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A Hybrid RNN-CNN based Motor Imagery Tasks Classification Approach Using MEG Brain Signals for BCI Applications

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Abstract: *Magnetoencephalography (MEG) has become a pioneering technology in Brain-Computer Interfaces (BCIs) for neurorehabilitation, which significantly improves communication and motor rehabilitation for people with neurological conditions, especially stroke survivors. MEG-based BCIs allow users to regain control over their motor and cognitive functions by providing precise temporal and spatial resolution for detecting neural activity. The MEG has several benefits including reduced distortion from the skull and scalp, its non-invasive nature, and the ability to capture deep brain activity, all of which enhance the effectiveness of BCI systems. This study focuses on classifying motor and cognitive tasks using various models, including Recurrent Neural Networks (RNNs), one-dimensional Convolutional Neural Networks (1DCNNs), and a hybrid approach. The effectiveness of the models in classification tasks was evaluated using various metrics such as accuracy, recall, precision, and F1-score. Significantly, the hybrid model exhibited enhanced performance relative to the other models, achieving marked improvements in both classification accuracy and robustness. These results underscore the promise of MEG BCI technology for neurorehabilitation and stress the need for the development of sophisticated classification models to support the recovery of motor and cognitive abilities in people with neurological conditions. This study adds to the expanding research focused on enhancing the quality of life for affected individuals by utilizing innovative BCI solutions, leveraging the unique capabilities of MEG technology to enable more effective neurorehabilitation interventions.*

Keywords: *Brain-Computer Interface (BCI), Magnetoencephalography (MEG); Motor Imagery (MI); Cognitive Imagery (CI); Recurrent Neural Networks (RNN); One-Dimensional Convolutional Neural Networks (1D CNN).*

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1. Introduction

The use of magnetoencephalography (MEG) brain signals for classifying imagery tasks has become a major area of focus in brain-computer interface (BCI) research. MEG signals significantly impact neurorehabilitation by providing a non-invasive, high-resolution measure of brain activity (Xu et al., 2022; Li et al., 2023). MEG has been used to examine how brain activity correlates with movement kinematics in the development of motor-based BCIs (Paggiaro et al., 2016). They can guide strategies, help develop new technologies, facilitate communication in patients with motor impairments, and enable the control of devices using brain activity. MEG is becoming an essential tool in both clinical and research settings, offering valuable insights into brain function and helping to diagnose and treat neurological disorders (Fred et al., 2022). These developments lead to enhanced patient outcomes and an overall improvement in quality of life. However, the high cost and limited availability of MEG systems pose challenges for widespread adoption and dataset creation (Rathee et al., 2021).

MEG is a versatile tool with a wide range of applications in research and clinical settings. It enables real-time tracking of neural activity, which enhances our understanding of brain function. In clinical practice, MEG has proven particularly valuable for epilepsy surgeries and functional brain mapping (Hegazy & Gavvala, 2022). Its potential in stroke assessment is notable, as it does not disrupt brain tissue (Kim & Davis, 2021). Stroke ranks as the second most common cause of death worldwide and frequently results in considerable disabilities, making neurorehabilitation essential. Many survivors experience enduring motor impairments (Chang et al., 2023). MEG provides in-depth insights into brain activity and connectivity, allowing clinicians to evaluate the functional status of brain regions impacted by stroke. This information helps create personalized rehabilitation strategies that meet the distinct requirements of every patient. By enhancing our understanding of the brain's compensatory mechanisms for lost functions, MEG contributes to better rehabilitation outcomes for stroke patients. Moreover, it can monitor neuroplastic changes, providing valuable feedback on rehabilitation success and helping to adjust treatment plans. MEG motor-based BCI enables patients to control devices through their brain activity, significantly enhancing the quality of life for stroke survivors (Yang et al., 2024; Mucileanu et al., 2024). As technology and analytical techniques advance, MEG is set to propel significant progress in neuroscience and broaden its clinical applications.

MEG signal classification has been a key area of research due to its potential for decoding brain activity and understanding cognitive processes. Several approaches have been suggested to overcome the challenges in processing and classifying MEG signals. Deep Learning (DL) techniques automatically extract relevant features from large datasets, minimizing the reliance on manual feature engineering. This leads to the creation of more precise classification models (Essa & Kotte, 2021). Deep learning has significantly altered the way sequential data is analyzed by making it possible to build sophisticated models that can recognize complex patterns and connections within the data. In a study (Caliskan et al., 2017), researchers developed a deep neural network-based classifier to distinguish MEG signals elicited by various visual stimuli, including faces and scrambled faces. The proposed approach outperformed conventional classification techniques, achieving 80.85% average accuracy. In this paper, the authors introduced a hybrid gated recurrent network (HGRN) designed for inter-subject visual decoding of MEG signals in response to various visual stimuli, specifically faces and scrambled faces (Li et al., 2021). This approach outperformed existing methods, with the proposed HGRN achieving an accuracy of approximately 71%. Additionally, (Özer et al., 2023) compared two neural network structures for classifying these signals: a multilayer neural network (MLN) and a probabilistic neural network (PNN). The findings indicated a classification accuracy of 82.36% for the PNN and 77.78% for the MLN. The study by (Hosseini, 2019) implemented a hybrid approach for feature extraction, integrating surface Laplacian, Hurst exponent, Morlet coefficients, and Petrosian fractal dimension. Support Vector Machines (SVM) were then applied for classification. This approach exhibited high accuracy in identifying the location of attended stimuli during visual covert selective spatial attention tasks. However, the results are drawn from a limited sample size, raising concerns about potential overfitting. Moreover, while using a shorter time interval may enhance virtual time resolution, it risks compromising data quality and could result in the loss of important temporal information, potentially affecting classification accuracy. The study conducted by (Koskinen et al., 2012) employed Canonical Correlation Analysis (CCA) along with a Bayesian mixture of CCA analyzers to derive features from MEG data associated with speech envelopes. This method facilitated the identification of speech fragments heard by participants, revealing a shared time series of signals between MEG signals and speech envelopes within a specific frequency range. The paper by (Dash et al., 2020) also highlights the hierarchical structure of speech production, which transforms linguistic intentions into coherent speech sounds. The methods reviewed have demonstrated improved performance across diverse tasks, including visual stimulus classification, speech decoding, and the prediction of attentional focus.

Motor imagery (MI) signal classification is a crucial element of BCI systems, especially in the fields of medical rehabilitation and assistive technologies. Several studies have investigated the classification of motor imagery tasks from MEG signals, exploring various approaches to improve accuracy and robustness. The work by (Sabra & Wahed, 2011) uses an SVM classifier to accurately classify the direction of wrist movements, while Adaptive Neural Networks (ANN) are employed by (Zubarev et al., 2019) to decode MEG signals. The study by (Halme & Parkkonen, 2018) compared the performance of various classification techniques for motor imagery tasks using signals from both MEG and EEG recordings. The authors concluded that multi-task joint feature learning, combined with logistic regression and l2,1-norm regularization, yielded the highest performance. The authors (Roy et al., 2020) investigated how different channel selection methods affect the performance of MEG-based BCI. Their findings indicated that not all sensors have an equal influence on classification accuracy, highlighting the importance of implementing effective channel selection strategies. By utilising state-of-the-art methods, they achieved notable enhancements in classification accuracy across multiple frequency bands. In (Tang et al., 2024), the authors introduced a coherence-based channel selection method designed to identify task-relevant channels while minimizing noise and redundancy. Their approach utilized Riemannian geometry for feature extraction and demonstrated superior performance compared to conventional methods like common spatial patterns and power spectral density in classification tasks. Despite the accuracy not being exceptionally high, the studies reviewed highlight the potential of different approaches for classifying motor imagery tasks from MEG signals. Further research is required to build on these findings and create more reliable MEG-based BCIs.

Conventional machine learning methods typically necessitate manual feature engineering, which can be quite demanding and may fail to capture all relevant information in MEG data. In contrast, deep learning models are proficient at autonomously identifying the most pertinent features from the data, thereby streamlining the process and enhancing the capacity of the model to recognise complex patterns without the need for manual intervention. By capturing nonlinear and hierarchical relationships within the data, deep learning models are capable of extracting more distinctive features, resulting in improved classification accuracy. Recent studies have shown the effectiveness of integrating deep learning techniques into comprehensive MEG analysis pipelines, improving reliability and reproducibility of BCI systems (Ferrante et al., 2022). For example, artificial neural networks (ANNs) have proven effective in classifying kinesthetic and visual imagery of hand movements based on MEG data (Kurkin et al., 2020). Moreover, deep neural networks have been utilized for the automatic diagnosis of neurological disorders (Aoe et al., 2019) and fully automated spike detection and dipole analysis in epileptic MEG data (Hirano et al., 2022). These studies emphasize the essential contribution of deep learning approaches in boosting the reliability, accuracy, and efficiency of BCI systems that employ MEG data, illustrating how deep learning can propel advancements in the field of neurotechnology.

The MEG data collected from participants engaged in various imagery tasks, including motor and cognitive imagery, often contains interference and artifacts that can diminish the system's accuracy (Rathee et al., 2021). To enhance classification accuracy, it is crucial to preprocess the data to eliminate these disturbances (Treacher et al., 2021). Once the data has been processed, it can then be used in the classification process with different algorithms. These algorithms aim to identify patterns in the MEG signals associated with different imagery tasks and use this information to classify new, unseen data. There is a need for the development of more robust and efficient classification methods to boost the reliability and accuracy of MEG-based BCI for imagery tasks. Such advancements could facilitate a wide array of applications, including the development of BCI systems for individuals with paralysis or other motor disorders, as well as the creation of more precise and effective BCI systems for gaming and other purposes.

A significant amount of research has focused on classical machine-learning techniques for analyzing motor imagery data obtained from magnetoencephalography (MEG). However, the utilization of deep learning techniques in this field is still relatively constrained. Existing studies have demonstrated that deep learning methods are effective in classifying MEG signals, offering several advantages over traditional machine learning techniques. This study explores different Recurrent Neural Network (RNN) and One-Dimensional Convolutional Neural Network (1DCNN) architectures. We compare the performance of these models with a hybrid architecture that combines 1DCNN and Bidirectional Long Short-Term Memory (BiLSTM). The goal is to enhance the predictive accuracy and testing effectiveness of motor and cognitive imagery data.

This article is structured to offer a thorough overview of the study. The introduction outlines the main objectives and significance of the research, complemented by a review of relevant literature in this field. Subsequently, the materials and methods section offers a detailed description of the dataset and the analytical approaches employed. The implementation details and evaluation metrics section discusses the models utilized and the performance metrics applied to assess their effectiveness. In the results and discussion section, the main findings are highlighted and accompanied by visual aids, that aid in understanding their implications in a broader context. The conclusion distills the key contributions of the study while also suggesting directions for future research initiatives.

2. Materials and Methods

This section explores the different deep-learning techniques for classifying MEG signals, focusing on Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). RNNs effectively identify and model temporal relationships in MEG data through their recurrent connections, which allows them to handle complex temporal patterns. CNNs, on the other hand, identify features within MEG signals using convolutional and pooling layers and are particularly beneficial for tasks that involve extracting spatial and temporal characteristics (Tang et al., 2020). This research explores various architectures of RNNs, specifically including Simple RNN (SRNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Bi-directional LSTM (BiLSTM) in addition to 1DCNN. We assess the effectiveness of these models compared to a hybrid architecture that combines BiLSTM with 1DCNN. Figure 1 illustrates the workflow of this study. The methodology is detailed in the following subsections.

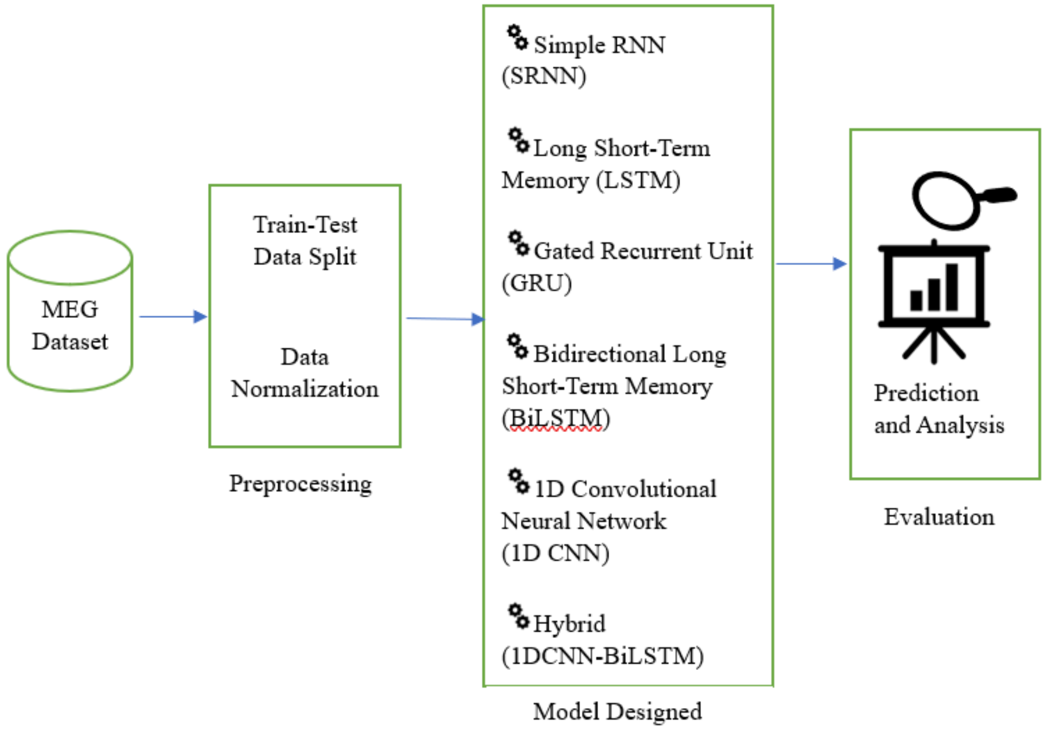

Figure 1. Workflow diagram

2.1 Dataset Description

The MEG dataset employed in this work was created by (Rathee et al., 2021), who gathered data from 17 participants using an Elekta Neuromag system featuring 102 triple-sensor groups, with each group consisting of one magnetometer and two gradiometers, resulting in a total of 306 sensors. Each participant completed two sessions, with 50 trials allocated to each of the four mental imagery tasks, resulting in 200 trials overall. The tasks included two motor imagery (MI) activities—imagining the movement of the hands and the feet—and two cognitive imagery (CI) tasks, which involved performing mathematical subtraction and generating words. During the motor imagery tasks, participants were instructed to mentally simulate movements of either their hands or feet in response to visual prompts shown on the screen. In contrast, during the cognitive imagery tasks, participants executed simple arithmetic operations, such as subtracting two presented numbers or generating words that corresponded to letters of the English alphabet presented as cues. Each trial lasted 7,000 milliseconds. To preprocess the raw MEG signals and remove artifacts, the Independent Component Analysis (ICA) algorithm was employed (Philip et al., 2024). Following this preprocessing, the cleaned signals were used for classification.

MEG is vital for stroke recovery and rehabilitation because it reveals the link between brain activity and motor function. It makes it possible to map brain activity in real time, which aids in determining the neural correlates of motor recovery and the regions involved in motor control (Paggiaro et al., 2016). MEG can identify early indicators of motor recovery, enabling focused treatments and individualized rehabilitation plans based on each person's unique brain function. Insights into the effectiveness of treatment interventions and the underlying neural mechanisms of recovery can also be gained by tracking changes in brain activity over time (Ramos-Murguialday et al., 2013). In the long run, better patient outcomes in stroke rehabilitation may result from future developments in MEG analysis methods.

2.2 Recurrent Neural Networks

Recurrent Neural Networks (RNNs) are a specialized class of neural networks designed to handle sequential data effectively. Their distinguishing characteristic is the feedback connection, which enables the model to maintain an internal state, crucial for capturing temporal dependencies. This research investigates four primary RNN models - SRNN, LSTM, GRU, and BiLSTM.

2.2.1 Simple RNN (SRNN)

Simple Recurrent Neural Networks (SRNNs) are a subclass of RNNs designed specifically for the analysis and modeling of sequential data. They utilize recurrent connections to capture temporal dependencies within the data but lack memory cells or gating mechanisms to regulate the information flow. The core architecture of an SRNN is composed of three primary layers:

- Input Layer: Receives the sequence of input data, a series of time-dependent observations.
- Hidden Layer: The recurrent connections are established in this layer. At each time step, the hidden state is modified based on the current input and the hidden state from the previous time step. This mechanism enables the network to retain a form of memory over the sequence.
- Output Layer: Generates predictions based on the hidden state, providing the final output for each time step in the sequence.

In the forward pass, the SRNN processes a sequence of inputs by sequentially updating its hidden state. At each time step, the new hidden state is computed based on the current input and the hidden state from the prior time step. This iterative process allows the network to capture temporal dependencies within the data (Mienye et al., 2024; Dutta, 2019). The architecture of the Simple RNN is depicted in Figure 2.

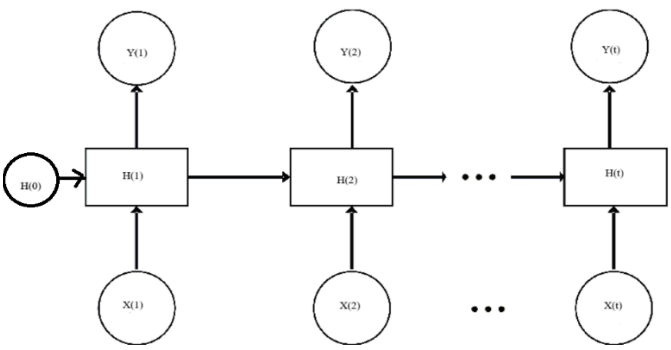

Figure 2. Simple RNN structure

The equation for the hidden state at each time step is given by

$$H(t) = \tanh(W_h H(t-1) + W_x X(t) + b) \quad (1)$$

where $H(t)$ – hidden state at time t
$H(t-1)$ – previous hidden state
$X(t)$ – input at time t
W_h, W_x – weight matrices of hidden state and input respectively
b - bias

Also, the output at each time step $Y(t) = W_o H(t) + b_o$ (2)
where W_o is the weight matrix and b_o is the bias for the output

This approach enables the SRNN to effectively identify and learn temporal relationships within the data, rendering it suitable for applications like sequence classification and time series forecasting.

2.2.2 Long Short-Term Memory (LSTM)

LSTMs, illustrated in Figure 3, are a specialized variant of RNNs adeptly designed to effectively capture long-term dependencies in sequential data. In contrast to standard RNNs, which rely on a single activation function, LSTMs employ a more intricate internal architecture comprising four interconnected components. These components work together to regulate the flow of information, enabling LSTMs to tackle the vanishing gradient problem that often hinders the training of deep neural networks. The fundamental unit of an LSTM model includes the following key components (Rehman et al., 2019; Sun & Zhao, 2021):

- Input Gate: Regulates the intake of new data into the cell state, allowing the network to selectively update its internal state based on the present input. It determines which parts of the incoming data should be added to the memory.
- Forget Gate: Controls the removal or modification of information in the cell state. It enables the network to discard irrelevant or outdated information, helping to maintain a stable and relevant internal state over time.
- Output Gate: This gate regulates the information sent to the output and hidden state, enabling the network to selectively produce relevant outputs.
- Cell State: This element empowers the model to store and utilize long-term dependencies from the input data effectively.
- Hidden State: This state signifies the output of the LSTM cell and transmits information to the following time step, enabling the network to preserve knowledge from prior inputs over an extended duration.

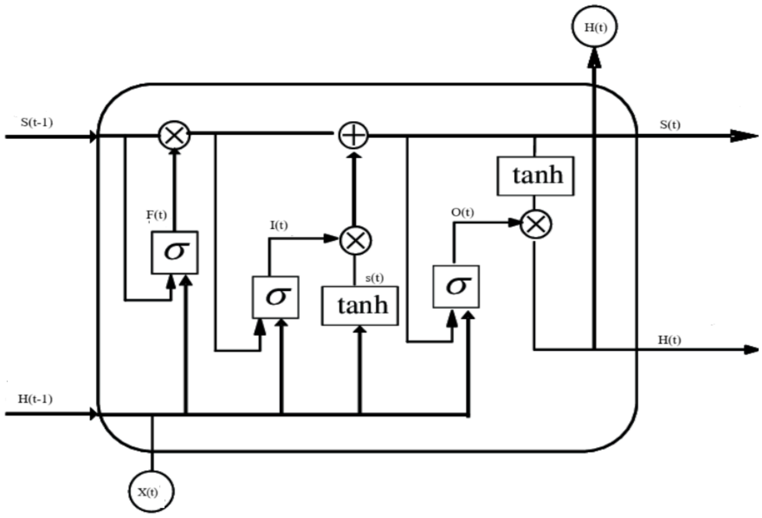

Figure 3. LSTM network architecture

The update equations for the LSTM network at each time step (t) can be expressed as follows:

$$\text{Input gate, } I(t) = \sigma\,(W_i\,[H(t\text{-}1), X(t)] + b_i) \quad (3)$$

$$\text{Forget gate, } F(t) = \sigma\,(W_f\,[H(t\text{-}1), X(t)] + b_f) \quad (4)$$

$$\text{Output gate, } O(t) = \sigma\,(W_o\,[H(t\text{-}1), X(t)] + b_o) \quad (5)$$

Candidate cell state, $s(t) = \tanh(W_s\,[H(t-1), X(t)] + b_s)$ (6)

Cell state, $S(t) = F(t) \odot S(t-1) + I(t) \odot s(t)$ (7)

Hidden state, $H(t) = O(t) \odot \tanh(s(t))$ (8)

where W is the corresponding weight matrix and b is the bias

The inclusion of these gates enables LSTMs to efficiently regulate the information flow, allowing them to retain information from previous inputs for an extended period. This capability enables LSTMs to accurately estimate outputs in complex sequential data.

2.2.3 Gated Recurrent Unit (GRU)

GRUs simplify the architecture of traditional LSTMs by merging the forget and input gates into a single gate called the update gate, which reduces both the number of parameters and overall complexity (Rana, 2016; Yao et al., 2021). A GRU comprises two core components: the reset gate and the update gate. The update gate regulates the extent to which the previous hidden state is retained and the amount of new input that is integrated, whereas the reset gate determines how much past information to discard when processing new inputs. The hidden state is a crucial component that handles sequential data by integrating past information to influence current predictions.

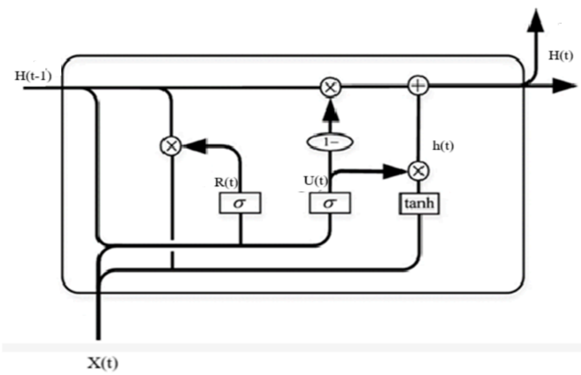

Figure 4. GRU network

This streamlined design enables GRUs to learn dependencies in sequential data effectively while maintaining computational efficiency.

$U(t) = \sigma(W_u\,[H(t-1), X(t)])$ (9)

$R(t) = \sigma(W_r\,[H(t-1), X(t)])$ (10)

$h(t) = \tanh(W_h\,[R(t) \odot [H(t-1), X(t)]])\ H(t)$ (11)

$H(t) = (1-U(t)) \odot H(t-1) + U(t) \odot h(t)$ (12)

where U(t) and R(t) are the update and reset gate respectively
h(t) is the candidate's hidden state

2.2.4 Bidirectional LSTM (BiLSTM)

BiLSTM models are engineered to capture dependencies in forward and backward directions within input data, which is particularly beneficial for analyzing the temporal dynamics of MEG signals. This architecture combines the outputs from two LSTM networks: one analyzes the input sequence in a forward direction while the other does so in reverse. This dual approach allows the model to effectively leverage past and future contexts, making it especially effective for tasks that necessitate a holistic understanding of the entire input sequence.

During the forward pass, the BiLSTM processes a sequence of inputs using both the forward and backward LSTMs. The forward LSTM processes the input sequence by updating its hidden and cell states based on the present input and the previous hidden state. On the other hand, the backward LSTM operates in reverse, updating its states using the present input along with the next hidden state. This approach results in the retention of two separate hidden states for each time interval. The outputs from both LSTMs are subsequently combined to form the final result (Yao et al., 2021). In short, the BiLSTM model is designed to learn temporal patterns in MEG data and classify the signals into various categories, such as different cognitive or sensory states. Figure 5 depicts the BiLSTM design.

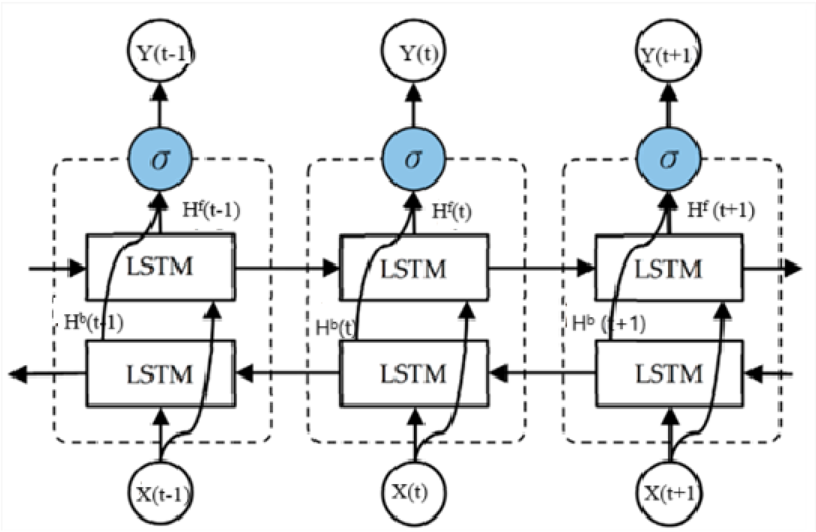

Figure 5. BiLSTM network architecture

2.3 Convolutional Neural Networks

One-Dimensional Convolutional Neural Networks (1DCNNs) are a specific kind of Convolutional Neural Network (CNN) designed to handle data in one-dimensional formats, like time series, text, and audio signals. In contrast to standard 2D CNNs that are optimized for image analysis, 1DCNNs are uniquely designed to extract meaningful features from sequential data. The fundamental architecture of a 1DCNN comprises multiple layers, with each layer playing a key role in the investigation of the input data (Kim et al., 2020; Hamad et al., 2020).

- Convolutional Layers: These layers utilize a series of filters on the input data, traversing the sequence to extract significant features. The filters are designed to detect local patterns and relationships present in the data.
- Activation Functions: Incorporating non-linearity into the model, these functions facilitate the capture of complex patterns and relationships within the data. ReLU, Sigmoid, and Tanh are the common activation functions utilized in 1D CNNs.
- Pooling Layers: These layers achieve dimensionality reduction of the feature maps through downsampling, which lowers the number of parameters while ensuring that essential information is preserved. This process also helps lower computational complexity.

- Flatten Layer: This layer transforms the outputs from the convolutional and pooling layers and reshapes them into a one-dimensional feature vector, making the data ready for the next layers.
- Dense Layers: Comprising fully connected neurons, these layers handle classification or regression tasks. They process the one-dimensional feature vector and produce the output class.

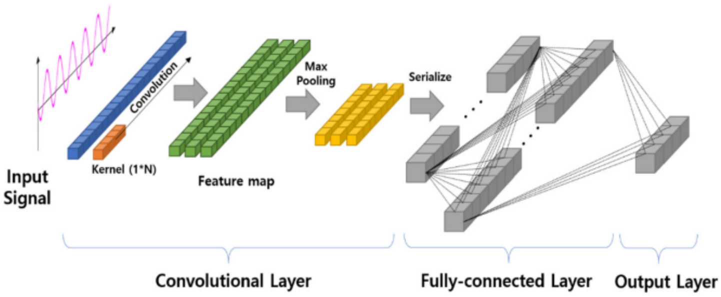

Figure 6. 1DCNN (General architecture)

Figure 6 depicts the overall structure of a 1D CNN, which processes one-dimensional input data, such as vectors, by applying a convolutional layer featuring a 1 × N kernel. During the forward pass, the 1D CNN takes a sequence of inputs and applies filters to extract features by convolving them with the input data. The resulting output is then passed through an activation function. Next, a pooling operation is performed to lower both the spatial dimensions and the parameter quantity. This process is repeated over multiple layers. The output is flattened into a single-dimensional feature vector, which is then passed through dense layers for classification or regression. By utilizing the strengths of convolutional and pooling layers, 1D CNNs can successfully detect local patterns and interrelationships within sequential data.

2.4 Hybrid Architecture

The combination of RNNs and CNNs leverages the strengths of both models to improve the overall performance (Hamad et al., 2020). This study integrates BiLSTM with 1D CNN to effectively capture both spatial and temporal patterns in sequential data. The 1D CNN is particularly skilled at extracting local features from input data using convolutional layers, making it particularly suitable for applications that require the analysis of time-series data or one-dimensional signals, such as audio or sensor data. By incorporating RNNs, which are designed for sequence processing and maintaining temporal relationships, this combined architecture can model long-range dependencies and capture temporal dynamics that may be missed by CNNs alone. This synergy results in improved performance, leading to more accurate predictions and better generalization on complex sequential tasks (Mienye et al., 2024; Huang et al., 2024). Figure 7 illustrates the hybrid architecture.

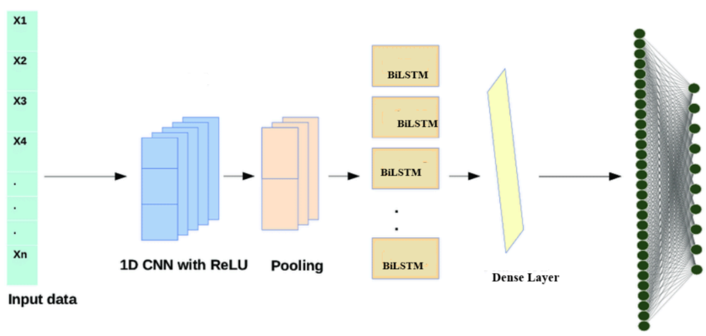

Figure 7. Hybrid architecture (1DCNN- BiLSTM)

3. Implementation Details and Evaluation Metrics

This section details the implementation of multiple classification models intended for class prediction. To ensure a thorough evaluation of these models' predictive abilities, we assessed their performance across multiple metrics, including accuracy, precision, recall, and F1 score.

3.1 Implementation Details

The models were trained and tested on randomly chosen subsets of data from participants engaged in four distinct tasks, with a total of 40,000 samples. Of these, 32,000 samples were designated for training, while 8,000 samples were reserved for testing. Before training the models, the input data underwent several preprocessing steps, including normalization and scaling, to standardize all features to a common scale. In addition, data augmentation was employed to expand the dataset and boost the robustness of the models.

In our work, we constructed an SRNN that includes a single recurrent layer with 50 units. This layer processes sequential data to capture temporal dependencies. After the recurrent layer, a Dense layer with 5 units was added to serve as the output layer implemented for handling multi-class classification. We utilized the Root Mean Square Propagation (RMSProp) optimization algorithm to enhance performance and improve convergence and the loss function was also calculated. Table 1 provides a detailed overview of the parameters for the other RNN models.

Table 1. Model Parameters used for LSTM, GRU and BiLSTM

Parameter	LSTM	GRU	BiLSTM
Units	50	50	50
Dropout rate	0.2	0.2	0.2
Output Units	5	5	5
Activation Function	Softmax	Softmax	Softmax
Loss Function	Categorical Crossentropy	Categorical Crossentropy	Categorical Crossentropy
Optimizer	Adam	Adam	Adam

The 1D CNN model is structured with an initial 1D convolutional layer (Conv1D) featuring 32 filters and a kernel size of 3, activated by the ReLU function. Following this, a max pooling layer (MaxPooling1D) is applied to minimize the dimensionality of the feature maps with a pooling size of 2. The output produced by the pooling layer is then transformed into a one-dimensional vector with the help of a Flatten layer. The architecture includes a fully connected dense layer with 64 units, also activated by ReLU, and finishes with an output layer containing 4 units that apply softmax activation to calculate the probabilities for each of the four classes. The model uses categorical cross-entropy as its loss function during compilation and incorporates the Adam optimizer, known for its adaptive learning rate, which facilitates faster convergence and improves overall robustness. The proposed hybrid model, 1DCNN-BiLSTM, utilizes the same parameters as the 1D CNN while incorporating two BiLSTM layers, each with 64 units. The first LSTM layer outputs sequences, allowing its output to be passed to the second LSTM layer, which does not return sequences.

3.2 Evaluation Metrics

The efficacy of a classification model can be evaluated using several metrics. In addition to accuracy, significant metrics for assessing the model's performance encompass precision, recall, and F1-score (Grandini et al., 2020). Accuracy indicates the ratio of correctly classified instances to the total instances in the dataset, giving a general insight into the model's predictive effectiveness.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \tag{13}$$

Precision calculates the ratio of true positives (accurately identified instances) to the total positive predictions made by the model. In contrast, recall gauges the ratio of true positives to all actual positive instances within the dataset. The F1-score, representing the harmonic mean of precision and recall, provides a balanced assessment of both metrics.

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{14}$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{15}$$

$$\text{F1-Score} = \frac{2 * \text{Precision} * \text{Recall}}{(\text{Precision} + \text{Recall})} \tag{16}$$

where TP: number of true positives, TN: number of true negatives, FP: number of false positives, and FN: number of false negatives.

These metrics provide a comprehensive evaluation of a classification model's effectiveness. Accuracy reflects the model's overall correctness, while precision highlights the reliability of its positive predictions. Recall measures the model's ability to detect all relevant instances, and the F1 score offers a balanced perspective between recall and precision. By examining the above metrics, practitioners can acquire a meaningful understanding of the model's strengths and weaknesses, allowing them to make informed decisions for its improvement and optimization.

4. Results and Discussion

This section summarizes the results of our experimental investigations into classifying preprocessed MEG data using various classification models. We explored RNN models, including SRNN, LSTM, GRU, and BiLSTM, as well as a 1DCNN and a hybrid model (BiLSTM-1DCNN) that combines both approaches. The hybrid model demonstrated enhanced performance relative to other models. We assessed the performance of the models by measuring accuracy, precision, recall, and F1-score. Our findings reveal that the hybrid model recorded the highest accuracy at 94.6%, outperforming both the RNN models and the 1DCNN model. Table 2 summarizes these findings, offering a systematic comparison of the performance metrics for each model.

Table 2. Performance metrics of the models

Model	Average Accuracy	Precision	Recall	F1 Score	Computation time/epoch
SRNN	0.667	0.65	0.64	0.645	129s
LSTM	0.753	0.759	0.753	0.759	363s
GRU	0.833	0.916	0.779	0.842	246s
BiLSTM	0.896	0.893	0.884	0.889	532s
1DCNN	0.921	0.911	0.92	0.915	28s
Proposed hybrid (1DCNN-BiLSTM)	0.946	0.939	0.941	0.939	234s

The robust performance of the proposed hybrid model stems from its capability to effectively capture both temporal dependencies and spatial hierarchies within the MEG data. Its high precision, recall, and F1 score reflect a well-balanced capability to accurately identify relevant instances while minimizing false positives. The 1DCNN model achieves an accuracy of 0.921, demonstrating the effectiveness of convolutional layers in extracting important features from the data. The BiLSTM model also performs well, with an accuracy of 0.896; however, it has a significantly longer computation time, suggesting that while it is effective, it may not be as efficient in terms of training duration. In contrast, the LSTM and GRU models show lower accuracies of 0.753 and 0.833, respectively, and also require longer computation time than the 1DCNN. Notably, the proposed hybrid model has a more efficient computation time compared to the BiLSTM alone. This suggests that combining the 1DCNN with BiLSTM layers improves the model's performance while significantly shortening the overall training time.

The RNN model, while capable of processing sequential data, faced challenges in fully utilizing the spatial features present in MEG recordings, which led to lower classification accuracy. In contrast, the 1DCNN demonstrated a strong capability to detect local patterns in the data, resulting in enhanced performance relative to the RNN alone. However, it was the combination of these two architectures in the hybrid model that enabled a more thorough analysis of the data, ultimately achieving the highest classification accuracy. This indicates that integrating different model architectures can leverage their respective strengths while compensating for their weaknesses.

To perform a more thorough evaluation of the model, we charted the validation loss across the training epochs, as depicted in Figure 8. The graph illustrates a steady decline in validation loss for both the 1D CNN and hybrid models, indicating effective learning and generalization to unseen data. Notably, the hybrid model exhibited a more pronounced reduction in validation loss compared to the other models, which correlates with its superior classification accuracy. This trend highlights the hybrid model's ability to minimize overfitting while maximizing performance.

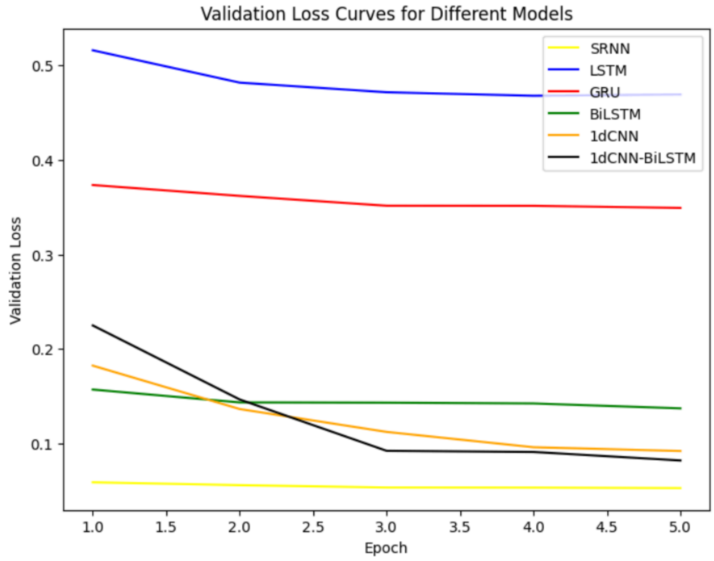

Figure 8. Validation loss Curves

This investigation represents a novel application of deep learning algorithms to a specific MEG dataset. Currently, very few research efforts have been made to utilize deep learning techniques on this dataset. The impressive accuracy of the hybrid model suggests that deep learning can effectively reveal complex patterns within intricate neurophysiological data. This has the potential to improve diagnostic and prognostic capabilities in clinical settings.

As neuroimaging technology advances, there is significant potential to explore hybrid models and their various applications further. This exploration could yield important insights into brain function and neurological disorders. Our findings highlight the effectiveness of advanced machine learning techniques for analyzing MEG data, establishing a strong foundation for future research into deep learning applications in this field. We encourage the continued integration of deep learning methodologies in MEG research, as this could greatly enhance the accuracy and reliability of BCI systems and other neurorehabilitation strategies. Ongoing research in this area is crucial for improving our understanding and treatment of neurological conditions.

5. Conclusion

In conclusion, our research underscores the efficacy of the hybrid model in classifying MEG imagery data, demonstrating a significant enhancement in accuracy relative to conventional RNN and 1DCNN architectures. This finding suggests that integrating diverse modeling approaches can substantially improve performance in neuroimaging applications. While the hybrid model demonstrated superior performance, the additional computational time required emphasizes the need for optimization techniques to enhance training efficiency. Future investigations may aim to enhance model architectures to decrease training time without compromising accuracy. Additionally, exploring the application of this methodology to larger datasets or different types of neuroimaging data may provide further insights into the robustness and generalizability of the hybrid approach. As research in this domain advances, we can expect enhancements in the accuracy and reliability of MEG signal classification, potentially offering novel insights into brain function and cognitive processes.

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