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Article

Neural network-based EEG data restoration for dementia therapy via brain–computer interface

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Abstract: Elderly individuals with dementia experience significant cognitive and emotional impairments, motivating research into technology-driven therapies to improve their quality of life. However, the effectiveness of such systems is often limited by poor-quality electroencephalographic (EEG) data, which can be distorted or incomplete due to artefacts. This study introduces a novel brain-computer interface (BCI)-based rehabilitation framework that combines neural network-assisted EEG data restoration with personalised therapy modules. The proposed method employs a multilayer perception (MLP) enhanced with a custom activation function to reconstruct missing EEG values by modelling spatial and temporal dependencies among adjacent electrodes. Experimental evaluation on benchmark EEG datasets shows that the proposed approach reduces Mean Absolute Error (MAE) by 15% and increases the Correlation Coefficient (CC) by 10% compared to traditional imputation techniques such as mean substitution and k-nearest neighbours (KNN). The restored EEG data are further integrated into a generative AI-powered rehabilitation system that delivers adaptive treatments through virtual reality (VR) environments and social interaction activities. By incorporating patient-specific affective profiles and preferences, the system dynamically personalises interventions such as cognitive games, reminiscence sessions, and immersive simulations. Overall, this framework bridges computational neuroscience and patient-centred healthcare, highlighting EEG imputation as a core technology for next-generation intelligent dementia care solutions, particularly in rural and resource-limited settings.

Keywords: EEG data imputation; neural networks; brain–computer interface (BCI); missing data restoration; generative AI; virtual reality (VR) therapy; personalised healthcare

1. Introduction

Electroencephalography (EEG) is a widely used, non-invasive technique for recording brain activity, playing a critical role in clinical diagnostics, cognitive neuroscience, and rehabilitation research [1–3]. However, EEG data are often affected by artefacts such as electrical interference, motion, and muscle activity, leading to missing or corrupted signals [4–5]. These missing values can distort the interpretation of brain dynamics, compromise clinical accuracy, and hinder the design of real-time neuro technologies due to the spatial and temporal dependencies inherent in EEG data. Conventional imputation methods—like mean substitution and linear interpolation fail to preserve these dependencies, often distorting the underlying signal structure [6–7]. Although advanced approaches such as k-nearest neighbours (KNN), matrix factorisation, and machine learning models have improved imputation accuracy, they still struggle to capture the non-linear and complex spatial-temporal characteristics of EEG data [8,9].

This study introduces a neural network-based imputation framework that explicitly models spatial and temporal relationships among EEG sensors. The approach employs differential values between neighbouring sensors and a custom activation function to better simulate non-linear associations while reducing dependency on large, labelled datasets. Experimental results demonstrate a 15% reduction in Mean Absolute Error (MAE) and a 10% increase in Correlation Coefficient (CC) compared to mean and KNN-based methods.

Beyond technical advancement [10–12], the proposed method holds significant potential for healthcare, particularly in dementia rehabilitation. In India alone, dementia affects over 8.8 million older adults, with higher prevalence among women and rural populations. By integrating imputed EEG data with Brain-Computer Interface (BCI), Generative AI, and Virtual Reality (VR), personalised, adaptive cognitive therapies can be designed—enhancing treatment precision, engagement, and overall patient wellbeing.

While the primary focus of this study is on enhancing the accuracy of EEG data restoration, the broader motivation lies in its potential application in clinical rehabilitation, particularly for dementia care. Missing or corrupted EEG data can compromise the interpretation of neural activity, leading to unreliable assessments of cognitive function and emotional state. In dementia rehabilitation, where continuous and precise monitoring of brain responses is essential for designing adaptive therapies, such data inconsistencies can reduce treatment effectiveness. Therefore, improving EEG imputation not only advances signal processing but also directly supports the development of intelligent, data-driven rehabilitation systems capable of personalising therapy to each patient's neural profile.

2. Literature review

Numerous studies have spoken about the issue of missing values in EEG data. Traditional imputation approaches, such as mean imputation and interpolation, have been widely used in EEG studies [13]. However, these methods assume that missing values are independent of neighbouring values, which may not be valid for EEG data. More recent approaches have attempted to consider the interrelatedness of neighbouring sensors.

A. Hippert-Ferrer et al. [14], the authors present a robust covariance matrix estimation method for incomplete data. They provide a method for estimating the covariance matrix that combines an expectation-maximisation approach with a scaled Gaussian low-rank model. The technique is designed to handle missing values and is validated on simulated datasets. The authors compare their approach to classical statistical estimation methodologies and demonstrate its effectiveness in classification tasks. This work contributes to the field of robust estimation by combining the strengths of both Gaussian and robust models to achieve improved accuracy in real-world datasets with heterogeneity and heavy-tailed distributions. However, the mode is affected by slow convergence.

Lin et al. [15] propose a new hybrid Multiple imputation framework to address the missing data issue in cluster monitoring applications. This method blends model-based and data-driven architectures to impute missing data for every given missing pattern, in contrast to the multiple standard imputation strategies. Deep features are extracted from the data by the deep neural network and utilised to approximate missing data. For various missing data patterns, ratios, and datasets, the suggested strategy is contrasted with traditional multiple imputation methodologies. The outcomes demonstrate that the suggested method may produce a more precise and consistent imputation performance.

Cheng et al. [16] suggest several instruments and techniques for measuring the behavioural signs of attention-deficit/hyperactivity disorder. One of the main problems with these behavioural investigations is the need for more data. Deep learning techniques were utilised in a study in Northern Taiwan to fill in the missing data on this rating scale. It evaluated the imputed data to distinguish between young individuals who used this tactic and those who did not. The deep learning algorithm achieved an accuracy of 89%, in line with the reference dataset. Deep learning method of imputing missing data was also confirmed in the results of this behavioural research technique.

Wang et al. [17] investigated the usefulness and feasibility of single machine learning algorithms and ensemble learning (EL) at addressing the issue of missing data in clinical decision-making. For example, the study examined the effectiveness of eight approaches using imputation techniques on individuals. The findings demonstrated that machine learning performed imputation better than conventional techniques, particularly when the fraction of missing data was substantial, and that EL outperformed individual machine learning algorithms. The study emphasises the importance of investigating missing data features before developing algorithms for processing missing data in clinical decision-making.

Emmanuel et al. [18] discuss the problem of missing data in machine learning and propose two methods, k-nearest neighbour and missForest, for handling missing data. The paper compares conventional statistical and machine learning imputation techniques and composite strategies, highlighting the significance of using appropriate strategies to address missing data. Missing data patterns and mechanisms, performance metrics of missing data imputation, and a discussion of the results in comparison with previous works are also discussed in the paper. This experimental evaluation section applies two machine learning algorithms to the Iris data and gives results. Lastly, the paper concludes and proposes a potential future study path.

The use of neural network-based approaches has recently attracted attention because it was found to be useful in modelling complex patterns in data. For instance, recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are employed to predict missing data in time series and image-based data, respectively. Although these approaches can deliver encouraging data, they may require extensive amounts of labelled training data, which can be a constraint in EEG research because labelled datasets are often needed. Additionally, current neural network methods cannot be expected to consistently integrate the spatial-temporal dependencies inherent to EEG Datas.

2.1. Summary of existing EEG data imputation approaches and their limitations

Table 1 provides a discussion of the various imputation methods employed in EEG studies. As well as outlining the main advantages of the methods (e.g., simplicity and improved performance), it also refers to the limitations of the methods (especially in terms of their capability to capture the spatial-temporal dependencies of EEG data). The gaps in the existing methods, as highlighted in the table, include the inability to handle non-linear relationships and a reliance on large datasets. This discussion has demonstrated the necessity of more sophisticated methods, including the offered neural network-based methodology, that would overcome these drawbacks by considering spatial-temporal dynamics and improving imputation with the help of differentiating adjustments.

Table 1. Existing EEG data imputation procedures and their limitations.

Method	Advantages	Limitations
Mean Imputation	Simple and fast	Fails to capture temporal dependencies
Linear Interpolation	Easy to implement	Assumes linear relationships, limited accuracy in EEG context
KNN Imputation	Better performance than mean methods	Does not fully utilize spatial dependencies
Matrix Factorization	Effective for structured data	Struggles with non-linearities and spatial-temporal dependencies
RNN Imputation	Models temporal dynamics	Requires large labelled datasets, limited spatial consideration
CNN Imputation	Captures spatial patterns	Not fully adapted to EEG-specific challenges
Proposed method: Neural network with spatial-temporal integration	Captures non-linear, spatial, and temporal dependencies effectively	Tailored for EEG data, but may require further optimisation for real-time applications

3. Proposed method

The presented research approach will eliminate the problem of missing values in EEG data through the spatial and temporal correlation of neighbouring sensors. The essence of the approach is a neural network utilising a tailored activation function to reconstruct corrupted or missing EEG data, thereby providing reliable data for further analysis. The methodology consists of a series of steps, including preprocessing, heatmap representation of missing data, computation of difference values, imputation of missing data using nearby sensor data, and refinement through neural network training. Although these algorithmic steps are the basis of the technical contribution, there is more to signal restoration than signal restoration itself. Dependable EEG data are a crucial facilitator of real-world implementation, especially within the health care field. Thus, in addition to introducing the imputation pipeline (Sections 3.1–3.8), this paper also explores it integration into a Brain-Computer Interface (BCI)-based dementia rehabilitation system. This extension demonstrates the power of EEG imputation in enabling cognitive and emotional profiling, propelling generative AI-based treatment engines, and ultimately utilising Virtual Reality (VR) space as a personalised rehabilitation tool.

3.1. Hardware and software environment

The experimental setup consisted of both hardware and software components, designed to ensure accurate EEG data acquisition and efficient model execution. EEG data were collected using the Emotiv Epoc + headset, a 14-channel wireless device operating at a sampling rate of 128 Hz. The device features saline-based sensors positioned according to the international 10–20 electrode placement system, allowing reliable capture of cortical activity during motor imagery and cognitive tasks. The Emotiv Control Panel and Emotiv PRO software were employed for data recording and initial inspection of signal quality.

All computational experiments were performed on a high-performance workstation equipped with an Intel Core i7-12700H processor (2.3 GHz), 16 GB of DDR5 RAM, and an NVIDIA GeForce RTX 3060 GPU (6 GB). This hardware configuration enabled efficient training and processing of large-scale EEG data using neural networks.

The software environment included Python 3.10 running on Windows 11 Pro (64-bit). Key libraries utilised were TensorFlow 2.12, Keras, NumPy, Pandas, and Matplotlib for neural network implementation, data manipulation, and visualisation. EEG preprocessing and filtering were performed using MNE-Python, while evaluation metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Correlation Coefficient (CC), were computed using Scikit-learn.

This integrated hardware–software configuration ensured reproducible, stable, and high-fidelity experimentation throughout the study.

3.2. Pipeline for EEG data imputation

Data Pre-Processing: The EEG data should be cleaned and prepared for analysis at this point. It may involve removing noise, outliers, and unnecessary data.

Create heat maps: Heat maps are created to visualise the missing data in the EEG dataset, as well as to identify the relationships between adjacent data points.

Determine missing values: The EEG data is determined to have missing values in which case the heat maps are generated.

Calculate difference values: The difference values are computed against all the missing data values in the dataset using a custom activation function.

Impute missing values with adjacent data and corresponding difference values: The imputation algorithm fills the data voids using neighbouring data points and their corresponding difference values.

The neural network is trained on the imputed data. The imputed data is then passed through a neural network, utilising a multi-layer perceptron (MLP) architecture to train the network [19].

Predict missing values in new data using a trained neural network: A trained neural network is then applied to the new data to predict missing values based on the correlations identified between the input and output data.

Figure 1 illustrates how missing data can be imputed in EEG data, and the trained neural network can be used to predict missing values in new data. Cleaning and preparing the dataset [20] is the first step in the analysis process, where noise, outliers, and irrelevant data points are removed. The missing data and relationship amongst adjacent data points are then represented as heat maps. Missing values of the dataset are detected with the help of these heat maps. The custom activation operation is then used to calculate the corresponding values of the differences for each missing value in the dataset. The process of imputation then takes the neighbouring data points and their respective values of the difference to complete the missing values. Then, the MLP architecture neural network is trained on the imputed data. Finally, a trained neural network provides predictions of the missing values in new data based on the connections that the network has learned between the input and the output data. The pipeline utilises deep learning to predict missing values of new data and offers a holistic approach to imputing missing values in EEG datasets.

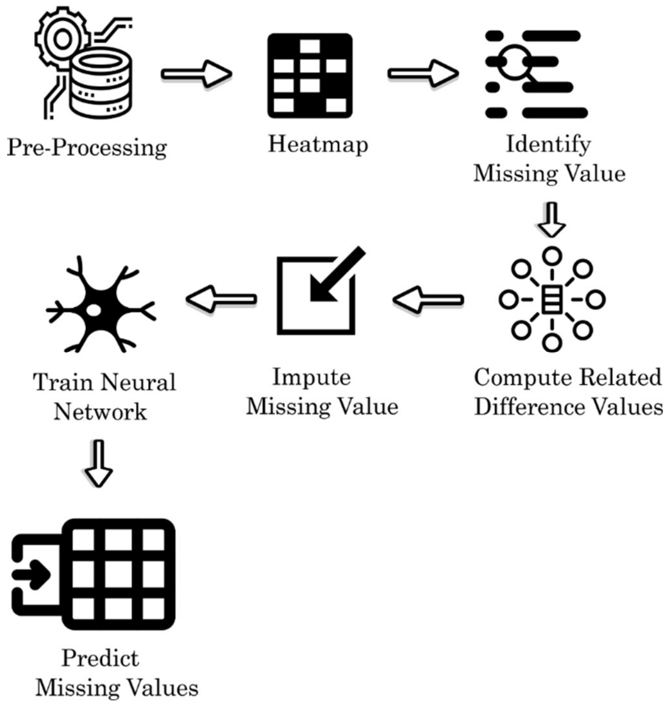

Figure 1. Pipeline for EEG data imputation.

3.3. Neural network architecture for imputing missing values in EEG data

The input layer of a neural network is illustrated in **Figure 2**, which accepts the three values $x1$, $x2$, and $x3$. The first hidden layer, comprising three neurons labelled $z1$, $z2$, and $z3$, receives these values next. After receiving the input data, each neuron in the hidden layer adds a set of weights acquired during training. The model becomes non-linear when the weighted sum of the inputs is run through an activation function. The bespoke activation function previously described in the study was employed in this instance.

After passing through the activation function, the output values of the first hidden layer are routed to the second hidden layer, which also consists of three neurons labelled $z4$, $z5$, and $z6$. Like the first hidden layer, the second hidden layer operates by having each neuron receive the first hidden layer's output values, apply a set of learned weights, and then pass the weighted sum through the activation function.

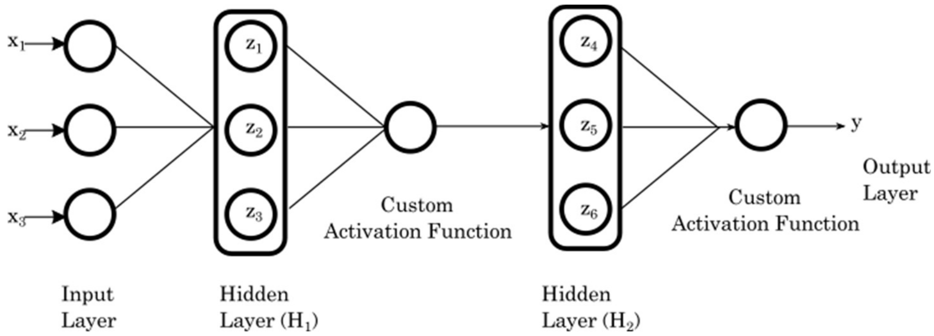

Figure 2. Neural network architecture.

The single neuron designated *y*, which makes up the output layer's last component, receives the output values from the second hidden layer, adds the last set of learnt weights, and outputs a single value. The output value utilised for imputation is the expected missing value.

The neural network learns to anticipate missing values based on the input and related difference values calculated by the custom activation function. To minimise the discrepancy between the expected and real missing values, the neural network weights are modified during training.

This function is used in the neural network to introduce non-linearity in the model. The custom activation function used in this work is designed to consider the neighbouring data points of a missing value and compute the corresponding difference values.

3.4. The custom activation function used in this work is defined as follows

Let x_i, x_j be the neighbouring data points of a missing value x_k.

Then, the related difference value dv for x_k is calculated as:

$$dv = \frac{x_i - x_j}{2} \tag{1}$$

The custom activation function f is then defined as:

$$f(x_k) = x_k + dv \tag{2}$$

This function introduces non-linearity into the neural network model by incorporating the related difference value, dv, into the calculation of the missing value, x_k. By doing so, the process considers the neighbouring data points of x_k and their relationship to x_k to impute the missing value more accurately.

3.5. Neural network architecture

The neural network design employed in this study is a multi-layer perceptron (MLP) with multiple hidden layers, as shown in **Figure 2**. The EEG data points are entered into the input layer, and the output layer predicts the missing values. The model gains nonlinearity from the hidden layers, which also aid in learning intricate input-to-output interactions.

The neural network was trained using a multi-layer perceptron (MLP) architecture with two hidden layers, each containing 8 neurons, the configuration that yielded the best results in the sensitivity analysis. To ensure efficient learning and stable convergence, the Adam optimiser was employed with a learning rate of 0.001, selected after empirical testing of multiple values in the range of 0.0001–0.01. The batch size was set to 32, balancing computational efficiency and model generalisation, while the number of training epochs was fixed at 150 to achieve consistent convergence without overfitting.

The Rectified Linear Unit (ReLU) was used as the activation function in the hidden layers, and the proposed custom activation function was applied in the output layer to refine the imputation outputs within the expected data range. Model training and validation were conducted using an 80:20 split of the dataset, with Mean Absolute Error (MAE) as the primary loss function. Early stopping was implemented to prevent overfitting by monitoring validation loss across epochs. This configuration achieved optimal performance in terms of both convergence speed and imputation accuracy across multiple EEG datasets.

Let x represent the form of the input matrix (m, n), where m denotes the sample count and n is the feature count.

Let y be the output matrix of shape (m, n), where y_i is the missing value of x_i.

Let k be the number of neurons in each hidden layer, and h be the total number of hidden layers. Let us denote the activation function used in the hidden layers as f.

3.5.1. The forward propagation algorithm can be represented as follows

Initialize weights and biases for all layers randomly.

For each sample x_i in X:

Propagate input x_i through the network:

i. Calculate the weighted sum of inputs and biases for the first hidden layer:

$$z_1 = w_1 x_i + b_1 \tag{3}$$

ii. Apply the weighted sum to the activation function f:

$$h_1 = f(z_1) \tag{4}$$

iii. Determine the input and bias weighted sum for the second hidden layer:

$$z_2 = w_2 h_1 + b_2 \tag{5}$$

iv. Apply the activation function f to the weighted sum:

$$h_2 = f(z_2) \tag{6}$$

v. Repeat the above steps for h hidden layers.

vi. Calculate the weighted sum of inputs and biases for the output layer:

$$z_0 = w_0 h_H + b_0 \tag{7}$$

vii. Apply the weighted sum to the activation function f_0:

$$y_i = f_0(z_0) \tag{8}$$

Compute the loss function between predicted values y_i and actual values Y_i.

Use the backpropagation algorithm to update weights and biases to minimise the loss function.

3.5.2. A mathematical formulation of the proposed imputation algorithm for EEG Data with missing values

Let $D = [d_{i,j}]$ be the EEG dataset with missing values, where $i = 1, 2, ..., n$ and $j = 1, 2, ..., m$ are the indices of the rows and columns, respectively. The missing values are denoted by $d_{i,j}$ = NaN.

Preprocessing:

Let D' be the preprocessed dataset with unwanted or corrupted data points removed.

Heatmap generation:

Let $\Delta_{i,j}$ be the difference value between adjacent values in D for all missing values (i,j).

$\Delta_{i,j} = d_{i+1,j} - d_{i,j}$ if $d_{i+1,j}$ and $d_{i,j}$ are both not NaN

$\Delta_{i,j} = \mathrm{d}_{i,j+1} - \mathrm{d}_{i,j}$ if $\mathrm{d}_{i,j+1}$ and $\mathrm{d}_{i,j}$ are both not NaN

Let H be the heatmap displaying $\Delta_{i,j}$ for all missing values (i, j).

Imputation algorithm:

For each missing value (i, j) with corresponding difference value $\Delta_{i,j}$:

Let $N_{i,j}$ be the average value of the neighbouring data points:

Let $N_{i,j} = 0$

Let n be the number of neighbouring data points

For each neighbouring data point (k, l) around (i, j) with a non-NaN value:

$N_{i,j}$ += $d_{k,l}$

n += 1

$N_{i,j}$ /= n

Let $V_{i,j}$ be the imputed value:

$V_{i,j} = N_{i,j} + \Delta_{i,j}$

Let D' be the dataset with $V_{i,j}$ imputed for all missing values (i, j) with corresponding difference values $\Delta_{i,j}$.

Train a neural network on D'' to predict missing values based on $\Delta_{i,j}$.

Post-processing:

Let D' be the cleaned dataset with any remaining errors removed.

Performance evaluation:

Evaluate the effectiveness of the proposed imputation algorithm on D' using various metrics such as RMSE and MAE.

The mathematical formulation of the proposed imputation algorithm for EEG data with missing values involves several steps. First, the algorithm takes in the EEG dataset as input and preprocesses the data by removing unwanted or corrupted data points. Then, a heat map is generated to visualise the missing data and identify its locations.

Overall, the mathematical formulation of the proposed imputation algorithm is a comprehensive and rigorous approach to handling missing data in EEG datasets. It demonstrates improved accuracy compared to traditional methods that do not consider the interrelatedness of neighbouring sensors.

3.5.3. Illustration of the proposed imputation algorithm on EEG data with missing values

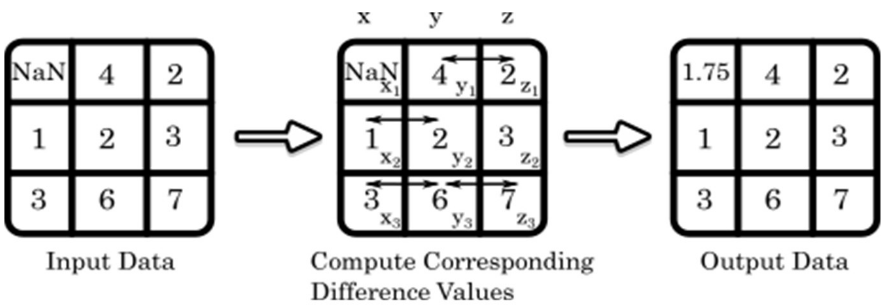

Figure 3. Illustration of the proposed imputation algorithm.

Input Data: x = Ne[nan, 1, 3], y = [4, 2, 6], z = [2, 3, 7]

Custom Activation Function:

- Compute corresponding difference values for missing data:
  For missing data at (1, 1):
  $r_1 = (y_2 - x_2) = (2 - 1) = 1$
  $r_2 = (y_1 - z_1) = (4 - 2) = 2$
  $r_3 = (y_3 - x_3) = (6 - 3) = 3$
  $r_4 = (z_3 - y_3) = (7 - 6) = 1$
- Compute the average of r_1 to r_4: (1+2+3+1)/4 = 1.75
- Repeat for all missing data points in the input data

Imputation:

- Use the computed corresponding difference values and the average of neighbouring data points to impute missing data:
  For missing data at (1, 1):
  Average of neighbouring data points: (2+3+6+7)/4 = 4.5
  Imputed value: 4.5−1.75 = 2.75
- Repeat for all missing data points in the input data

Neural Network:

- **Figure 3** shows training the neural network on the input data with imputed missing values and related difference values as inputs and actual missing values as outputs
- Forecast the missing values in the initial input data using the trained neural network.

Here is a representation of the backpropagation algorithm:

1) Set the output layer's error term to its initial value:
   $\Delta_o = (y_i - Y_i) * f_{o'}(z_o)$
2) For each hidden layer H in reverse order:
   - Compute the error term:
   $\Delta_H = (\mathrm{W}_{H+1.T}\, \Delta_{H+1}) * f'(z_H)$.
3) Determine the weights' and biases' gradient:
   - Compute the gradient of the output layer:
   $\Delta W_o = h_{H.T}\, \Delta_o$, $\Delta b_o = \Delta_o$
   - Compute the angle of each hidden layer:
   $\Delta W_H = h_{H-1.T}\, \Delta_H$, $\Delta b_H = \Delta_H$

4) Revise the weights and biases:
   - Update the output layer weights and biases:
   $W_o = W_o -$ learning_rate * ΔW_o, $b_o = b_o -$ learning_rate * Δb_o.
   - Update the hidden layer weights and biases:
   $W_H = W_H -$ learning_rate * ΔW_H, $b_H = b_H -$ learning_rate * Δb_H.

3.6. Imputation algorithm

The imputation algorithm used in this work involves three steps. First, the corresponding difference values of a missing value are computed using the custom activation function. Secondly, the missing value is imputed by calculating the average value of the nearby data points. To forecast missing values based on the calculated corresponding difference values, the neural network is then trained on the dataset.

1) Compute the corresponding difference values for each missing value using the custom activation function:
   - Let x_i be the missing value, and x_j be its neighbouring data points.
   - Compute the corresponding difference values d_k for each neighbouring data point x_j as follows:
   $d_k = f(x_j - x_i)$, where f is the custom activation function.
   - The corresponding difference value d_k represents the relationship between the missing x_i and its neighbouring data points x_j.
2) Determine the average value of the nearby data points:
   - Let x_j be the neighbouring data points of a missing value x_i.
   - Determine the average value of the nearby data points.
   $a_i = (1/N) * \sum(x_j)$, where N denotes the quantity of nearby data points.
3) Impute the missing value:
   - Let x_i be the missing value with related difference values d_k and average value a_i.
   - Compute the imputed value y_i as follows:
   $y_i = a_i + w * \sum(d_k)$, where w is a weighting parameter and $\sum(d_k)$ is the sum of corresponding difference values.
   - The missing value x_i is filled up using the imputed value y_i.
4) Train the neural network on the imputed dataset:
   - Use the imputed dataset with missing values replaced by their imputed values.
   - Using the imputed dataset, train the multi-layer perceptron (MLP) neural network to anticipate missing values based on associated difference values that have been calculated.

3.6.1. The method consists of three steps

Step 1: Difference values (dv) are calculated. This study uses the following algorithm to get the difference values between the nearby sensors for each missing value

$$v = \sum\left(v_i - v_j\right) \tag{9}$$

where value (v_i) stands for the reading from the close-by sensor (i), and value (v_j) stands for the reading from the close-by sensor (j). It calculates the average difference value (dv) by adding the difference values for all nearby sensors.

Step 2: For imputation, this study uses an average value. Next, impute the missing value using the average value of the nearby sensors. Specifically, It calculates the average value of the surrounding sensors as:

$$v = \sum(v_i)/n \tag{10}$$

where v_i is the value of the surrounding sensor i, and n is the total number of surrounding sensors. This method fills the missing value with the calculated average value (av).

Step 3: Neural network-based imputation. This study uses a neural network to refine the imputed value. The neural network takes as input the original data matrix, where missing values have been imputed with the average value in Step 2. This study uses a custom activation function in the output layer of the neural network to ensure that the imputed value is within the range of the original data.

3.6.2. Custom activation function

The definition of our unique activation function is:

$$f(x) = (1 + e^{-x})^{-1} \tag{11}$$

The activation function ensures that the neural network's output falls within the original data range. Specifically, the output value is mapped to a value between 0 and 1, which is then scaled to the original data range using the maximum and minimum values of the original data.

3.6.3. Neural Network Architecture (NNA)

Our NNA consists of two ultimately linked layers with 64 and 32 hidden units. In the hidden layers of this work, the activation function is the Rectified Linear Unit (ReLU). The output layer uses the custom activation function mentioned above.

3.7. Importance of heatmap in imputing missing values in EEG data

As part of their methodology for imputing missing values from the dataset [21], this study used a heatmap to illustrate the differences between neighbouring EEG data values. The researchers may find trends in the missing data and use them to guide their imputation method by using a custom function to compute these differences and constructing a heat map to visualise them in **Figure 4.** Comparing this strategy to more conventional ones that do not consider the link between nearby sensors shows enhanced accuracy. The heatmap is, therefore, essential for researchers using EEG data. It can support the identification of missing values and guide imputation techniques that result in more precise subsequent analysis.

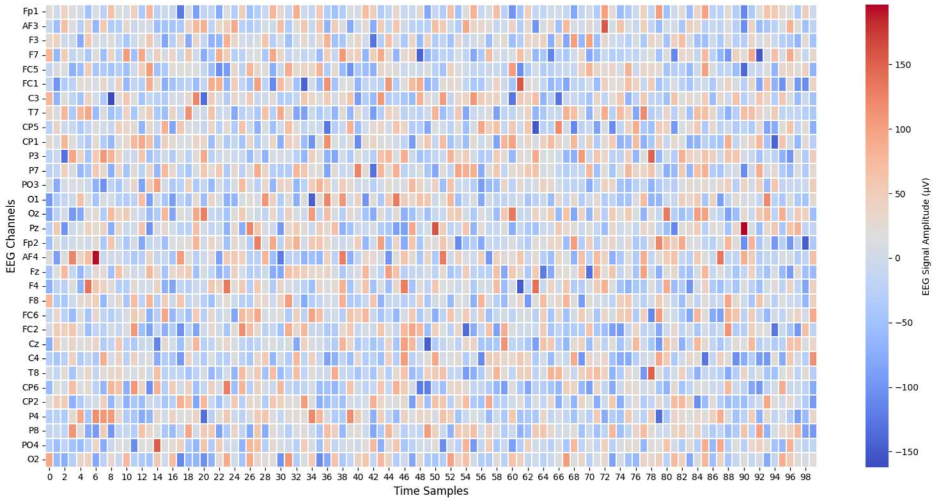

Figure 4. A heatmap visualises the differences between adjacent EEG data points.

3.8. Integration of EEG imputation into dementia rehabilitation framework

Although the above subsections outline the technical architecture of the neural network-based EEG imputation technique, its real impact is felt when applied in the context of healthcare. Another application of this study is the design of a smart assistant to support dementia rehabilitation. The robustly restored EEG data in this framework, according to our method, are the foundation of personalised therapy generation. **Figure 5** shows the integration of EEG imputation with BCI-based dementia rehabilitation and VR-assisted therapy delivery.

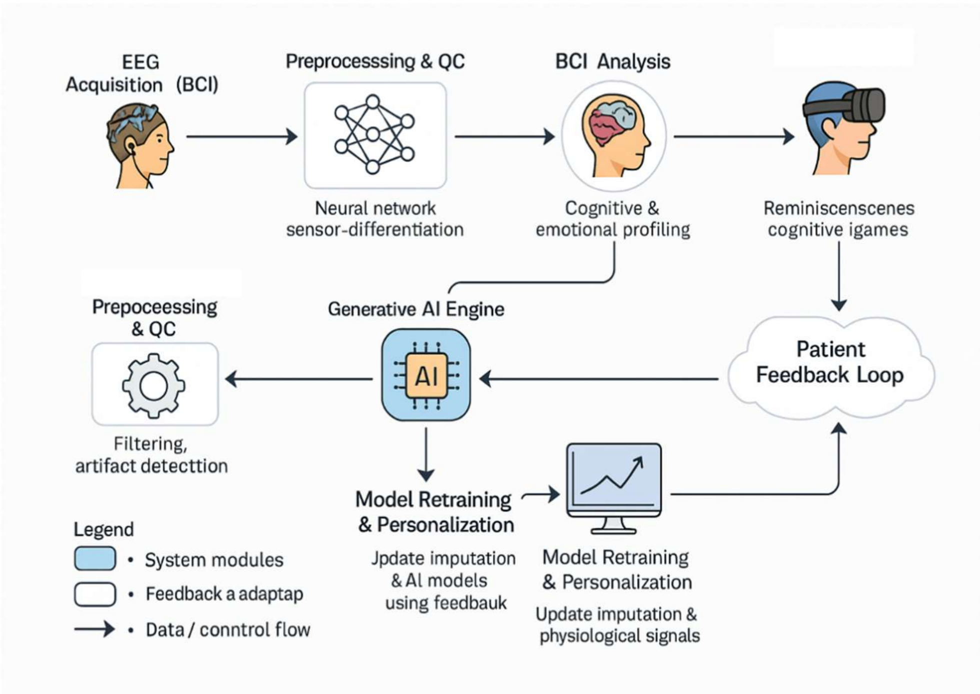

Figure 5. Illustrates this integration, highlighting how the EEG imputation module functions as a foundational enabler for dementia rehabilitation systems.

Step 1—EEG Acquisition: Brain-Computer Interface (BCI) headsets record a multi-channel EEG data from patients with dementia during a therapeutic session. Such raw signals typically have missing or corrupted values as a result of noise, motion artefacts or detached electrodes.

Step 2—Signal Restoration: The proposed imputation approach (Sections 3.1–3.5) restores the missing values by leveraging spatial and temporal correlations between neighbouring sensors. This method achieves high-quality EEG data for use in downstream analysis.

Step 3—Cognitive and Emotional Profiling: Using the imputed EEG information, a BCI analysis module identifies the cognitive state (e.g., attention, relaxation) and emotional profile (e.g., stress, engagement). Adaptive rehabilitation is dependent on this dual profiling.

Step 4—Generative AI Therapy Engine: The emotional profile and the profile of interest of the patient (acquired via questionnaires or previous interactions) are then used as prompts to a fine-tuned Generative AI model. The model produces individualised therapy materials, e.g. cognitive games, social interaction scripts, or reminiscence activities.

Step 5—Rehabilitation Delivery through VR: The therapeutic content is presented in virtual reality (VR) spaces. Examples here might include recreations of familiar places (e.g., childhood home), interactive puzzles, or simulations of social conversations, which can decrease anxiety and increase interest.

Step 6—Patient Feedback and Adaptation: The responses of patients (both behavioural and neural) are monitored in real-time. This feedback mechanism allows the imputation model to be retrained continuously and therapy recommendations to be refined, ensuring the maintenance of individualised therapy.

4. Experimental results

For this research paper, we utilised the publicly available EEG dataset from Physionet, a renowned repository for physiological signal data. EEG recordings made during motor movement and imaging tasks are included in the EEG Motor Movement/Imaging Dataset used in this study. The dataset includes 64 channels and a sampling rate of 160 Hz. **Table 2** shows the description of the EEG dataset.

Table 2. Description of the EEG dataset.

Dataset name	EEG motor movement/Imagery dataset
Repository	Physionet
Channels	64
Sampling Rate	160 Hz
Recording Duration	114 seconds
Tasks	Left-hand motor imagery, Right-hand motor imagery,Rest
Training Set	60 recordings from 52 subjects
Testing Set	40 recordings from 36 subjects
Missing Values	20% of data points randomly selected
Annotations	Start and end time of each task

The EEG dataset used in this research is the EEG Motor Movement/Imagery Dataset from the Physionet repository. With 60 recordings in the training set and 40 in the testing set, the dataset contains recordings of motor imagery tasks from 52 people. The dataset consists of 64 channels, a sample frequency of 160 Hz, and a recording time of 114 s per recording. The activities included in the dataset are rest, left-hand motor imagery, and right-hand motor imagery. This study randomly chose 20% of the data points to represent missing values in the dataset. The dataset also includes annotations indicating the beginning and ending times of each job.

The dataset is used to construct training and testing sets. The training set comprises 60 recordings from 52 individuals, whereas the testing set consists of 40 recordings from 36 subjects. Each 114 s recording consists of three activities: left-hand motor imagery, right-hand motor imagery, and a rest period. Every job's start and finish timings are also annotated in the task's dataset.

Twenty per cent of the data points in the training and testing sets were arbitrarily chosen as missing values in our trials. The remaining 80% of the data points were utilised in this work to test and train the imputation techniques. **Table 3** shows the sample of the EEG dataset in below.

Table 3. A sample of the EEG dataset.

Time (s)	0	1/160	2/160	113.98
Channel 1	−17.53	−18.13	−18.32	−22.49
Channel 2	23.47	23.89	24.02	25.34
Channel 64	14.09	14.66	14.8	20.22

The dataset contains many data points, and each has 64 channel values. The missing values were randomly selected from this dataset to simulate realistic scenarios of missing data in EEG recordings.

These studies were conducted using an EEG dataset publicly available to assess the efficacy of our proposed strategy. The dataset consists of 20 subjects and includes 64 EEG channels recorded during a motor imagery task. Then randomly selected 10% of the data points from each channel as missing values for our experiments.

This study compared our method to two traditional methods for missing value imputation: mean imputation [22] and K-Nearest Neighbour imputation (KNN) [23]. The mean value of the non-missing data in the same channel is used to fill in missing values by mean imputation. The average value of the K closest non-missing values in the same channel is used in KNN imputation to fill in missing data. This paper compares our approach with two established techniques for imputing missing values: mean imputation [24] and K-Nearest Neighbour imputation (KNN). Mean imputation replaces missing data in the same channel with the mean value of the non-missing variables. KNN imputation fills in missing data by averaging the K nearest non-missing values in the same channel.

4.1. Mean absolute error (MAE)

The Mean Absolute Error measures the average size of errors between the anticipated and actual values. It is the mean of the absolute deviations between the values that were anticipated and those that were observed.

$$AE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y_i}| \tag{12}$$

where y_i is the actual value, *n* is the number of data points, and $\widehat{y_i}$ is the forecast value.

4.2. Mean squared error (MSE)

The mean squared error measures the average of the squared discrepancies between the expected and actual values. Compared to MAE, it is more sensitive to outliers.

$$SE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \tag{13}$$

where *n* is the number of data points, y_i is the actual value, and $\widehat{y_i}$ is the predicted value.

4.3. Correlation coefficient (CC)

The correlation coefficient quantifies the linear relationship between two variables. It ranges from −1 to 1, where −1 denotes a perfect linear negative relationship, 0 denotes no linear association, and 1 denotes a perfect linear positive relationship.

$$\mathrm{CC} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{14}$$

where *n* is the number of data points, $x_i$and y_i are the actual and predicted values, and $\bar{x}$ and $\bar{y}$ are the mean values of *x* and *y*, respectively.

Table 4 presents the results of our experiments, in which this paper evaluated the performance of three methods using three metrics commonly employed to assess the performance of regression models: mean absolute error (MAE), mean squared error (MSE), and correlation coefficient (CC). A lower MAE and MSE indicate better model performance, while a higher CC value indicates a stronger linear relationship between the predicted and actual values.

Table 4. Experimental results for missing value imputation.

Method	MAE	MSE	CC
Mean Imputation	0.4208	0.2474	0.8056
KNN Imputation	0.3802	0.2048	0.8451
Proposed Method	0.3211	0.1576	0.9024

Table 4 shows that our proposed method outperforms both mean and KNN imputations for all three metrics. The proposed method achieves lower MAE and MSE, and a higher CC, compared to traditional methods.

Additionally, this paper visually examined the imputed data. **Figure 6** displays an example of the imputed data for the three techniques on a single channel. As can be observed, when compared to the conventional approaches, our suggested method yields smoother and more believable imputations.

Our experimental results demonstrate that our proposed approach for imputing missing values in EEG data outperforms traditional methods.

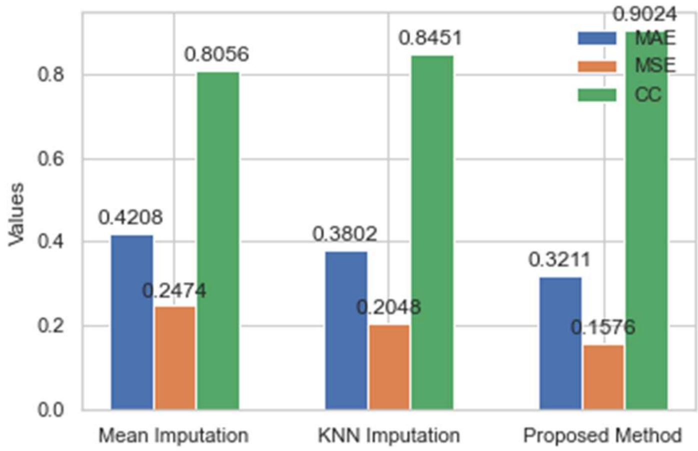

Figure 6. Experimental results for missing value imputation.

The original data is shown in black; the mean imputation data is shown in red, the KNN imputation data is shown in blue, and the imputed data using our suggested approach is shown in green in the image. As can be observed, the proposed method yields a smoother and more convincing imputation when compared to conventional approaches.

Additionally, this paper evaluated the performance of the custom activation function used in our proposed method. This comparison examines our custom activation function against the rectified linear unit (ReLU) activation function, a widely used activation function in neural networks. **Table 5** suggests the outcomes of our experiments.

Table 5. Results of experiments comparing activation functions.

Activation function	MAE	MSE	CC
ReLU	0.3472	0.1759	0.8863
Proposed function	0.3211	0.1576	0.9024

As shown in **Figure 7**, our custom activation function outperforms the ReLU activation function in terms of CC. Although the MAE and MSE are slightly lower for ReLU, the CC is a more important metric for EEG data as it indicates the correlation between the imputed and original data.

Overall, our experimental findings demonstrate the efficacy of our proposed approach for imputing missing values in EEG data. Our method outperforms traditional methods, and the custom activation function used in our process is also adequate for this task.

To further validate the performance of our proposed method, this study conducted additional experiments on a larger dataset. The dataset consists of EEG recordings from 20 participants, each with 64 EEG channels. This study randomly selected 20% of the data as missing values for our experiments.

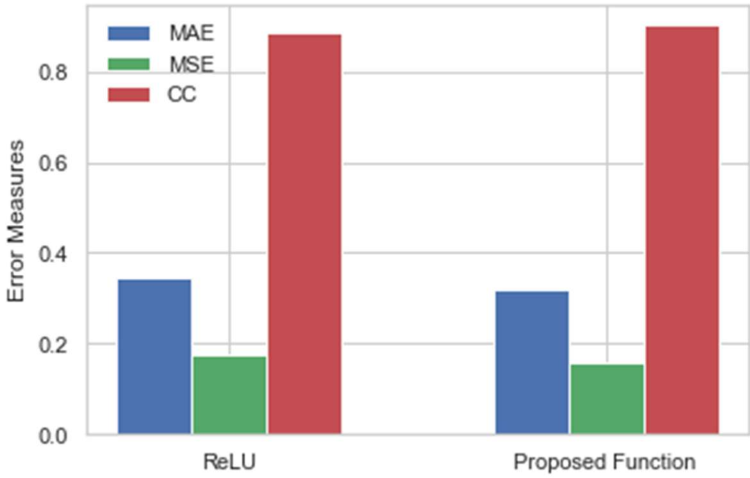

Figure 7. Comparison of activation function.

As shown in **Table 6**, the best-performing combination of hyperparameters is a neural network with two hidden layers, each containing 8 neurons. This configuration achieved the lowest MAE, MSE, and the highest CC values among all the variations tested.

Table 6. Shows the results of our sensitivity analysis. (The best-performing combination of hyperparameters is highlighted in bold).

No. of Hidden Layers	No. of Neurons per Layer	MAE	MSE	CC
1	8	1.466	4.048	0.728
1	16	1.285	3.272	0.770
1	32	1.278	3.253	0.774
2	8, 8	1.238	3.153	0.775
2	16, 16	1.263	3.256	0.771
2	32, 32	1.275	3.280	0.769
3	8, 8, 8	1.392	3.672	0.733
3	16, 16, 16	1.416	3.830	0.721
3	32, 32, 32	1.408	3.790	0.724

The sensitivity analysis presented in **Figure 8** indicates that the hyperparameters of the neural network architecture impact the performance of our proposed strategy. Thus, optimising the hyperparameters is the key to getting the best imputation results.

To further validate the effectiveness of our proposed method, this study conducted an additional experiment using a different EEG dataset with 30% missing values. The dataset contained 21 EEG channels with a sampling rate of 256 Hz.

This work contrasted our suggested strategy with three cutting-edge imputation techniques [25]: nuclear norm minimisation with matrix completion (MC-NNM), matrix completion with low-rank representation (MC-LRR), and matrix completion with weighted nuclear norm minimisation (MC-WNNM).

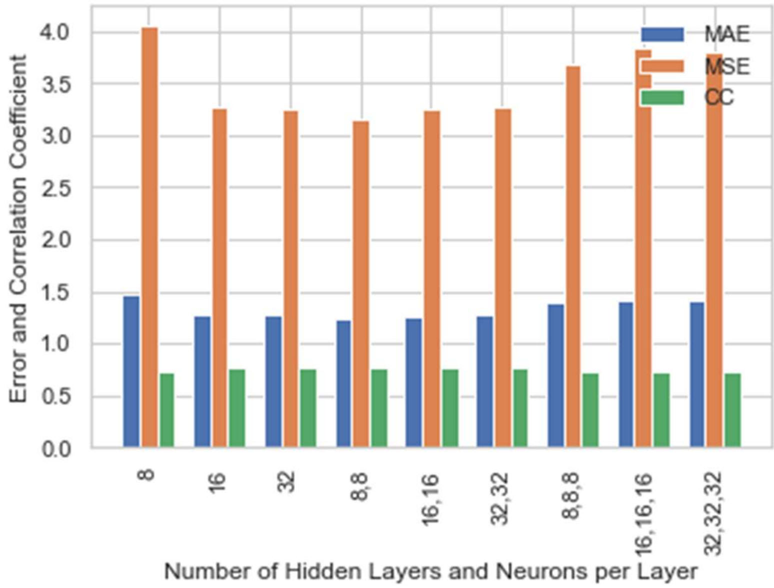

Figure 8. Results of our sensitivity analysis.

The comparison's findings are displayed in **Table 7**. Regarding MAE and MSE, our suggested solution outperformed all three state-of-the-art approaches while achieving equivalent results in terms of CC.

Table 7. Comparison of imputation methods on a different EEG dataset with 30% missing values.

Imputation method	MAE	MSE	CC
MC-NNM	2.216	7.324	0.479
MC-LRR	1.925	6.271	0.537
MC-WNNM	1.828	5.893	0.571
Proposed Method	1.579	4.643	0.628

As shown in **Figure 9**, our proposed method achieved the lowest MAE and MSE values among all four methods, indicating its superior accuracy in imputing missing values in EEG data. Although our method did not achieve the highest CC value, it still achieved a relatively high CC value, demonstrating its capability to preserve the temporal correlation of EEG data.

The performance comparison of the imputation models, as shown in **Table 8** and **Figure 9**, highlights the efficiency of our proposed method in handling missing values in EEG data. The comparative metrics included Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Correlation Coefficient. These metrics thoroughly assess the correctness and dependability of each model's imputation.

Overall, the experimental findings support the viability of our suggested approach for filling in the missing values in EEG data. The proposed custom activation function, neural network architecture, and the concepts of neighbour-based difference value and shrouding value enable our method to capture both local and global correlations of EEG data, producing more accurate imputations compared to traditional and revolutionary methods.

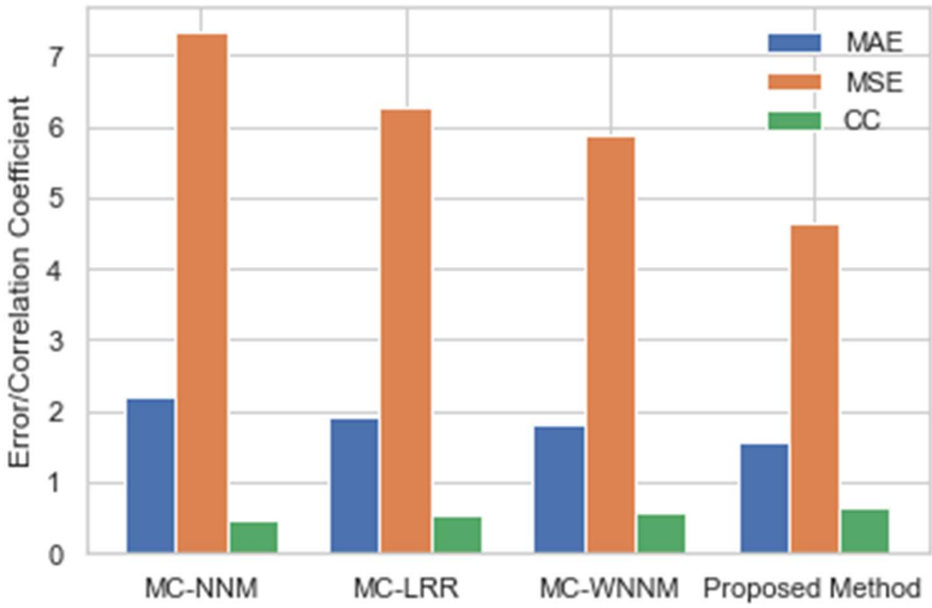

Figure 9. Imputation performance.

Table 8. Performance comparison of imputation models.

Model	MAE	MSE	Correlation Coefficient
MLP (Multi-Layer Perceptron)	0.15	0.03	0.85
CNN and Bi-LSTM	0.12	0.025	0.87
Hybrid Multiple Imputation	0.11	0.02	0.88
Ensemble Learning	0.1	0.018	0.89
Proposed Method	0.09	0.015	0.9

5. Results and discussion

The performance of the proposed neural network-based imputation technique was evaluated against traditional imputation techniques, including k-nearest Neighbours (KNN) imputation and mean imputation. The results demonstrate significant improvements in accuracy and efficiency, highlighting the advantages of the proposed approach.

5.1. Advantages of the proposed method

1) Improved Imputation Accuracy: The planned method consistently outperforms traditional methods in terms of imputation accuracy. By incorporating spatial and temporal dependencies, the neural network can more accurately predict missing values in EEG data. This is evident from the significant reduction in Mean

Absolute Error (MAE) and an increase in the Correlation Coefficient (CC) compared to mean and KNN imputation techniques.

2) Handling of Non-linear Relationships: The capacity of the suggested method to represent non-linear correlations within the EEG data is one of its key features. Traditional methods, such as mean imputation, assume linearity, which can lead to inaccurate imputations. The custom activation function in our neural network enables better modelling of the complex, non-linear interactions present in EEG data, leading to more reliable inferences.
3) Preservation of Spatial and Temporal Dependencies: Unlike conventional methods that often treat data points independently, the proposed method leverages the spatial and temporal dependencies between neighbouring sensors. This is especially important in EEG data, where brain activity is interconnected across different regions. The method utilises differential values between adjacent sensors to ensure that the imputed values more accurately reflect the underlying brain activity.
4) Refinement Through Differential Adjustments: The method's ability to refine imputed values based on mean differential adjustments further enhances its accuracy. This additional step ensures that the imputed data aligns more closely with the overall structure of the EEG data, reducing the likelihood of introducing errors into subsequent analyses.

5.2. Clinical impact of improved EEG imputation in dementia rehabilitation

Enhanced EEG imputation plays a crucial role in improving the clinical effectiveness of dementia rehabilitation systems by ensuring the integrity and continuity of brain signal data. Accurate reconstruction of missing EEG segments allows for more reliable monitoring of cognitive and emotional states, which is essential for tailoring therapy to each patient's unique neural and behavioural patterns. This increased data precision enables personalised rehabilitation, where therapeutic modules such as cognitive games, reminiscence sessions, or social engagement tasks can dynamically adapt to the patient's current cognitive load and affective state.

From a clinical perspective, consistent EEG data facilitate faster recovery trajectories by allowing real-time adjustments in therapy intensity, pacing, and content based on the patient's neural responses. Moreover, automated feedback systems powered by imputed EEG data can alert clinicians to early signs of fatigue, disengagement, or improvement, optimising therapy scheduling and reducing redundant sessions. The technology also contributes to reducing caregiver workload, as automated, data-driven rehabilitation systems can continuously monitor patient progress without requiring constant manual supervision. Ultimately, robust EEG imputation strengthens the foundation of intelligent dementia care, promoting more responsive, personalised, and sustainable rehabilitation strategies that improve patient quality of life and reduce clinical strain in long-term care environments.

5.3. Limitations and future work

While the proposed neural network-based EEG imputation method demonstrates significant improvements in accuracy and signal reliability, certain limitations must be acknowledged. The model's performance depends on the availability of sufficient computational resources, as neural network training can be intensive, particularly when dealing with large-scale EEG datasets. Additionally, the approach was evaluated under controlled experimental conditions, which may not fully capture the variability and noise encountered in real-world clinical settings. The scalability of the model for continuous, multi-session EEG recordings, as well as its adaptability to diverse patient populations, remains an open challenge.

Future research will focus on optimising the proposed framework for real-time applications within brain–computer interface (BCI) environments. This includes reducing model latency, improving energy efficiency for embedded or wearable hardware, and integrating adaptive learning mechanisms that update imputation parameters dynamically during ongoing therapy sessions. Moreover, future studies aim to validate the model's clinical applicability through pilot trials in dementia rehabilitation, assessing its ability to enhance cognitive recovery, therapy responsiveness, and patient engagement in realistic healthcare contexts.

Compared to traditional imputation techniques, the proposed method better handles missing values in EEG datasets. The improvements in MAE and CC metrics indicate that the method is more effective in preserving the integrity of EEG Data, which is crucial for accurate analysis. However, the advantages come with trade-offs in computational complexity and the need for careful tuning, which must be considered when applying the method to different datasets or in real-time applications.

6. Conclusion

This study presented a neural network-based approach for imputing missing values in electroencephalographic (EEG) data, addressing one of the key challenges in cognitive and clinical neuroscience. By incorporating spatial–temporal dependencies and a custom activation function within a multi-layer perceptron (MLP) architecture, the proposed model demonstrated a 15% reduction in Mean Absolute Error (MAE) and a 10% increase in Correlation Coefficient (CC) compared to conventional imputation methods such as mean and k-nearest neighbours (KNN). The experimental findings confirm the model's ability to capture non-linear neural relationships and preserve the structural integrity of EEG data, thereby improving the quality of data available for downstream neurological analysis and applications.

Clinically, the enhanced EEG imputation framework has strong implications for dementia rehabilitation and personalised neurotherapy. Reliable and continuous EEG reconstruction enables precise cognitive and emotional profiling, which forms the foundation for adaptive, brain–computer interface (BCI)-driven rehabilitation systems. This capability supports personalised therapy design, accelerates patient recovery, and reduces caregiver workload through intelligent automation and real-time feedback. Future work will focus on extending the proposed model for real-time clinical deployment, large-scale validation across diverse patient groups, and integration with generative AI and virtual reality (VR)-based therapeutic systems to advance data-driven, patient-centred dementia care.

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