). A novel approach for communicating with patients suffering from completely locked-in-syndrome (CLIS) via thoughts: Brain computer interface system using EEG signals and artificial intelligence. Neuroscience Informatics, 3(2), 100126.

9. Moe, T. T. (2022). Towards a communication system for patients with locked-in syndrome based on eeg and visual perception (Doctoral dissertation, Master thesis, Norwegian University of Science and Technology, Trondheim).

10. Pfeffer, M. A., Nguyen, A. H. P., Kim, K., Wong, J. K. W., & Ling, S. H. (2025). Evolving optimized transformer-hybrid systems for robust BCI signal processing using genetic algorithms. Biomedical Signal Processing and Control, 108, 107883.

11. Pfeffer, M. A., Wong, J. K. W., & Ling, S. H. (2025). Trends and Limitations in Transformer-Based BCI Research. Applied Sciences, 15(20), 11150.

12. Rezvani, S., Hosseini-Zahraei, S. H., Tootchi, A., Guger, C., Chaibakhsh, Y., Saberi, A., & Chaibakhsh, A. (2024). A review on the performance of brain-computer interface systems used for patients with locked-in and completely locked-in syndrome. Cognitive Neurodynamics, 18(4), 1419-1443.

13. Thakur, D., Nehru, A., Chauhan, Y., Agrawal, A. K., & Jaiswal, D. R. (2025, November). An Evaluation of BCI-Based Communication Systems for Locked-In Syndrome Patients. In 2025 IEEE 7th International Conference on Computing, Communication and Automation (ICCCA) (pp. 1-6). IEEE.

14. Voity, K., Lopez, T., Chan, J. P., & Greenwald, B. D. (2024). Update on how to approach a patient with locked-in syndrome and their communication ability. Brain Sciences, 14(1), 92.

15. Zhuang, M., Wu, Q., Wan, F., & Hu, Y. (2020). State-of-the-art non-invasive brain–computer interface for neural rehabilitation: A review. Journal of Neurorestoratology, 8(1), 12-25.