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Pictorial Task Assistance System using Electroencephalography Signals

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1. Abstract:

Neuromuscular disorders are a significant health problem globally. Patients may experience paralysis, muscle weakness, and communication problems because of these disorders. We propose a Pictorial Task Assistance System to help patients with communication issues using Electroencephalography (EEG). We developed an interface for patients containing an image of food and water. We collected EEG data from 25 healthy students using the Muse headset and Muse monitor app for our study, while they selected one of the images. The EEG data was used to train three supervised machine-learning algorithms for classification. The labels were acquired manually from participants. Using 10-fold cross-validation the results demonstrated that the Random Forest (RF) classifier achieved 88% accuracy, K-Nearest Neighbors (KNN) 80%, and 76% accuracy in Logistic Regression (LR) in the classification of food and water images. These results suggest that the proposed system has the potential to be a useful tool for patients suffering from neuromuscular disorders to perform communication for their necessary tasks.

Keywords: Pictorial Speller BCI; Electroencephalography (EEG); Motor Neuron Disease (MND); K-Nearest Neighbor.

2. 1. Introduction

NMDs are conditions that disrupt nerve-muscle communication, posing challenges for those affected. As the world population ages, understanding NMDs becomes vital due to increasing health issues. NMDs not only cause physical difficulties but also deeply impact daily life, independence, and overall well-being. The economic burden of managing NMDs is felt by healthcare systems globally [1, 2]. MNDs are complex; we must grasp their forms. ALS, a prevalent MND, decays both motor neuron types. This decay causes muscle weakness and spasticity, leading to paralysis. Recent studies have shed light on ALS progression factors. These insights pave the way for potential therapies. PBP, an ALS subtype, affects the bulbar region primarily. This effect results in difficulties in speaking, swallowing, and breathing. Recent studies have delved into PBP’s clinical diversity. These studies reveal unique features and progression patterns. PMA is characterized by the selective decay of lower motor neurons. This decay leads to muscle weakness and atrophy. Extensive research aims to distinguish PMA from other MNDs. This research focuses on understanding PMA’s unique characteristics. PLS primarily involves the decay of upper motor neurons. This decay results in spasticity and muscle stiffness. Current research is refining PLS diagnostic criteria. This research also aims to uncover PLS’s genetic basis. BCIs are useful tools for these patients. These tools have proven transformative, enabling direct control of external devices via brain signals. This technology holds significant potential, especially in healthcare, assistive technology, and HCI. The birth of BCI technology can be traced back to the mid-20th century. BCIs work by recording and interpreting brain signals, with early experiments involving invasive methods like ECoG. Non-invasive methods include EEG, MEG, and fMRI. The accuracy and efficiency of decoding these brain signals have been significantly improved by advances in signal processing algorithms and machine learning techniques[7, 8]. BCIs offer speller systems, a promising way to significantly enhance the quality of life for patients who would otherwise be unable to communicate. Farewell and Donchin introduced the BCI speller system. Patients chose letters in these systems. In 2010, BCI spellers were made for the disabled. Many spelling systems exist for brain injury victims. These systems need updates over time. Some can't convey messages without standard spelling. BCIs use motor imagery (MI). MI generates unique brain patterns. These patterns control external devices. Other control paradigms have been explored. ERPs and SSVEPs expand application range. BCIs have helped those with motor disabilities. BCIs have huge healthcare potential. BCIs control prosthetic limbs. They restore motor function in paralyzed patients. This technology has a transformative impact. BCIs restore independence for those with limited motor function. Neural decoding translates brain signals into commands. Closed-loop systems provide real-time feedback. This feedback enhances BCI-controlled device adaptability. Bidirectional communication is more intuitive and responsive. Challenges persist despite progress. Signal reliability and user adaptability are challenges. Personalized calibration is needed. Current research addresses these issues. AI integration and hybrid BCIs are being explored. BCIs facilitate communication. Neuroscience, engineering, and computer science are combined. Research in this field is evolving. BCI technology refinement and application expansion are promising. Hybrid BCIs and AI techniques advance the field. Signal processing decodes brain signals. Machine learning algorithms have improved BCI systems.

2.1. Problem Statement

Neuro-muscular disorders can hinder communication. This can lead to isolation and a lower quality of life. But, there's a technology, BCI, that uses brain signals for communication. We suggest a "Pictorial Task Assistance System". It's beneficial for those with communication disabilities. This promising technology could aid many struggling to communicate with the world.

2.2. Research Objectives

The research work aims to enable patients with severe disabilities to communicate their desired activity accurately. The use of a wireless EEG device is proposed, which is relatively comfortable for patients to record their brain signals. We have proposed an assistive system that uses pictures of desired activity to simplify task communication, making it more accessible and convenient for patients. In this study, our objectives are data collection, preprocessing of EEG data, feature extraction and selection, and classification of EEG data into two groups, food and water. The proposed system empowers patients to express their desires for routine tasks quickly and easily.

3. Proposed Solution

We have presented the proposed methodology of the Pictorial Task Assistance System in Fig 1. using a visual representation. It unfolded across four key phases: data acquisition, data preprocessing, feature extraction and selection, and classification. On the basis of classification, one of the two options is selected on the graphical user interface.

3.1. Data Acquisition

Participants: In the data acquisition phase, a cohort of 25 healthy undergraduate participants from the University of Engineering Technology Taxila was engaged. The group consisted of 13 males and 12

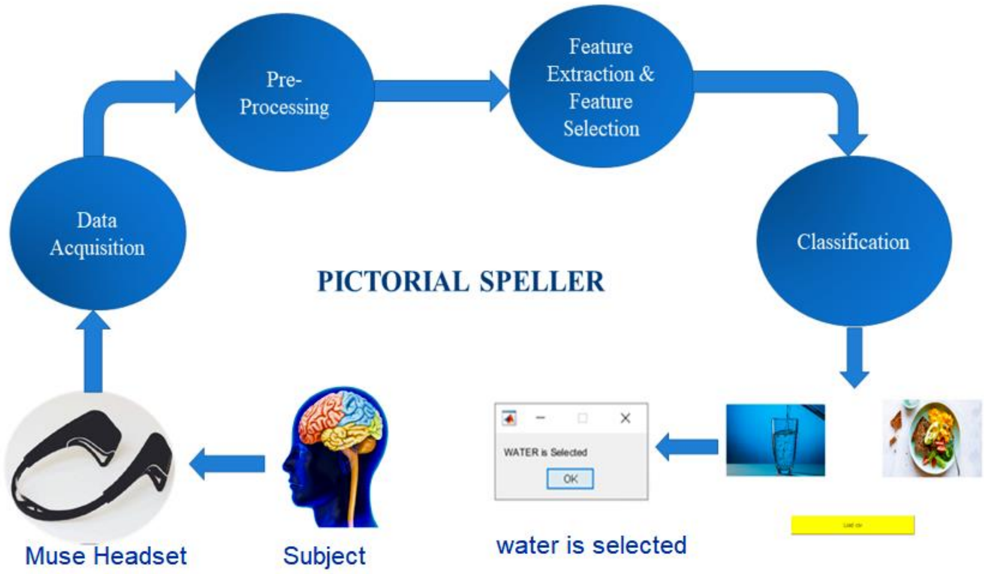


Figure 1: Proposed methodology of pictorial task assistance system

females, aged between 18 and 25.

We used MATLAB to design a graphical user interface. During the study, each subject was shown a total of four pictures that represented four classes of detection: food, light, fan, and water, corresponding to hunger, light, air conditioning, and thirst detection, respectively. Each picture was displayed for 3 seconds followed by a black screen gap of 3 seconds. The purpose of this black screen was to reset the emotional state of the subjects and offer them time to relax without any emotional content.

Each participant was exposed to a specific interface presenting stimuli related to food and water while seated with their heads covered by a Muse headset. The Muse headset recorded neural activity for 2 minutes, utilizing a sampling rate of 256. During this recording, seven electrodes—TP9, TP10, AF7, and AF8— Fp1, Fpz, and Fp2, as reference sensors embedded in the Muse headset were employed to capture neural signals. Participants skipped meds and alcohol for a day for clean data. We picked a silent lab for optimal data collection. We arranged a table, chair, and Muse headsets in this space. Participants were seated and equipped here. A screen displayed food and water images. Participants chose images that reflected their hunger and thirst. They noted their choices on paper, enabling dual responses. The Muse headset captured brain signals as participants engaged with the stimuli. This provided us with key neural data. We manually verified the signal accuracy post each session. This meticulous method guaranteed accurate and reliable data, crucial for data collection. Lastly, the data was wirelessly transferred to an app for further analysis.

3.1.1. MUSE Headset for Data Acquisition

As illustrated in Fig 2, The Muse headset stands as an innovative tool for acquiring neurophysiological data, offering a non-invasive and user-friendly solution for monitoring brain activity. Utilizing seven electroencephalography (EEG) channels strategically placed across the scalp, the Muse headset captures electrical signals generated by the brain's neuronal activity. The placement of these sensors corresponds to key areas associated with different cognitive functions, The Muse headband features seven electrodes. Four are channel sensors. Two sensors are on the forehead. Two are behind the ears. They are labeled TP9, TP10, AF7, and AF8. The device also uses three other forehead sensors. They are Fp1, Fpz, and Fp2. They serve as reference sensors. The Muse headset gives a detailed view of the user's mental state [19]. Users wear the Muse headset to collect data. The device records and sends EEG signals to a connected device. This allows for real-time brainwave pattern monitoring. It aids research in areas like neurofeedback, meditation, and mental performance.

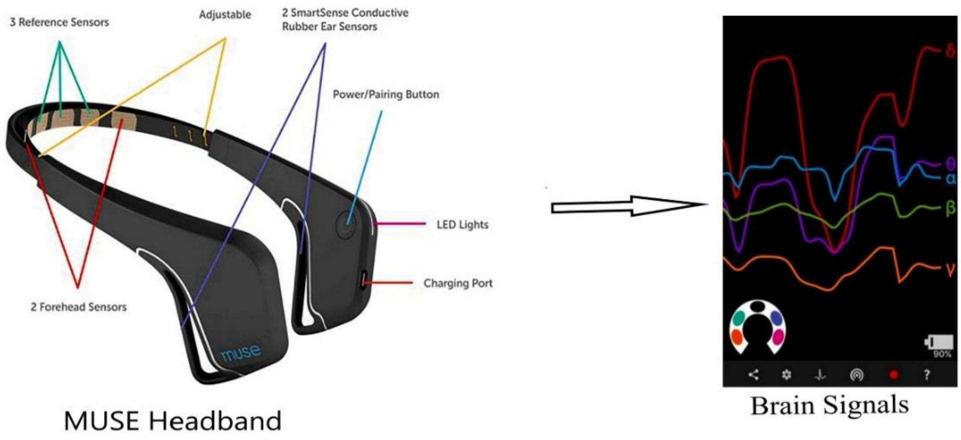


Figure 2: MUSE headset with brain signals

3.2. Preprocessing

In the preprocessing stage, the Muse headset's collected data undergoes a refinement process to eliminate noise. The Muse headband utilizes its embedded filters to automatically eliminate noise from the raw data. The recorded data may contain two types of noise: the first type stems from artifacts like heartbeat, eye movement, blinking, and facial movements, while the second type is environmental noise. The Muse headband records 256 samples in a second, which determines its sampling rate.

3.3. Feature Extraction and Selection

Features were extracted from the preprocessed EEG data to identify patterns related to food and water. The details of the features for each electrode are given by the following Equations:

Amplitude (S_{max}): Equation (1) shows the maximum signal value:

$$S_{max} = \max[t] \tag{1}$$

Amplitude (S_{min}): Equation (2) shows the minimum signal value:

$$S_{min} = \min[t] \tag{2}$$

Average (avg): Equation (3) shows the average amplitude of the same interval t:

$$\text{Avg}=\frac{1}{N}\sum s(t) \tag{3}$$

Power(pow): Equation (4) shows the power of the signal during the time interval:

$$\text{Pow}=t\frac{1}{T}\sum|s(t)^2| \tag{4}$$

Energy(E): Equation (5) shows the energy of the signals equal to the square of the absolute sum of the magnitude of the movement.

$$E = \sum s(t)^2 \tag{5}$$

3.4. Classification

Classification techniques were applied to the selected features crucial for identifying "Food" and "Water". There are two different classes, employing binary classification with distinct classes represented as 0 and 1, and the data underwent classification using the WEKA tool. WEKA, an open-source environment facilitating data extraction, was utilized after noise removal to ensure clean data.

Features were extracted from the original signals, redundant elements were eliminated, and null values were eradicated. The data was labeled in the post-preprocessing through a manual form, to ask the participants what they had chosen during data acquisition and tick the selected image it be food or water. Three algorithms underwent exploration, and through rigorous evaluation, the most effective algorithmic approach for integration into the proposed system was pinpointed. For classification, three distinct supervised learning classifiers, Random Forest, KNN, and Logistics Regression were employed, each detailed below.

3.4.1. K-Nearest Neighbor

The K-Nearest Neighbors (KNN) algorithm is a simple, yet effective classification algorithm used in machine learning. It operates based on the principle that data points with similar features tend to belong to the same class. KNN classification is succinctly explained in reference [20]. It operates by assessing how similar a data point is to its nearest neighbors within a feature space. The algorithm utilizes features that signal reactions to food and water. KNN stands out in the broad spectrum of machine learning algorithms due to its instinctive approach. It doesn't presume anything about the data distribution, qualifying it as a non-parametric method. This feature renders KNN adaptable and suitable for a variety of problems.

The power of the algorithm is rooted in its simplicity - it measures the distance from a test sample to all training samples and then picks the K-nearest samples. The majority vote then decides the class of the test sample. KNN locates the closest K neighbors for every data point, judging by feature resemblance. Subsequently, it assigns the data point to the prevalent class found among these neighbors. As a result, the data point gets categorized, such as identifying hunger or thirst responses to respective stimuli. KNN's effectiveness stems from its straightforwardness and flexibility. It shines in scenarios where patterns defy precise mathematical description.

3.4.2. Random Forest

The Random Forest algorithm (RF) is an ensemble learning method. It outputs the mode of the classes or mean prediction of individual trees. Let's explain how RF works in classification [21]. During classification, this technique constructs many decision trees. Each tree is built considering a random subset of features and data points. This contributes to the ensemble's diversity. In the classification stage, the input data, made up of features, is passed through the decision trees. Each tree assigns a class label independently based on its trained features. The final classification decision is made by aggregating all trees' predictions, often through majority voting. RF is effective in handling complex and high-dimensional data. It provides robust and accurate classification results. Its ability to mitigate overfitting and handle noisy features makes it a valuable algorithm in scenarios where diverse and reliable classification outcomes are crucial, such as in the analysis of neural responses to food and water stimuli. While the testing step involves passing the testing dataset through every tree that was predefined during learning, the random forest stage consists of selecting just a few features from all the features provided for each class. We used this algorithm and got maximum accuracy.

3.4.3. Logistics Regression

Logistic Regression (LR) is a tool for data analysis. When dealing with large datasets, it proves to be quite useful. A sigmoid curve is used by LR to illustrate the correlation between dependent and independent variables. It's crucial to remember that logistic regression performs optimally when the target variables are nearly equally distributed in substantial datasets. Avoiding high levels of multicollinearity is crucial for accurate results. It's the correlation between independent variables. It can make rating variables difficult. Logistic Regression (LR) is a common algorithm for binary classification. LR shines in machine learning due to its straightforwardness and effectiveness. It's a statistical model that employs a logistic function to depict a binary dependent variable. The charm of LR is its capacity to offer probabilities and categorize new samples using both continuous and categorical inputs. For binary classification issues (those with two class values), it's often the first choice. It predicts the probability of an instance belonging to a class [22]. In the context of the given data, which includes extracted features, LR works by modeling the probability that a set of features belongs to a class. The algorithm estimates coefficients for each feature. The logistic function is used to calculate the probability of a data point belonging to a class. The model is trained on the available data. During classification, it assigns a class label based on the probabilities. LR is suitable when the relationship between features and classes is linear. It's valuable in scenarios where interpretability and simplicity are important.

4. Experimental Results

We collected EEG signals from 25 healthy male and female students between the ages of 18 and 25, with an average age of 20.57 years. These students were all undergraduates at the University of Engineering and Technology Taxila. After preprocessing, and removing any outliers from our dataset, we focused on two classes: food and water. We used feature selection to extract relevant features from the original data and discard any redundant elements after feature extraction. We then used a specific classifier on the reduced feature set. To facilitate this process, we developed a graphical user interface for the "Pictorial Task Assistance System" that displays two images on a screen as a task for the participant. The participant then selects food or water, which is displayed on the screen of a graphical user interface. Participants labeled the data manually on a provided form.

We pass the dataset to the classification software WEKA [23], using all default parameters and 10 fold cross-validation technique. Our results show that the Random Forest (RF) classifier achieved 88% accuracy, K-Nearest Neighbors (KNN) 80%, and 76% accuracy in Logistic Regression (LR). These results suggest that our system is a useful tool for patients suffering from neuromuscular disorders to interact with their surroundings. Performance parameters for the RF classifier, which outperformed the rest of the two classifiers, are shown in Table 1.

Table 1: Performance parameter of random forest classifier

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	PRC Area
Water	0.84	0.08	0.91	0.84	0.88	0.86	0.88
Food	0.91	0.15	0.84	0.91	0.88	0.86	0.78
Average	0.88	0.11	0.88	0.88	0.88	0.86	0.83

Assessment of performance parameters of the Random Forest classifier, used for the classification of food and water exhibits a strong overall performance, as evidenced by various evaluation metrics. The True Positive Rate (TP Rate) for both water (84%) and food (91%) suggests a commendable ability to correctly identify positive instances in each class. However, the False Positive Rate (FP Rate) for water (8%) and food (15%) indicates a moderate tendency to classify negative instances as positive. The Precision metric is high for both water (91%) and food (84%), indicating accurate positive predictions. A strong Recall is observed for both classes, demonstrating a good capability to detect positive instances. The F-Measure, a balance of precision and recall, is robust for both water and food. The Matthews Correlation Coefficient (MCC) provides a balanced measure, though its values are slightly lower for both classes. The classifier's effectiveness is further confirmed by the ROC Area and Precision-Recall Curve Area. The weighted averages point to an overall accuracy of 88%, reflecting a well-balanced sensitivity-specificity trade-off. These metrics collectively portray a Random Forest classifier that performs well in distinguishing between food and water classes, with strengths in correctly identifying positive instances and maintaining a balanced precision-recall trade-off.

5. Comparative Analysis

In the comparative analysis with other studies, it becomes evident that while various speller systems have been developed, some with a focus on alphabetical systems and others incorporating images, each system presents its unique characteristics and challenges. It seems that there is a gap in the research regarding the use of pictorial representations to illustrate basic routine needs such as food and water.

In this first experiment shown in Table 2 [26], seven healthy individuals with no history of neurological issues participated. These subjects were seated comfortably in an armchair, facing an LCD monitor screen, with a speaker nearby providing auditory cues. EEG signals were collected using a 64-channel EEG cap and Brain Vision/Recorder at a sampling rate of 1000 Hz. The experiment involved two sessions, each conducted on separate days to avoid interference. Session 1 focused on imagined speech, while session 2 centered on visual imagery. Each session consisted of 22 blocks, with twelve words related to the task and a rest class, making a total of 286 blocks across both sessions.

The system involves visual and speech stimuli, requiring two separate data collection sessions. This method is very time-consuming, and the patient needs to be trained before using this system. The system uses 64 electrodes to measure brain activity in only seven participants and relies on two sessions for its data. In contrast, our proposed system uses only four electrodes and includes 25 participants, resulting in an 88% accuracy rate. This is especially noteworthy considering the way we used it.

In the second experiment of Table 2 [27], the study involved 11 participants, with an average age of 19.91 ± 0.83, took part. The EEG was amplified through a 16-channel system, and three different rapid serial visual presentation (RSVP) paradigms were evaluated. The only difference between these paradigms was the type of stimulus used: (i) white letters (WL), (ii) famous faces (FF), and (iii) neutral pictures (NP). An example of the RSVP paradigm over time was demonstrated using the Famous Faces (FF) interface. The experiment comprised two sessions. In the first session, participants were shown letters and pictures of famous faces such as singers or actresses, and were required to match them. Following this task, a neutral picture was shown. Although this experiment may not directly assist individuals with disabilities in their daily activities, the findings could contribute to the development of new technologies that could aid them in the future.

Table 2: Comparison with previous studies

Year	Stimuli	Subjects	electrode	Dataset	Classification	Accuracy
2019 [24]	LCD (show 12 words &picture)	7(2-sessions)	64	Private	RLDA, CSP	62%
2021 [25]	Letters & Pictures	11	16	Private	SWLDA, P300, RSVP	85%
2022 [26]	Picture	01(covid-19) (3-sessions)	20	Private	SVM classifier	61%
Proposed System	Pictorial show	25	07	Private	Random Forest	88%

In the third experiment of Table 2 [28], a single participant was observed over three sessions while they imagined and observed various images such as flowers, hammers, faces, and scenes. The experiment involved one offline session using flower and hammer stimuli and three offline sessions using face and scene stimuli. Additionally, there was one interactive session using real-time BCI technology, where the participant was instructed to imagine specific images or to rest. The system provided feedback-based output on the participant's neural data. The last two real-time BCI runs included six trials each of faces, scenes, and rest presented in random order. The system also displayed some pictorial shows but did not cater to specific daily desires.

6. Discussion

This study focuses on designing a Pictorial Task Assistance System that can be used by people with disabilities to communicate their basic needs easily. Traditional communication systems rely on spelling, and word choice, which may not be accessible to everyone. Unlike the prior studies, the experiments are kind of similar in using simulation-based methods, but we are working on a graphical user interface, therefore does not have a comparison for our specific goal. Even though BCI introduced a pictorial Task Assistance System. This lack of attention to fundamental aspects makes it difficult for us to compare our studies. We have designed a system that requires only one session and does not take much time to fulfill the patients' desires. Using brain signals, a Pictorial Task Assistance System shows images of food and water that the patients can choose from interface to express what they need. This system used seven electrodes to conduct the study and gathered data from twenty-five participants.

The dataset is passed to the classification software WEKA we utilized 10-fold cross-validation, a widely acknowledged technique in machine learning, to evaluate our classifier's performance. This approach involved dividing the dataset into ten equal parts, training the classifier on nine of them, and testing it on the remaining part. We repeated this process ten times, ensuring each part served as the test set once. We obtained a robust assessment of the classifier's generalization ability by averaging performance metrics across iterations. This method allowed us to optimize model parameters and mitigate overfitting risks, enhancing confidence in its real-world applicability. The algorithms used for classification are Random Forest, KNN, and Logistic regression. The accuracy achieved by these algorithms is 88%, 80%, and 76% respectively as shown in Table 3.

Table 3: Result of classifiers

S. No.	Classifiers	Correctly Classifiers	Incorrectly Classifiers
1	Random Forest	88%	12%
2	KNN	80%	20%
3	Logistic Regression	76%	24%

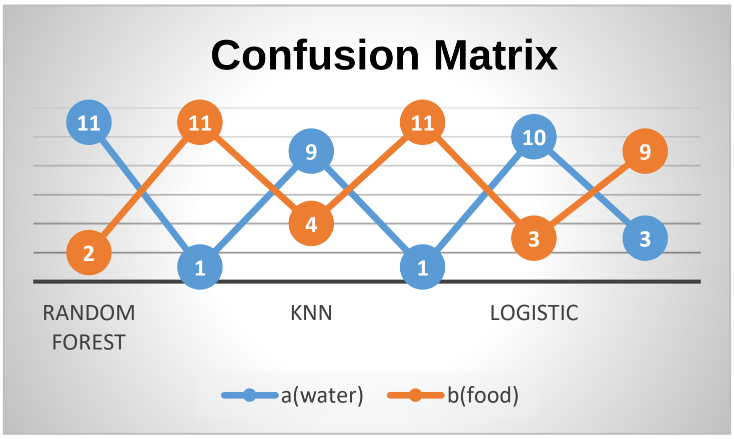
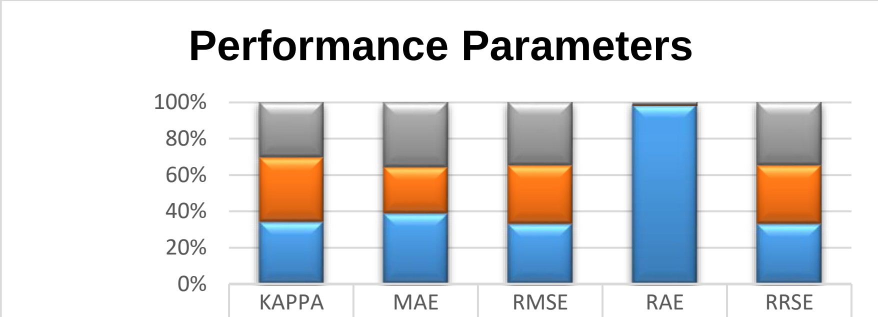


Figure 3: Confusion matrix for classifiers used in this study

The confusion matrix for all 3 classifiers is shown in Figure 3, Where a is classified as water and b is classified as food. The instances of water are shown in blue color whereas instances of food are shown in orange color. Other performance parameters for these algorithms are shown in Figure 4.

It is evident from the above discussion that RF classifier performance was superior in this scenario than that of other classifiers. Therefore, RF is our proposed classifier to be used in the implementation of the pictorial assistance system. For implementation, we designed a MATLAB-based graphical user



	KAPPA	MAE	RMSE	RAE	RRSE
Logistic	0.5192	0.3135	0.4633	62.28%	91.94%
KNN	0.6032	0.2245	0.4303	44.60%	85.39%
Random Forest	0.5833	0.3396	0.4435	67.4281	88.03%

Figure 4: Performance parameter for algorithms used in this study

interface for the disabled patient. On which a total of two pictures that represented two classes of detection: food and water, corresponding to hunger, and thirst detection, were shown respectively. Each picture was displayed for 3 seconds followed by a black screen gap of 3 seconds. EEG was recorded during this selection activity. The recorded EEG data was fed to the pictorial assistance system. With the help of a trained RF classifier, our system identified the desired activity for the disabled patient. A screenshot of our developed MATLAB-based GUI is shown in Figure 5.

Figure 5: GUI of the prototype developed in MATLAB

7. Conclusions and Future Direction

In conclusion, the Pictorial Task Assistance System presented in this research demonstrates an advancement in empowering patients with communication disability to interact with the world through precise image selection, facilitated by the incorporation of a pictorial interface. The diligent application of multiple classification techniques and the optimization of feature extraction across key stages have yielded impressive levels of accuracy, signifying a significant stride forward. These outcomes hold immense promise, opening avenues for disabled patients to communicate through their brain signals. Our vision extends beyond communication to encompass control over lighting and air conditioning. By committing to continual enhancement and upgrading of the current system, our goal is to not only provide a means of communication but also empower individuals facing communication challenges to independently manage their environmental settings. This approach promises to further enrich their quality of life, reflecting the potentially transformative impact of BCI research.

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