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ORIGINAL RESEARCH

EEG-Based Motion Intention Detection for Robotic Rehabilitation: Evaluating Classification and Regression Algorithms

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Abstract
Rehabilitation robots have shown significant efficacy in restoring lost motor functions in stroke survivors by providing compliant assistance during rehabilitation tasks. However, accurately understanding the desired motion intention (DMI) of the subjects is a significant challenge in providing effective robotic assistance. This work aims to determine the desired motion intention (DMI) for compliant robotic assistance through the analysis of upper limb motions using electroencephalography (EEG) signals. A group of fifteen individuals who were in good health carried out six distinct exercises. These movements were categorized using decision trees, random forest, and deep learning algorithms. Using deep learning, we achieved the highest accuracy rates, reaching 82% for movement-to-movement classification and 90% for movement-to-rest classification. The random forest method achieved superior performance compared to the other algorithms in regression tests, with an accuracy rate of 83%. The results demonstrate the effectiveness of our proposed EEG-based classification and regression techniques in detecting DMI for robotic help in rehabilitation.The study was conducted with a small sample size, exclusively involving healthy subjects, which is a critical factor to consider. This may limit the generalizability of the results, particularly when populations with motor impairments are taken into account. However, the study offers valuable insights into the potential of the EEG-based models for real-time rehabilitation applications despite this limitation.

Keywords EEG signals · Desired motion intention · Rehabilitation · C-RNN · Machine learning · Deep learning

Introduction

Robotic rehabilitation has emerged as a crucial technology in aiding individuals recovering from neurological disorders, including stroke, spinal cord injuries, and cerebral palsy. These assistive systems leverage advanced control mechanisms to provide precise, adaptable support during physical therapy. Compliance control in rehabilitation and assistive robots plays a crucial role in user ease and comfort. One of the big problems in providing appropriate compliance is measuring human intention. Without correct measurement of a human's desired motion intention (DMI), existing compliance controls cannot correctly tolerate motion and assist accordingly. Electroencephalography (EEG), a non-invasive

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method for monitoring brain activity, has shown significant potential in bridging this gap by capturing the electrical signals associated with motor intention. These signals can be processed to control robotic rehabilitation systems directly, enhancing their responsiveness and personalized adaptability. Therefore, the estimation of DMI is critical. Desired motion intention (DMI) for rehabilitation and assistive robots can be estimated using either biological or non-biological-based sensors [1–3]. Many authors have worked on non-biological-based DMI estimation [4–7].In this study, we have focused on biological-based electroencephalography (EEG) sensors to estimate DMI due to their valuable benefits. It was found that EEG-based assistive robots achieve a better recovery rate than the traditional methods [8–12]. Study shows that using EEG-based rehabilitation, improved Fugl–Meyer motor assessment (FMMA) can be achieved [13], where FMMA represents the capability of a subject to control its motors.

The main challenge in EEG-based rehabilitation is to detect the subject's motor imagination (MI) to perform a given task [14–17]. For this purpose, many feature extraction algorithms have been studied. These algorithms include common spatial pattern (CSP) [13], Linear Discriminant Analysis [18], support vector Machines [19], convolution neural network [20, 21] and convolution recurrent neural network (C-RNN) [22, 23]. In [18], the focus remained on linear discriminant analysis based classification, which is a very basic classification method [24]. This method is famous for reducing the dimension (of input data). The common spatial pattern is effectively used to classify motor imagery. On the other hand, the downside is that it highly depends on the frequency band. This limits its applications because it requires a wide frequency band of the frequency band suited for each individual [25], which is very inconvenient. In the literature, the above literature [14–16] support vector machine and deep learning, convolution neural networks, and convolution recurrent neural networks have focused on the development of a new algorithm for classification. However, these algorithms could only achieve either 59% accuracy or have been tested for limited applications (Table 1).

Furthermore, machine learning algorithms are often more suitable for real-time EEG-based detection of motor intentions (DMI) due to their lower computational complexity and faster training times compared to deep learning models, which require significant processing power and time. Real-time applications demand swift responses, and traditional machine learning methods such as support vector machines (SVMs) or decision trees can deliver this without the heavy computational overheads that deep learning models like CNNs and LSTMs typically impose.

In this paper, we have proposed an algorithm to estimate DMI. In the first phase, we have differentiated motion from the rest of the class. In further evaluation, we have classified the type of motion among the other motion classes (there were six motion classes, i.e. elbow flexion/extension, forearm supination/pronation, and hand open/close). After predicting the desired motion class, we used a regressor to estimate the desired motion (in terms of joint angles). This algorithm was evaluated using deep learning, decision trees, and random forest methods. In the binary classification, i.e. motion vs rest class, almost all the methods achieved 90% accuracy. In differentiating the type of motion, the deep learning algorithm outperformed decision tree and random forest. Finally, random forest regression achieved about 85% accuracy after predicting the suitable class. The data we used for our model was taken from the BNCI 2020 website [33].

Table 1 Summary of some main EEG-based motion intention detection algorithms and related literature

References	Methodology	Results	Contributions
Cerquitelli et al. (2023) [26]	Integration of machine learning in computer networks	Significant improvements in network efficiency and reliability	Highlighted the potential of machine learning to transform network management
Ang et al. (2012) [27]	Introduction of filter bank CSP for EEG feature extraction	Achieved higher classification accuracy in motor imagery tasks	Improved feature extraction method for motor imagery BCIs
Tabar et al. (2017) [28]	Use of CNNs for automatic feature extraction and classification	Outperformed traditional methods in motor imagery classification	Demonstrated the efficacy of deep learning for EEG signal analysis
Craik et al. (2019) [29]	Review of deep learning techniques applied to EEG data	Identified key trends and future directions for deep learning in BCIs	Comprehensive review highlighting the state-of-the-art in deep learning for BCIs
Lawhern et al. (2018) [30]	Design of a lightweight CNN for real-time EEG classification	Achieved high accuracy with low computational cost	Provided a practical solution for real-time BCI applications
Schirrmeister et al. (2017) [31]	Use of CNNs to decode various EEG patterns	Improved performance over traditional methods in multiple tasks	Advanced the application of CNNs in EEG-based BCIs
He et al. (2010) [32]	Development of an adaptive ensemble classifier for EEG signals	Improved adaptability and accuracy in non-stationary environments	Enhanced robustness of EEG classification in dynamic settings

All the results were obtained after 0.097 sec. onset movement. A smoothing filter was applied after regression.

Contribution in Proposed Research

- *Enhanced accuracy in movement classification:* The study demonstrates that deep learning algorithms significantly improve the accuracy of classifying different upper limb movements using EEG signals, achieving an 82% accuracy rate.
- *Effective movement vs. rest classification:* Able to achieve a better 90% accuracy rate in distinguishing movement from rest using deep learning; the proposed study ensures effective identification of when robotic assistance is needed.
- *Superior regression performance:* The desired motion intention was predicted with an 83% accuracy rate using random forest algorithms for regression tasks, helping with responsive adjustments in robotic assistance.
- *Comprehensive analysis of algorithms:* The proposed study conducts a comprehensive evaluation of the efficacy of decision tree, random forest, and deep learning algorithms in the context of classification and regression tasks.

Novelty of the Research

This study employs deep learning algorithms to analyze EEG signals for robotic rehabilitation, surpassing conventional methods. We included six distinct upper limb movements to enhance motion intention detection. Our approach addresses both regression (quantitative prediction of motion intention) and classification (movement vs. movement and movement vs. rest). Using a robust dataset generated by fifteen healthy subjects, we provide a foundation for future research involving patients with motor impairments, ultimately improving robotic rehabilitation systems.

Problem Statement

Our objective is to formalize the problem statement for EEG-based motion intention detection in robotic rehabilitation, with an emphasis on both classification and regression tasks. This entails the precise detection and prediction of motion intentions through the use of electroencephalography (EEG) signals, thereby improving the efficacy of robotic rehabilitation systems.

Classification Problem

Let $\mathbf{X} \in \mathbb{R}^{n \times m}$ be the matrix of EEG features, where n is the number of samples and m is the number of features extracted from the EEG signals. Let $\mathbf{y}_c \in \{1, 2, \ldots, k\}^n$ be the vector of class labels for movement classification among different movements, where k is the number of different movements. For the movement vs. movement classification problem, we aim to find a function $f_c : \mathbb{R}^m \to \{1, 2, \ldots, k\}$ that maps the EEG feature vectors to the corresponding movement classes. The objective is to maximize the classification accuracy, defined as:

$$\text{Accuracy}_c = \frac{1}{n} \sum_{i=1}^{n} \mathbb{I}(f_c(\mathbf{X}_i) = \mathbf{y}_{c,i})$$

where $\mathbb{I}(\cdot)$ is the indicator function that equals 1 if the argument is true and 0 otherwise.

For the movement vs. rest classification problem, let $\mathbf{y}_r \in \{0, 1\}^n$ be the binary vector indicating whether a sample corresponds to rest (0) or movement (1). We aim to find a function $f_r : \mathbb{R}^m \to \{0, 1\}$ that maps the EEG feature vectors to the rest or movement class. The objective is to maximize the classification accuracy, defined as:

$$\text{Accuracy}_r = \frac{1}{n} \sum_{i=1}^{n} \mathbb{I}(f_r(\mathbf{X}_i) = \mathbf{y}_{r,i})$$

Regression Problem

For the regression task, let $\mathbf{X} \in \mathbb{R}^{n \times m}$ be the matrix of EEG features and $\mathbf{y}_g \in \mathbb{R}^n$ be the vector of continuous values representing the desired motion intention (DMI) in some quantitative form (e.g., movement trajectory or force). We aim to find a function $g : \mathbb{R}^m \to \mathbb{R}$ that maps the EEG feature vectors to the corresponding DMI values. The objective is to minimize the mean squared error (MSE), defined as:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (g(\mathbf{X}_i) - \mathbf{y}_{g,i})^2$$

Summary of Mathematical Problem Statements

1. *Movement vs. movement classification:*

$$\max_{f_c} \frac{1}{n} \sum_{i=1}^{n} \mathbb{I}(f_c(\mathbf{X}_i) = \mathbf{y}_{c,i})$$

2. *Movement vs. rest classification:*

$$\max_{f_r} \frac{1}{n} \sum_{i=1}^{n} \mathbb{I}(f_r(\mathbf{X}_i) = \mathbf{y}_{r,i})$$

3. *Regression for desired motion intention (DMI):*

$$\min_g \frac{1}{n}\sum_{i=1}^{n}(g(\mathbf{X}_i) - \mathbf{y}_{g,i})^2$$

EEG-based motion intention detection for robotic rehabilitation is a crucial area of research with significant implications for healthcare and patient recovery. Rehabilitation robots have shown great promise in helping stroke survivors and individuals with motor impairments regain lost functions by providing tailored, compliant assistance during rehabilitation exercises. However, the effectiveness of these robotic systems heavily depends on accurately interpreting the user's desired motion intention (DMI). Here are some key reasons why this problem is essential: Enhanced rehabilitation outcomes can be achieved through accurate detection of DMI, which enables personalized robotic assistance. EEG-based methods offer real-time adaptation of this assistance, ensuring responsiveness to the patient's needs. By automating the detection of motion intentions, human supervision can be reduced, making rehabilitation sessions more efficient and accessible. This research contributes to advancements in BCI technology, enhancing our understanding of EEG signal interpretation and utilization for practical applications. Ultimately, these improved rehabilitation techniques can lead to faster recovery times and a better quality of life for patients with motor impairments. Despite significant advancements in robotic rehabilitation, several research gaps remain:

EEG-Based Motion Intention Detection Limitations

Most studies rely on traditional machine learning methods, with limited deep learning exploration. They often focus on a narrow range of movements, lack real-time adaptation, and provide insufficient comparative analysis of different algorithms. Additionally, many studies do not include a diverse dataset of healthy and motor-impaired subjects.

Objectives

The objective of this investigation is to evaluate the efficacy of deep learning algorithms in identifying motion intentions from EEG signals and to contrast their performance with conventional machine learning techniques. It will categorize upper limb movements to facilitate robotic rehabilitation and investigate the real-time adaptation of robotic assistance through EEG analysis. The study will also assess the performance of machine learning algorithms such as decision tree, random forest, and deep learning in both classification and regression tasks. This will be done using a dataset of fifteen healthy subjects, thereby establishing the foundation for future research that will involve patients with motor impairments.

Methodology

Human motion intention is crucial in driving the upper limb assist exoskeleton. If correctly estimated, a complaint motion can be achieved. Among existing methods, electroencephalography (EEG) signals do not require surgery and can be used for severely injured subjects. Keeping this potential application, this study has focused on DMI estimation using EEG signals. For this purpose, dataset from the BNCI 2020 competition has been used [18, 33]. Further descriptions of the present study and paradigms are presented in the following subsections to estimate DMI.

Subjects

In the study, fifteen (15) healthy subjects were employed. The age of all subjects ranges from twenty-two (22) to forty (40), with a mean age of twenty-seven (27) and a standard deviation of five (05) years. These subjects were paid for their participation [33]. Also, the research study was approved by the ethical committee of the Medical University of Graz [33].

Experimental Setup

Subjects were seated on an easy chair. Their right arm was attached to an upper limb exoskeleton. The exoskeleton was programmed to cancel gravitational effects with the subject's body mass so that the subject may be comfortable and not feel muscle fatigue. Figure 1 shows the electrode locations in 61 channel electroencephalogram for capturing brainwave activity. In Fig. 2 subject performs the desired motion intentions. The motor execution (ME) data of each subject was collected in a single session. All of the subjects were asked to perform six types of movements. These movements comprise elbow flexion/extension, forearm pronation/supination and hand open/close. The right upper limb performed all these movements for the motor execution session. All of these movements were started at a relaxed and naturally neutral position, i.e. the lower arm was extended to 120 degrees, the hand was half open, and the thumb was on the inner side. EEG signals for this position were classified as a rest state.

In the motor execution (ME) session, subjects were asked to execute sustained movements. Subjects were shown cues to record the EEG data for motor execution. At the start of the session (0 s), with the initial sound of a beep, subjects were requested to concentrate their gaze on the cross. After 2 s, a cue was presented to the subjects to perform a given task (like one of the six motions, i.e. elbow flexion/extension, wrist supination/pronation, or hand open/close). At the end of each trial, subjects were asked to move their

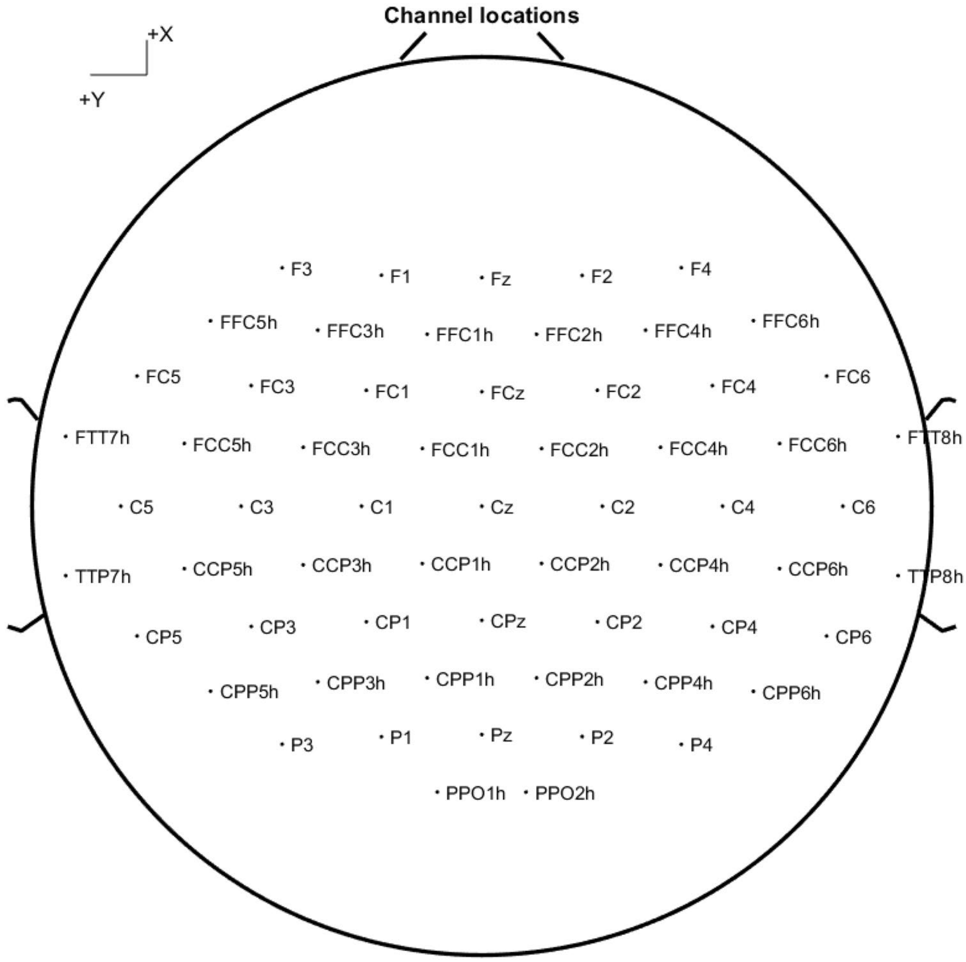


Fig. 1 61 channel EEG electrode location

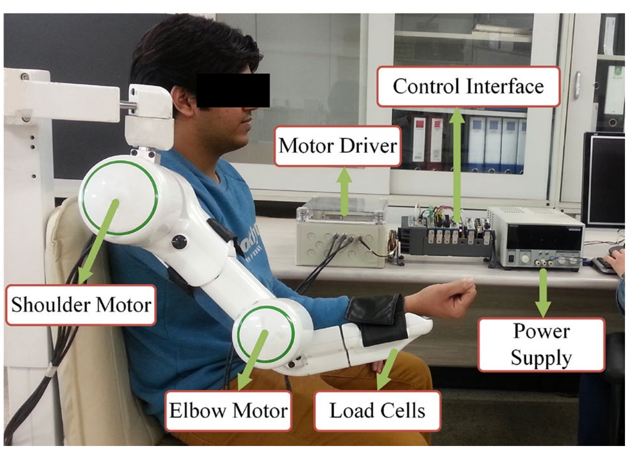


Fig. 2 A subject performing desired motion intentions in the controlled laboratory environment

arms back to the initial state. In every session, ten runs were recorded for a single subject. Each run contains 42 trials. This study recorded six (06) movement classes (elbow flexion/extension, wrist supination/pronation, or hand open/close) along with the rest of the class. Data from sixty (60) trials were collected for every single class.

Movements were normalized via standardized instructions, followed by 15 min of relaxation and then 5 min of practice of the target motion. Also, motion was followed by kinematics monitoring devices to ensure the speed and motion in the given manner. This movement was followed by analyzing the speed of each task and the trajectory within the specified time. Regarding data reproducibility, the baseline EEG was recorded in a relaxed state for all subjects. All EEG data and related exercises followed the same time epoch to perform each task in the same sequence to ensure consistency.

Dataset Collection

The EEG signals were measured from a sixty-one (61) channel headset containing active electrodes and four 16-channel amplifiers(g.tec medical engineering GmbH, Austria). These electrodes were placed on the temporal, central, parietal, and frontal areas of the subjects' heads. The location of these sensors over the head is shown in Fig. 1. The right mastoid was used as a reference (ground on AFz). To filter EEG signals, 8th order Chebyshev bandpass filter was employed (from 0.01 to 200 Hz) with a sampling rate of 512 Hz. A notch filter of 50 Hz was used to suppress power line interference. To ensure consistency in the movements among subjects, all participants were instructed to perform predefined motor imagery tasks (e.g., imagining hand grasps) following a standardized visual cue. These movements were chosen to minimize inter-subject variability. Additionally, all EEG data were pre-processed to normalize the signal amplitudes across subjects by applying z-score normalization to each subject's EEG signals, ensuring that individual differences in baseline EEG activity did not affect the classification and regression analyses.

Movement Recognition

To identify various movements in motor execution (ME) session, sensor data was collected from the goniometer and data glove. For elbow extension/flexion and forearm supination/pronation, elbow and wrist sensors were used, respectively. For hand opening/closing, the collected data from the gloves were used. Principal component analysis (PCA) was used to reduce the dimension obtained from the gloves. Only the first principal component was used for further processing. The absolute dissimilarity between the sensor data and the preceding time average defined a movement. If this difference crosses a certain threshold, it was taken that a movement had been performed (the threshold was defined for each sensor based on minimizing the false positive detections).

Preprocessing

The raw data of EEG signals were filtered with a 4th-order zero-phase Butterworth filter by using a band-pass filter (0.3–70 Hz). Furthermore, a notch filter was used to suppress the interference of unwanted line frequency 50 Hz. The processed data was taken care of for the artifacts. For this purpose, (1) values above/below a threshold of $-200\,\mu V$ and $200\,\mu V$ were marked respectively. Moreover, trials with abnormal joint probabilities and abnormal Kurtosis were also highlighted. To mark these anomalies, a threshold was used (which was five (05) times the standard deviation of static values of those trials). Before discarding the trials contaminated with artifacts, an average reference was found. For this purpose, the unfiltered data was filtered using a zero-phase fourth-order Butterworth band pass filter (0.3–3.0 Hz). Then, the filtered data were re-referenced to a standard average reference. After finding the re-referencing point, the trials being contaminated with artifacts in a previous method (the method in which the data was filtered from 0.3 to 70 Hz) were discarded.

Classification

For the motion analysis, two types of classifications have been considered: (1) In the first type of classification, six (06) types of movements (elbow flexion/extension, forearm supination/pronation and hand open/close) are classified against each other, (2) In the second type of classification, all six movements are classified are compared against the rest class. In this prospectus, the first type of classification is named motion-vs-motion, while the second class is named motion-vs-rest. In the motion-vs-rest classification, the recorded rest class had been classified against the aggregated motion class. This motion class was obtained by separating the specific data in which the motion had been performed. This separated data had been labelled as motion data. In the same way, data was collected for six different motions. This motion data had been blent with the rest data. The combined data of motion and rest were further included for classification. For the multiclass problem of motion-vs-motion, we used the 1-vs-1 classification strategy. It forms fifteen binary classes:

- Flexion vs extension.
- Flexion vs supination.
- Flexion vs pronation.
- Flexion vs hand open.
- Flexion vs hand close.
- Extension vs supination.
- Extension vs pronation.
- Extension vs hand open.
- Extension vs hand close.
- Supination vs pronation.
- Supination vs hand open.
- Supination vs hand close.
- Pronation vs hand open.
- Pronation vs hand close.
- Hand open vs hand close.

For classification, we used different 0.2-s time windows. To validate the classification, we used 10×10-fold cross-validation.

Machine Learning for the Estimation of Desired Motion Intention

After performing pre-processing and filtration, we extracted human motion intention estimation. Figure 3 shows a conceptual process flow chart for assist/rehabilitation exoskeleton using motion intention estimation. Algorithm 1 describes the working of EEG-based motion intention. Figures 4 and 5 are representations of DMI using ELM and RBFNN approaches respectively.

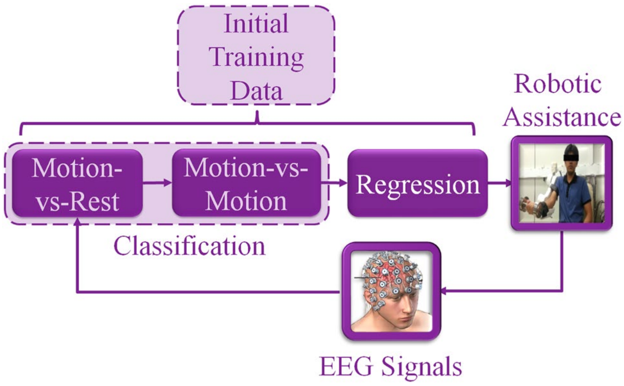


Fig. 3 First, three blocks are trained. These blocks are (1) motion-vs-rest, (2) motion-vs-motion, and (3) regression. Motion-vs-rest finds whether the input data belongs to the motion class or not. If it belongs to the motion class, the motion-vs-motion block finds the relevant class. After finding the relevant class, the Regression block predicts the desired motion intention. This Algorithm has been explained in Algorithm 1

Classification and Regression

For classification, we have used decision tree [34], random forest [35] and deep learning [36, 37] techniques. A brief introduction of the employed techniques has been presented below.

Decision Tree Algorithm [34]

The decision tree is implemented using a recursive procedure. This recursive procedure optimizes separation in a dataset. It is achieved by dividing the root node into two or more children. This procedure is repeated until termination conditions are met. For EEG-based classification, we have used this method to differentiate between various motions. We have employed [34] for this purpose. It has the advantage of the dataset, which have continuous

Algorithm 1 Motion intention estimation algorithm

Result: Predicted Motion Intention
Initialization - Input EEG Signals ;
if *(Do EEG signals belong to a motion class?)* **then**
  Find relavent motion class;
  Perform regression for relevent motion;
  Predict the intended motion by regression;
else
  No motion intended;
end

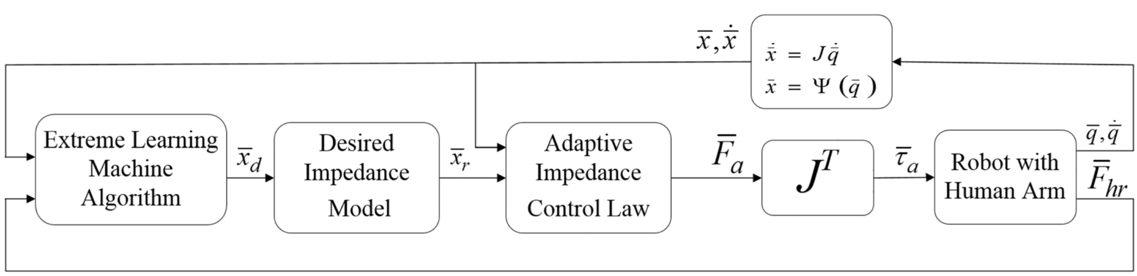
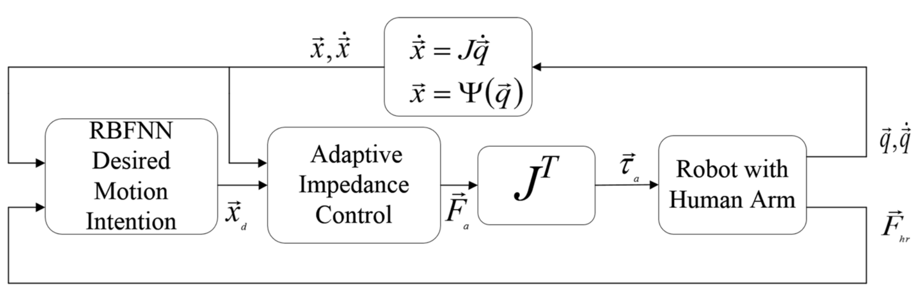


Fig. 4 Desired motion intention algorithm using extreme learning machine

Fig. 5 Desired intention algorithm using RBFNN



attributes. After classification, we used the same technique for regression. Using regression, we have estimated desired motion intention (DMI).

Random Forest Algorithm [35]

Random forest is an improved variant of the decision tree method [35]. Instead of using a single tree, it uses multiple trees to learn the same output. It is called ensemble learning. It is beneficial where different classes have an imbalance in datasets. This method is beneficial for handling these imbalances. Another reason for its good performance is its parallel architecture. This parallel architecture helps train the model faster. The accuracy of the random forest method mainly depends on a number of trees [38]. In general, the more the number of trees, the better it is. However, after some specific number of trees, its performance does not increase [39]. For optimized classification, we have used [35] method. This method effectively removes unnecessary trees for classification (Tables 2, 3). This helps in quick training of the model. The same method has been further extended for regression. To execute Regression, the same protocol has been followed as described in Sect. "Decision Tree Algorithm".

Deep Neural Network [24]

Deep learning or deep neural network is a multilayer perceptron (MLP) set with many hidden layers. Deep neural networks can learn complex models with these layers without manual intervention. It simply requires training data and time to learn the model. Deep learning contains deeper neural connections. These deeper neural connections tremendously improve the learning performance of a neural network. For this study, we have used deep neural networks for classification and regression [24, 36, 37]. First, we have gone through the classification problem. After figuring out the correct class, we applied regression to predict the right desired motion intention.

Results

Result Summary

The result summary is described in Table 4. The accuracy was measured after running the algorithm for 0.097 s, i.e. after the 50th iteration after movement onset. In general, all algorithms (deep learning, decision tree, and random forest) performed well for Mov-vs-Rest classification. For Mov-vs-Rest, we achieved more than 90% accuracy for all the algorithms. However, for Mov-vs-Mov, the deep learning algorithm outperformed other algorithms. After going

Table 2 Hyperparameters and architecture of random forest classifier

Category	Parameter	Value/description
Hyperparameters	$n_{\text{estimators}}$	100 (number of trees in the forest; more trees can improve performance but increase computation cost)
	criterion	'gini' (measures the quality of a split; alternatives include 'entropy')
	bootstrap	False (controls whether to use bootstrapping; all trees use the entire dataset if False)
	random_state	0 (sets the seed for random number generation for reproducibility)
Architecture	Ensemble method	Combines multiple decision trees to improve accuracy and reduce overfitting
	Tree training	Each tree is trained on a random subset of the data (with or without bootstrapping)
	Decision process	Each tree makes an independent prediction; final prediction is based on majority voting (classification) or average (regression)

Table 3 Hyperparameters and architecture of the artificial neural network

Category	Parameter	Value/description
Hyperparameters	*batch_size*	10 (number of samples processed before the model is updated)
	nb_epoch	100 (number of iterations over the entire training dataset)
	optimizer	'adam' (adaptive moment estimation optimizer)
	loss	'binary_crossentropy' (loss function used for binary classification problems)
Architecture	Input layer	61 input features
	Hidden layers	4 hidden layers with 183 units each, using ReLU activation
	Output layer	6 output units, using sigmoid activation (for multi-label classification)

Table 4 Summarized results-table shows average results of fifteen subjects with standard deviation

Algorithm	Classification accuracy % (Mov-vs-Rest)	Classification accuracy % (Mov-vs-Mov)	Regression accuracy %
Deep learning	93.5 ± 1.9	84.5 ± 3.2	75.0 ± 2.5
Decision tree	92.5 ± 2.1	82.5 ± 3.1	78.7 ± 3.1
Random forest	94.5 ± 1.1	78.2 ± 4.1	82.2 ± 2.1

All algorithms achieved resultant accuracy after 0.097 s, i.e., the 50th iteration after movement onset

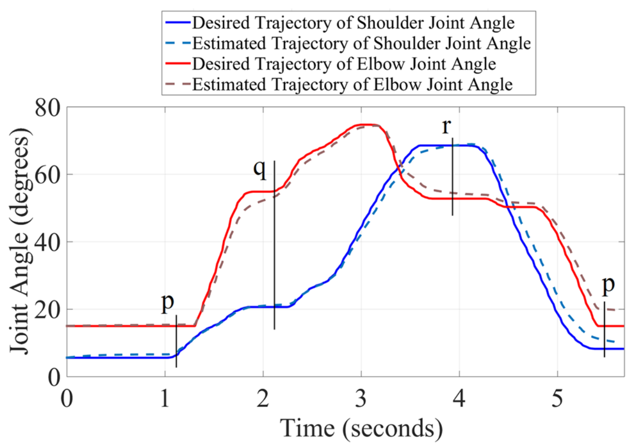


Fig. 6 Comparison of desired and estimated trajectories of shoulder and elbow joint angles over time

through classification, we performed regression to estimate DMI estimation. From Table 4, it can be seen that random forest outperformed other algorithms. It is worth mentioning that these results were obtained after a smoothing filter was applied to the output regression model. Details of each algorithm have been described in the subsections (Figs. 6, 7).

Classification Results—Confusion Matrices

Confusion matrices for deep learning, decision tree and random forest have been shown in Figs. 8, 9, 10, 11, 12 and 13. These confusion matrices are taken when the average classification has reached its maximum limit. These confusion matrices have relative numbering; the numbers sum up to 100%. Overall, the deep learning algorithm outperformed other algorithms (decision tree and random forest) in Mov-vs-Mov classification. It can be evident by the high score in diagonal in Fig. 9. There was no significant difference in mov-vs-rest classification among the three algorithms.

Confusion matrices for the decision tree, for mov-vs-rest and mov-vs-mov, have been shown in Figs. 10 and 11, respectively. Accuracy for mov-vs-rest and mov-vs-mov are within the acceptable range.

Confusion matrices for random forest, for Mov-vs-Rest and Mov-vs-Mov, have been shown in Figs. 12 and 13, respectively. Mov-vs-Rest classification is comparable to another algorithm. For Mov-vs-Mov, although the confusion matrix has high values in diagonal still, the score is not better than the deep learning confusion matrix (as shown in Fig. 9).

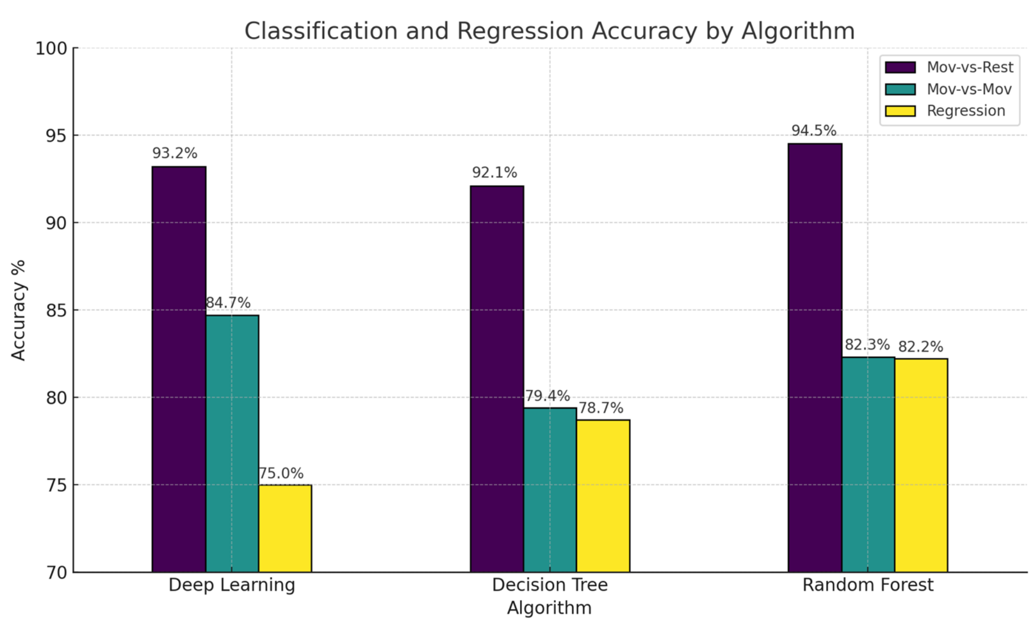


Fig. 7 Classification and regression accuracy % wise for different ML algorithm

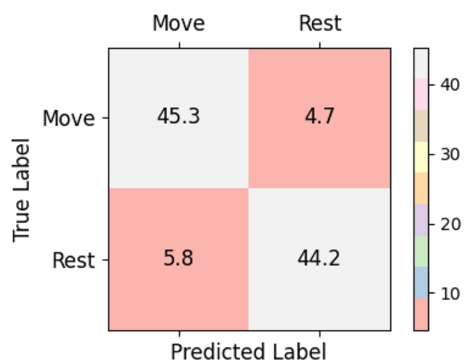


Fig. 8 Deep learning confusion matrix for Move-vs-Rest classification

Known						
Flex	15.2	0.3	0.4	0.6	0.3	0.4
Ext	1.6	11.1	0.2	0.4	0.3	0.2
Sup	2.0	0.3	13.2	0.5	0.3	0.6
Pro	2.1	0.4	0.3	12.9	0.3	0.4
Clo	2.1	0.4	0.7	0.6	12.4	0.4
Opn	2.2	0.4	0.5	0.7	0.4	14.7
Predicted	Flex	Ext	Sup	Pro	Clo	Opn

Fig. 9 Deep Learning Confusion Matrix for Mov-vs-Mov classification

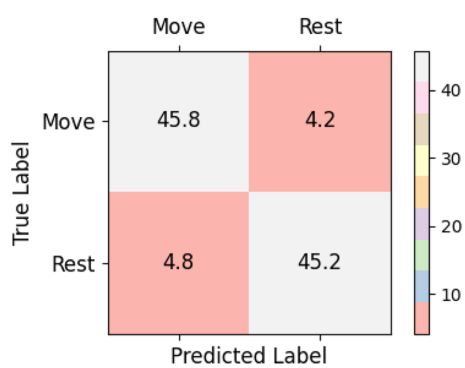


Fig. 10 Decision tree confusion matrix for Mov-vs-Rest classification

Known						
Flex	8.4	1.5	1.8	1.8	1.6	2.0
Ext	1.3	7.0	1.3	1.4	1.1	1.9
Sup	1.6	1.2	8.6	1.7	1.6	1.9
Pro	1.6	1.5	1.9	8.2	1.6	1.9
Clo	1.6	1.4	1.8	1.6	8.5	1.6
Opn	1.9	1.7	2.0	1.8	1.6	10.0
Predicted	Flex	Ext	Sup	Pro	Clo	Opn

Fig. 11 Decision tree confusion matrix for Mov-vs-Mov classification

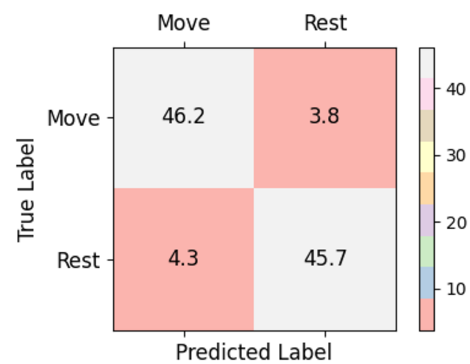


Fig. 12 Random forest confusion matrix for Mov-vs-Rest classification

Known						
Flex	12.1	0.3	0.3	0.4	0.3	0.4
Ext	1.3	8.9	0.2	0.4	0.2	0.2
Sup	1.6	0.2	10.6	0.4	0.3	0.4
Pro	1.7	0.3	0.2	10.3	0.3	0.3
Clo	1.7	0.3	0.6	0.5	9.9	0.3
Opn	1.7	0.4	0.4	0.6	0.3	11.7
Predicted	Flex	Ext	Sup	Pro	Clo	Opn

Fig. 13 Random forest confusion matrix for Mov-vs-Mov classification

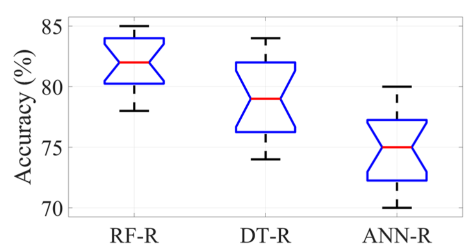


Fig. 14 Box plot of comparison—random forest regression (RF-R), decision tree regression (DT-R) and artificial neural network regression (ANN-R)

Regression Results

After going through mov-vs-rest and mov-vs-mov classification, we trained the model for the output angles. The results of the trained regression model (for deep learning, decision tree, and random forest) for subject 1 and run one have been shown in Figs. 15, 17 and 19. The error plots for all three algorithms have been shown in Figs. 16, 18, and 20. The results have been obtained after 0.097 sec, i.e. after the 50th iteration from the onset movement. A smoothing filter has filtered the regressor's output. The graph motion is for elbow flexion-extension motion. The regression summary is shown in Fig. 14. It shows that

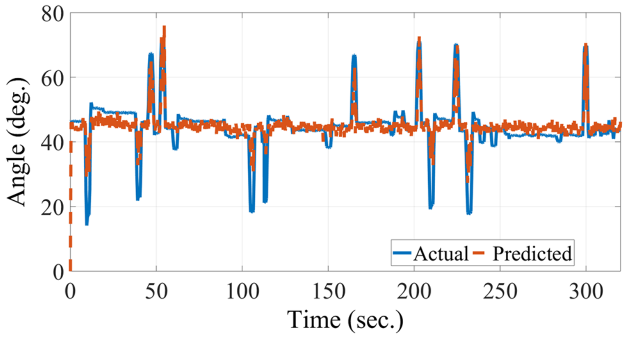


Fig. 15 Deep learning regression for elbow flexion/extension (for subject 1, run 1). Angle is in degrees. Smoothing filter is applied at the output

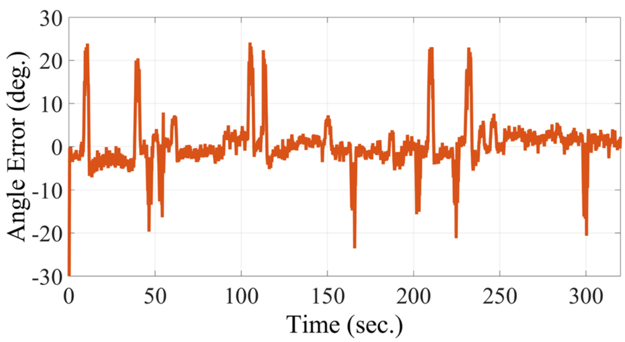


Fig. 16 Regression error for deep learning algorithm (for subject 1, run 1). angle error is in degrees. It can be seen that while flexion/extension motion execution, error is increased

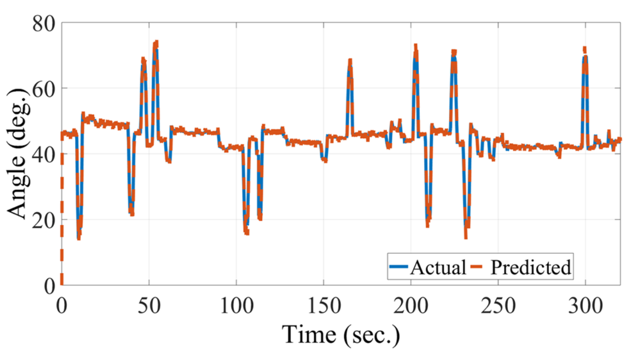


Fig. 17 Decision tree regression for elbow flexion/extension (for subject 1, run 1). Angle is in degrees. A smoothing filter is applied at the output

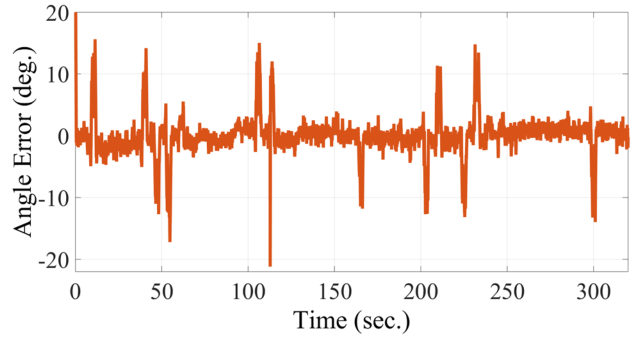


Fig. 18 Regression error for decision tree algorithm (for subject 1, run 1). Angle error is in degrees. It can be seen that while flexion/extension motion execution, error is increased

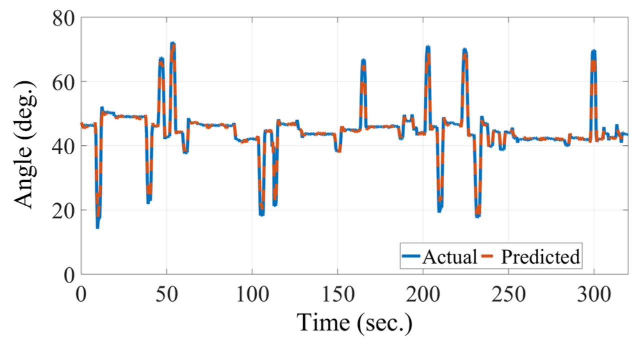


Fig. 19 Random forest regression for elbow flexion/extension (for subject 1, run 1). Angle is in degrees. A smoothing filter is applied at the output

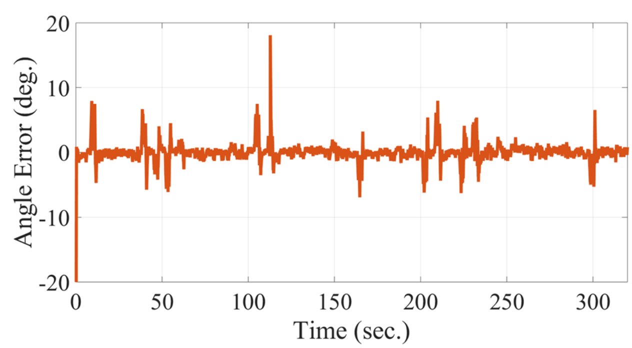


Fig. 20 Regression error for random forest algorithm (for subject 1, run 1). Angle error is in degrees. It can be seen that while flexion/extension motion execution, error is increased

random forests have the highest accuracy compared to decision trees and deep learning algorithms.

Figures 15 and 16 represent Deep Learning results. It is seen that the error is increased during motion, and it reaches 22°. This is because the correct prediction of the desired joint angle is difficult. So, there have been some errors; nevertheless, the predicted output points are in the correct direction. Average accuracy reaches up to 75%. It is of significant accuracy and can generate compliant assistance for rehabilitation robots.

Figures 17 and 18 represent decision tree regression results. As mentioned, the deep learning algorithm followed a similar trend for errors. During the motion, the error was increased, reaching up to 20°; overall, the error variations are lesser than in the deep learning algorithm. The interpretation of the results is similar to deep learning. The output of decision tree regression is slightly better than that of deep learning.

Figures 19 and 20 represent random forest regression results. Just like the previous one, the error was increased during motion. The errors generally remained less than 10° except at one point where it reached up to (about) 18°. Based on the results, it can be realized that although the algorithms' results are helpful for DMI estimation, the performance of random forest is better than deep learning and decision tree algorithms.

Discussion

As we see the confusion matrices and regression results, it is observed that all of these algorithms are very effective for desired motion intention (DMI) estimation. As a whole, the random forest algorithm outperformed other algorithms for classification and regression. It shows that the output of regression models can help the robot assist the patient in a compliant way. There has been a limitation. However, the present study estimated output angle, but estimating produced torque using EEG signals could be more appropriate. Also this study employed a small sample size and only included healthy subjects, which may limit the generalizability of the results to populations with motor impairments. Future research will expand the sample size and include individuals with motor impairments to evaluate the effectiveness of these algorithms in real-world rehabilitation scenarios.

Conclusion

In this study, we have compared deep learning, decision tree, and random forest algorithms to estimate desired motion intention so that a rehabilitation robot could assist the patient in a compliant way. We used electroencephalography (EEG) signals for this purpose. We studied six motion classes. These motions included elbow flexion/extension, forearm supination/pronation, and hand open/close. The study used data from fifteen healthy subjects who had performed motions in ten (10) runs. In each run, there were forty-two (42) trials. After filtration of the EEG signals, we first differentiated the mov-vs-rest class. If the motion was detected, we estimated the desired motion class (elbow flexion/extension, forearm supination/pronation, or hand open/close). After finding the desired motion class, we used regression models (deep learning, decision tree, and random forest) to estimate joint angles for DMI. For mov-vs-rest classification, we achieved an average 94.5% accuracy using the random forest classifier. For mov-vs-mov classification, the deep learning algorithm outperformed other algorithms; we achieved an average 84.7% accuracy. Further, regression was used to estimate the desired motion intention (DMI). For regression, the random forest regression method outperformed other algorithms. We achieved an average 82.2% accuracy. These accuracies were achieved after 0.097 s, i.e. 50th iteration after onset motion. The regression output was smoothed using a smoothing filter. Our findings suggest that the proposed algorithm has the potential to improve a rehabilitation robot's compliant motion assistance and, in turn, improve the recovery rate of stroke patients.

EEG-based motion intention detection in real-world rehabilitation could revolutionize patient care by personalizing rehabilitation protocols that dynamically adjust to individual needs. Rehabilitation robots can adapt their level of assistance using real-time EEG feedback, making rehabilitation more engaging through interactive systems and gamified exercises that encourage patients to be proactive in their recovery process. This integration would also demand the portability of EEG devices, robust robotic systems, and adaptive algorithms to facilitate interactions. Training therapists in EEG data interpretation and the effective utilization of the above systems would be needed, as would patient education about the merits of the technology.

This study has several strengths: it is a novel comparative study on the classification and regression algorithms in EEG-based motion intention detection, where previous literature was inadequate. Overall, the outcomes have shown the applicability of these techniques for real-time implementations in robotic rehabilitation, and the integration of different ML models provides insights into the comparative effectiveness of the methods. Furthermore, the study offers a sound footing for future research by demonstrating the feasibility of EEG-based systems in controlled settings. However, generalizing things and drawing conclusions based on the analysis of this particular interaction facet has drawbacks that should be mentioned. The small number of respondents involved, as well as the volunteers with no motor disorders in particular, prevents the expansion of the results to the populations with impaired motor functions - the focus of rehabilitation research. However, the environmental conditions of the laboratory may not always reflect actual life conditions for successful rehabilitation. Such factors indicate that an effort should be made to extend the study and test the feasibility of the methodology in different and more realistic environments, where signal quality and real-time performance may present even more significant problems.

Author Contributions Abdul Manan Khan: conceptualization, data curation, investigation, methodology, software, visualization, writing—original draft. Fatima Khan: Medical assistance as a doctor methodology, and ethical concern. Vijay Bhaskar Semwal: investigation, validation. Anshu Kumar Dwivedi: investigation, validation.Sheshikala Martha: investigation, validation, writing guidance. Vishwanath Bijalwan: conceptualization, coordination, resources, supervision, validation, writing-review and editing, project administration.

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Data Availability Statement The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request. Any specific scripts or code developed for data preprocessing and model training can also be shared upon request to facilitate reproducibility and further analysis by the research community. Please contact the corresponding author.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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