English and Romanian Brain-to-Text Brain-Computer Interface Word Prediction System

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***Abstract*—Brain-Computer Interface (BCI) can recognise the thoughts of a human through various electrophysiological signals. Electrodes (sensors) placed on the scalp are used to detect these signals, or by using electrodes implanted inside the brain. Usually, BCI can detect brain activity through different neuroimage methods, but the most preferred is Electroencephalography (EEG) because it is a non-invasive and non-critical method. BCI systems applications are very helpful in restoring functionalities to people suffering from disabilities due to different reasons. In this study, a novel brain-to-text BCI system is presented to predict the word that the subject is thinking. This brain-to-text can assist mute people or those who cannot communicate with others due to different diseases to restore some of their abilities to interact with the surrounding environment and express themselves. In addition, brain-to-text may be used in different control or entertainment applications. EMOTIV™ Insight headset has been used to collect EEG signals from the subject's brain. Feature extraction of EEG signals for BCI systems is very important to classification performance. Statistical-based feature extraction has been used in this system to extract valuable features to be used for classification. The datasets are sentences involving some commonly used words in English and Romanian languages. The results of the English language elucidated that K-Nearest neighbour (KNN) has a prediction accuracy of 86.7%, 86.1% for Support Vector Machine (SVM), and 79.2% for Linear discriminant analysis (LDA), while the Romanian language has a prediction accuracy of 96.1%, 97.1%, and 94.8% for SVM, LDA, and KNN respectively. This system is a step forward in developing advanced brain-to-text BCI prediction systems.**

Keywords—Brain-to-text; Brain-Computer Interface (BCI); Electroencephalography (EEG); Natural Language Processing (NLP); English language; Romanian language

I. Introduction

Communication between humans and machines is a desired concept for a long time. It was the aim of the Brain-Computer Interface (BCI). BCI can convert phonemes, binary responses, letters, and even words from brain activity [1]. BCIs can help people who have lost their ability to speak or move to restore communication with different body organs. Recently, the main coverage of BCI research is focused on restoring motor skills like, grasping, pointing, typing with a computer cursor [2], or choosing from a list of options. Other systems may use "steady-state evoked potentials" or "Event-Related Potentials (ERPs)" to spell text out [3]. A BCI system is a collection of hardware devices and software that uses various techniques to record the brain's activity [4]. The data collected through experiments in laboratory conditions give the necessary information about the computation of neural in human beings. The response of neurons may differ between experimental and behaving in natural conditions. Thus, developing powerful decoding algorithms that can deal with the difficulties of naturalistic behaviour is important in developing real-life applications of BCIs [5].

Two approaches to language neural decoding have been used in this field: invasive decoding, based on invasive brain recording methods like Electrocorticography (ECoG); and non-invasive decoding which depends on neuroimaging technologies like EEG. Language decoding from EEG brain activity is significant in developing commonly applicable BCI systems. This technology can help people who are unable to communicate or do daily activities because of severe neuromuscular diseases or disorders. It also offers a great opportunity for neuroscientists to study brain mechanisms or activity [6].

Many years ago, researchers have predicted whether humans and machines can communicate depending on natural speech-related brain activity. In recent years, scientific research has proposed that it is possible to recognise speech from the brain's neural signals like acoustic features or one of some separate words. Expressed words can be decoded from spoken speech through brain waves ECoG recordings [5], EEG recordings, etc.

Feature extraction and classification are important procedures in each BCI model [7]. Features are extracted from a signal obtained from electrodes. Features are distinguished in frequency, time, and spatial domain. Some features of EEG may have great elective power to observe different patterns of EEG. To design and implement a well-trained model, some features with high discriminating ability are required [8].

The performance of the BCI system is mainly relying on the vector's size of the feature, which is acquired from multiple channels. In the classification of the mental tasks, the training samples' availability of features is minimal. Usually, feature selection is used to improve the classification of mental tasks by eliminating unrelated and unnecessary features [9].

The paper describes a proposed brain-to-text system that is a simple, easy-to-implement, and cost-effective BCI system that aims to help mute or disabled people to communicate with others and electronic devices. The system may also be used for controlling purposes. The system can recognise English and Romanian languages; therefore, it is targeted individuals who can understand these languages. Considering this issue, the next sections practically describe how the brain thoughts can be translated into words starting from the literature review, the method and the techniques used in the study, and the results.

This paper is organised as follows: Section II of this study presents the literature review including background theory and related works. Section III presents the method of the research in detail. Section IV presents results and discussion, and Section V presents the conclusion and future work.

II. Literature Review

A. Background Theory

The brain of humans contains billions of connected neurons. The activity of neurons is varying according to different thoughts, where every thought generates a unique electric brain signal [10]. Brain signals can be detected using different invasive and non-invasive techniques [11]. Non-invasive techniques especially EEG, are widely used in BCI systems due to their ease of use and non-risk since it does not require a surgical invasion [12]. EEG has related to some challenges like low spatial resolution compared to invasive techniques, but it has a good temporal resolution, and may not detect a good signal due to the folding of the cortex or scalp-to-cortex distance [13]. The techniques of signal processing are required to remove the artefacts and noise from the raw EEG signals. This is performed by applying digital filters [4]. In recent years, these challenges have been highly reduced due to the development of hardware and smart software related to BCI research. The EEG signals of brain activity are detected using electrodes that measure the changes in voltage on the scalp [11].

EEG contains important data that will convert into useful information regarding responses to brain stimuli. The type of emotion and the accuracy level of the signal can be identified from the pattern of the brain waveforms. The processing of these signals can allow the control of external devices like the computer cursor, robotic arm, or wheelchairs. It also lets disabled people who have lost their ability to move or talk restore such abilities or express their emotions and thoughts. The signals of the brain can be analysed through three different steps:

- Signal Acquisition.
- Signal processing.
- Controlling.

Pre-processing step is important to convert the raw data into a useful and efficient format [14]. The obtained signal is processed to eliminate the artefacts, noise, etc. which could improve the resulting signal. The next step is to extract features from the signal, where the feature is a special measure from a part of a signal. In feature extraction, the most important features required for classification will be extracted.

Feature extraction of EEG signals is one of the important aspects related to the system of BCI due to its important task of obtaining the correct performance of the classification stage [15] because of the complex processes inside the brain [8]. EEG signals are non-stationary, while their spectrum varies with time. These signals need different feature extraction techniques [15].

In brain signals decoding, signal processing comprises two important steps: feature extraction and feature classification [16]. The process of EEG feature extraction involving generate discriminative data features from channels that can increase the variance difference among classes [17]. The huge number of input data increases the execution time and complexity of the system. Obtaining informative features will enhance and increase the accuracy of the classification [7].

The algorithms of feature extraction must handle the signal source, which is usually complex and noisy, and detect interesting features [8]. These algorithms are used to detect the features that are strongly connected with the intent of the subject. The optimal feature set is transferred directly to the classification algorithm that associates the feature with a task to be accomplished [17]. The success of the BCI system's classification is associated with the accuracy, efficiency, and proper selection of feature extraction, thus, improving the accuracy and efficiency of the system [18]. Feature extraction depends on temporal-spatial analysis and/or time-frequency. Some of the techniques used are wavelet transform, autoregressive (AR) models, Fourier transforms (FT), and statistical properties of the signal [8].

The next step is to translate the extracted features into commands to control an external device or to do different mental tasks [8].

The final stage is the classification process which may be solved by adaptive algorithms, linear analysis, non-linear analysis, neural networks, fuzzy techniques, etc. [10]. Classification algorithms used in this work are "K-Nearest Neighbour (KNN), Support Vector Machine (SVM), and Linear Discriminant Analyser (LDA)".

B. Related Works

The following related works introduce several solutions to the issue of BCI brain-to-text which introduced some forms of a utility function that deals with text aspects.

Shuxian Zou et al. [6] have proposed two decoding tasks, the first one is a word prediction task given a context and brain image. The second task is to generate a direct text from a given prefix and a brain image. To implement these tasks, they have proposed an approach that uses a powerful pre-trained encoder-decoder model. The model reaches 7.95% and 18.2% top1 accuracy for more than two thousand words of vocabulary on average for all task participants.

Christian Herff et al. [3], have implemented a brain-to-text system that forms single phones using “Automatic Speech Recognition (ASR)” by converting brain signals into the equivalent text representation during speaking. The results reveal that the proposed system can carry out phone error rates below 50% and word error rates as low as 25%.

G. NJayabhavani et al. [19], have proposed a BCI system to improve the typing of messages by building a mechanized system using a speller-based mechanized messenger. The smartphone, which contains a built-in speller application is connected to an EEG headset. They used wireless EEG neuroheadset-based P300 ERP for the realistic execution of the mechanized messenger. The smartphone application will be activated when a user wants to transmit a text. The obtained text is transferred after processing by the smartphone spell checker. The proposed system will let a user to text while performing other activities. In addition, the time required for typing will be much reduced. The accuracy of the system is about 98% in 16 seconds after target selection.

James W. Minett et al. [20], have analysed the performance of the P300 speller for the Chinese language’s text input. Depending on the implemented Row/Column and single character spellers, the performance of six different paradigms has been tested and compared for thirty Chinese readers. The accuracy of a single character speller is 63.3% of subjects have been capable of obtaining 80% or higher accuracy of classification for fifteen trials. Regarding the communication rate, the optimal paradigm is different from the speller of Row/Column in which stimuli are increased by changing the colour of the background. This paradigm attained 14.5 bits per minute communication rate. The input rate of this system is about 1.1 characters per minute which correspond to approximate 11,000 Chinese characters.

Kiran George et al. [21], have presented a design method to input a simple text acronym in a message through mind thoughts and natural facial expressions. They have shown that “commercially-off-the-shelf (COTS)” BCI technology as well as “Emotiv Control Panel Software Suite” can be used to translate mind thoughts and natural facial expressions into actions by pairing 12 of the most used acronyms of text. EMOTIV™ headset was used to capture the user’s Electromyography (EMG) and EEG data, while “Emotiv Control Panel Software” is used to translate the mind's thoughts and natural facial expressions into their corresponding text acronym.

Aasim Raheel et al. [22], have presented a powerful solution for using the muscular movement of the eye to type textual content. The fast and accurate movement of the eye can be observed using EEG. They have acquired EEG signals for many users to create a content spelling framework that uses the movement of a cursor over letter sets. All analyses were carried out on datasets of many users to set the indicator in three classes using them as an assist sign for content spelling. The system’s accuracy is 70% for the right movement, 80% for the left movement, and 79% for the blink.

The literature review elucidated that the combination of BCI and machines regarding text generation is a modern and promising study direction. It was also noticed that enhancements are required to improve writing performance while reducing the system's complexity. In this context, this study proposes a novel system that may fulfil the gap in brain-to-text research. The system is designed to predict words that human thinks and prints them on the screen. This system can predict some common English and Romanian language words. The system can assist mute people or those who lost their ability to speak due to different reasons like genetic factors, encephalitis, brain diseases and strokes, etc. to communicate with others or machines. Most brain-to-text research or projects discussed the English language only, while the proposed system can deal with the Romanian language as well. The strengths and weaknesses of some similar projects have been analysed as shown in Table I.

TABLE I. RELATED WORKS

Related project	Strengths	Weaknesses	What is new in this study
“Towards Brain-to-Text Generation: Neural Decoding with Pre-trained Encoder-Decoder Models” [6]	- Predict words and generate text from fMRI images.	- Low accuracy - Not in real-time - One language only	- Good accuracy - Two languages
“Brain-to-text: decoding spoken phrases from phone representations in the brain” [3]	- Convert brain activity into a text representati on. - Accurate brain signals.	- Clinical risks. ECoG invasive technique has been used. - Decode spoken speech, not thoughts. - One language only	- No risk - Decode thoughts - Two languages
“A speller based mechanized messenger for smart phones using brain mobile interface (BMI)” [19]	- Fast - Good accuracy - In real-time	- The user must select a character from a 6x6 matrix - One language only	- Decode thoughts to text directly - Two languages
“An assistive communication brain-computer interface for Chinese text input” [20]	- Good accuracy - Deals with different script language	- The user must focus on a character from a 6x6 matrix on a screen - One language only	- Decode thoughts - Two languages
“Automated sensing, interpretation and conversion of facial and mental expressions into text acronyms using brain-computer interface technology” [21]	- Decoding mental states and facial expressions. - In real-time	- Decode several expressions only - One language only - A combination of BCI and keyboard was used.	- Decode thoughts as words - Two languages - Keyboard input is not needed
“Real-time text speller based on eye movement classification using wearable EEG sensors” [22]	- Good accuracy - In real-time	- Decodes eye movement based on an alphabet grid, not thoughts - One language only	- Decode thoughts - Two languages

III. Method

To implement the proposed system, EEG data collected from a subject has been processed, feature extracted, and classified. Python programming language is used to code all the related signal processing operations and training. The training is carried out first using EEG data. EEG data are collected using EMOTIV™ Insight neuroheadset. The training model is saved after feature extraction and data classification. The prediction process is carried out through the training model by making predictions on new data received from the headset. Fig. 1 shows the basic architecture of the brain-to-text BCI system.

A. Signal Acquisition

To detect and collect EEG brain signals from the subject's head, EMOTIV™ Insight non-invasive neuroheadset has been used. Its 5-channel headset EEG system (see Fig. 2) contains semi-dry polymer electrodes designed for various use of BCI systems and research. EMOTIV™ Insight neuroheadset is made of lightweight materials and provides whole-brain sensing with improved advanced electronics to deliver robust and clean signals. This neuroheadset is compatible with computers and mobile devices and can be connected via Bluetooth Low Energy or a 2.4 GHz wireless dongle [23].

B. Data Collection

The data are recorded using EmotivPRO™. The subject whom the data was collected from is a female who is a native Romanian speaker and fluent in English. She is healthy and reported no history of neurological illness. The recorded data are divided into sentences where each sentence contains some common words. Four sentences in English, as well as four sentences in Romanian, were recorded to be trained. The subject is asked to think of some words in the English language (without speaking) separately during each time of the recording process. For example, the sentence "Boy eats home with family" has five words, each word recorded forty times. The recordings are collected using five sensors of the headset AF3, AF4, T7, T8, and Pz where the sampling rate is 128 samples per second for each channel. The recordings have been exported and saved to be used later in training. The INACTIVE case in which the headset is not worn by the subject is also recorded. The BLINK case is also considered and recorded to recognise the blinking status of the subject and to enhance training accuracy. The same procedure is applied for the remaining English sentences and the sentences in the Romanian language like "Eu merg acasa cu familia".

C. Feature Extraction

After data has been obtained and exported, the next step is to extract features from the collected data. The statistical features like max, min, average, median, and standard deviation are simple, easy to compute, and easy to implement. 25 features have been extracted and used in this BCI system (five features for each channel of the headset).

D. Classification Algorithms

Several machine learning classifiers have been tested in this study, which are SVM, KNN, and LDA. The SVM algorithm is a classifier based on statistical learning theory that is usually used for classification in BCI systems. SVM identifies the decision boundary between the class samples [24]. The linear SVM kernel function parameter has been chosen for this work due to its high computational speed and capability to deal with multi-class issues [8]. KNN is a supervised learning algorithm which is very easy to implement. It stores all the available cases and new cases have been classified depending on a similarity measure. KNN classifies them according to the featured values' estimation, which can be done by comparing the training data with testing data [10]. The distance weight function KNN parameter has been used in this work. One of the most popular classification algorithms in BCI is LDA [25]–[27]. It classifies a set of observations into predetermined classes. The three algorithms are usually used with BCI and work well with multi-class problems and large databases.

A cross-validation procedure has been applied to evaluate and test the performance of the three algorithms. The best values of cross-validation of the three algorithms and the nearest neighbours value of KNN are practically founded as illustrated in the results section.

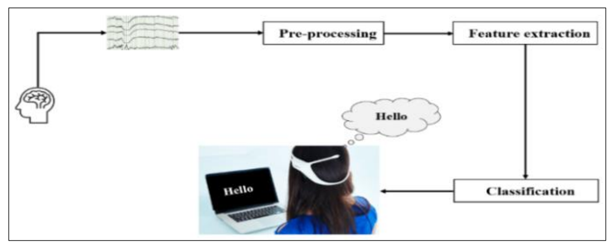


Fig. 1. Brain-to-text System Architecture.

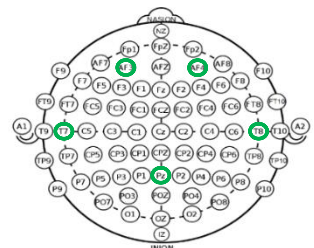


Fig. 2. Emotiv™ Insight Sensors (10-20 System EEG).

```
Begin
Initialise i = 0
#Set root directory of CSV files
For path, subdirectories, files in root:
    Get directoryList
    #Set path
    path_name = path+'/**/*.csv'
    Read CSV files
    For csvFiles in read_files:
        Extract features from all CSV files of each subdirectory
        Creating DataFrames
        Concatenate DataFrames together
    Endfor
    #Update i to get new subdirectory
    i=i+1
Endfor
#Divide data into attributes and labels
X = frame.drop('Word', axis=1)
y = frame['Word']
Specify training algorithm
Train the model using cross-validation
#Save the pretrained model
filename = 'final_model.sav'
End
```

Fig. 3. Training Pseudocode.

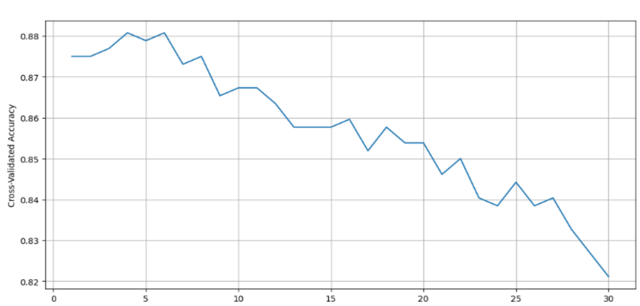
Fig. 3 shows the detailed pseudocode of the training process. As the EEG data are already collected from the subject and saved, the directory of these data must be specified to read the files and extract the feature. After specifying labels and attributes, the training starts using the three classification algorithms mentioned above through the cross-validation method.

IV. Results and Discussion

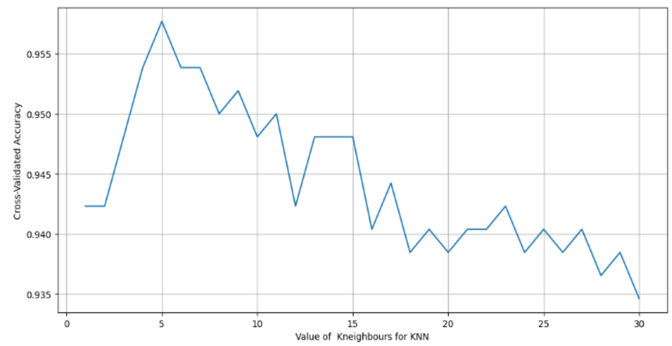
The parameters of the classification algorithms should be tuned to find the optimal hyperparameters. Specifying the optimal hyperparameters would enhance the overall performance and accuracy of the model. The “gridsearch” method has been used to find the optimal hypermeters efficiently. The training process has done separately for each English and Romanian dataset. Table II shows the optimal hyperparameters and the configuration of each dataset for KNN, SVM, and LDA which have been found practically. The percentage of data used for training and testing can also be found in Table II, which differs according to the language and algorithm used. Fig. 4, 5, 6, and 7 show Hyperparameters graphs of KNN, SVM, and LDA. Fig. 4 elucidates that the effective values of n-neighbours are 6 and 5 for both English and Romanian datasets while the curve start dropping after six leading to low accuracy. As can be shown in Fig. 5, the effective k-fold values could be between 5 and 10 in most figures of English and Romanian datasets, where the accuracy is slightly changed. The prediction accuracy of English words is 86.7% for KNN, 86.1% for SVM, and 79.2% for LDA while the prediction accuracy of Romanian words is 96.1%, 97.1%, and 94.8% for SVM, LDA, and KNN respectively. The confusion matrices of the three algorithms for English and Romanian are shown in Fig. 8 and Fig. 9. The results of Romanian words are more accurate than in English words most probably because the subject is a native Romanian speaker.

TABLE II. KNN, SVM, AND LDA HYPERPARAMETERS SETTINGS

Algorithm	**Parameters for the English dataset**	**Parameters for the Romanian dataset**
KNN	Number of neighbours = 6 Weight function = distance Number of kfolds = 8	Number of neighbours = 5 Weight function = distance Number of kfolds = 10
SVM	Kernel type = linear Number of kfolds = 10	Kernel type = linear Number of kfolds = 9
LDA	Slover = svd Number of kfolds = 8	Slover = svd Number of kfolds = 7

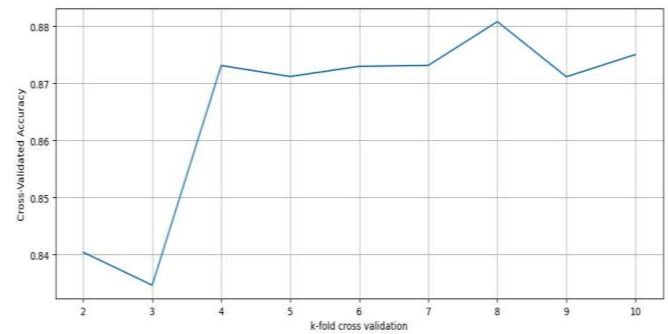


(a)



(b)

Fig. 4. (a). Number of k-neighbours of KNN-English., (b). Number of k-neighbours of KNN-Romanian.



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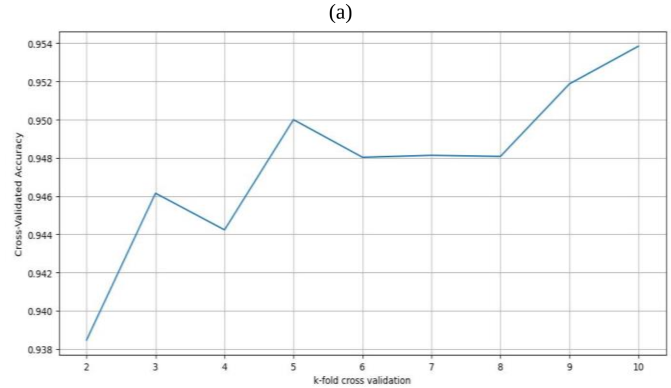
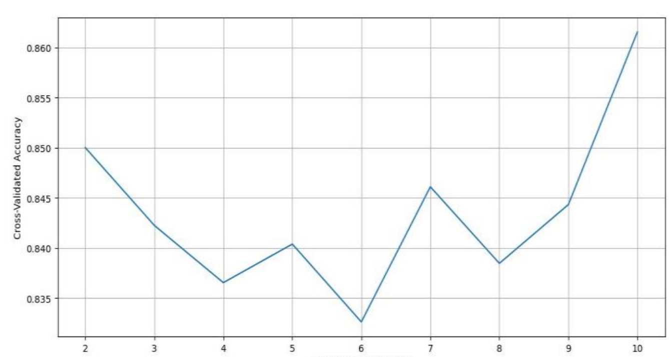


(b)

Fig. 5. (a) Performance of different k-fold of KNN-English. (b). Performance of different k-fold of KNN-Romanian.



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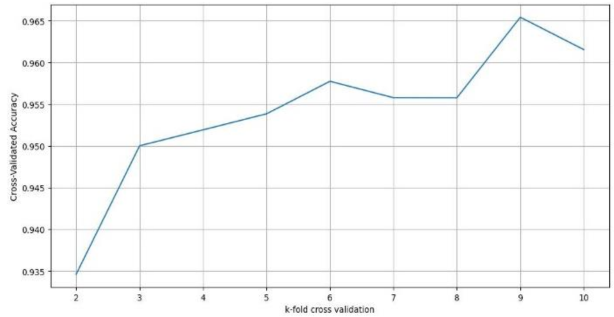

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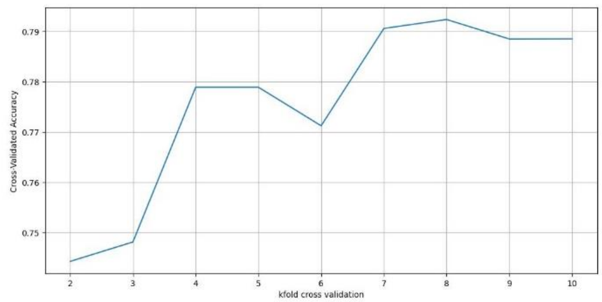
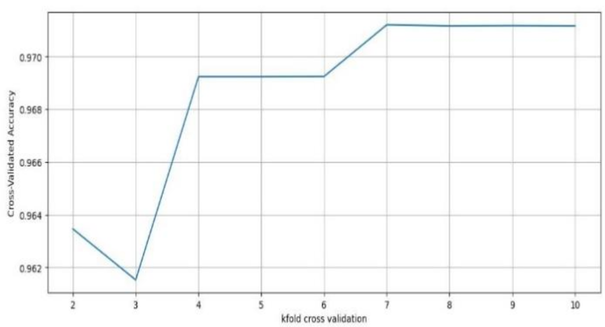
Fig. 6. (a) Performance of different k-fold of SVM-English. (b) Performance of different k-fold of SVM-Romanian.

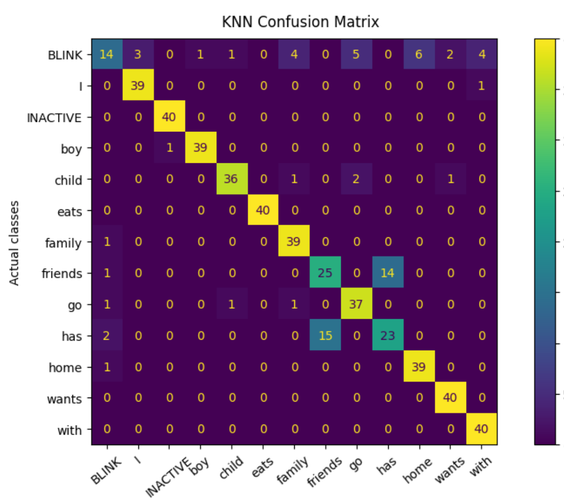


(a)



(b)

Fig. 7. (a). Performance of different k-fold of LDA-English. (b) Performance of different k-fold of LDA-Romanian.



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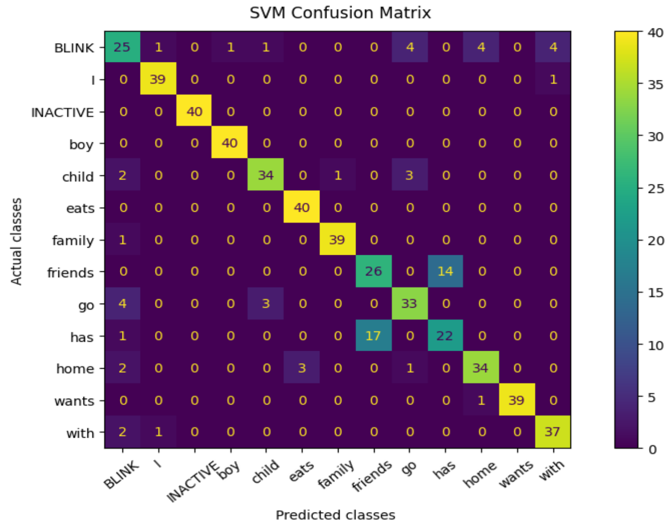

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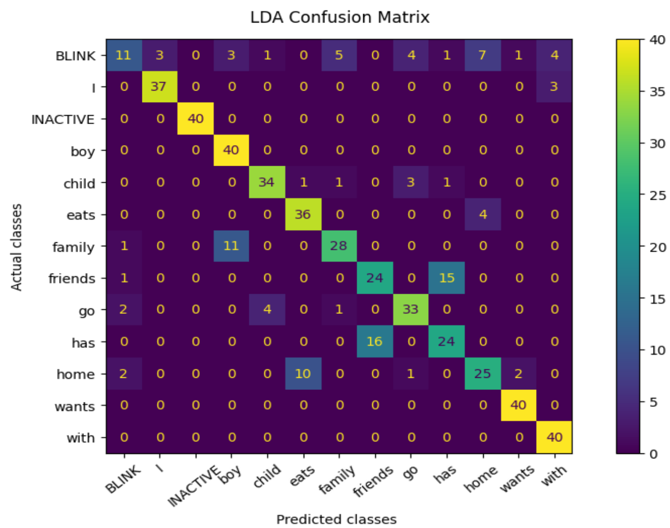
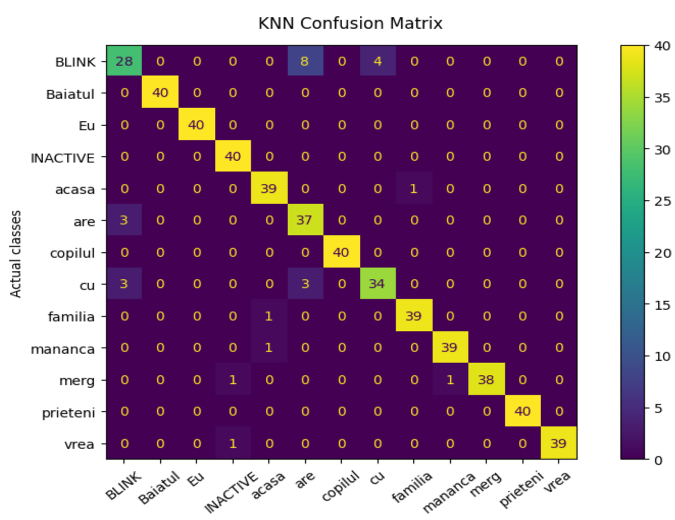
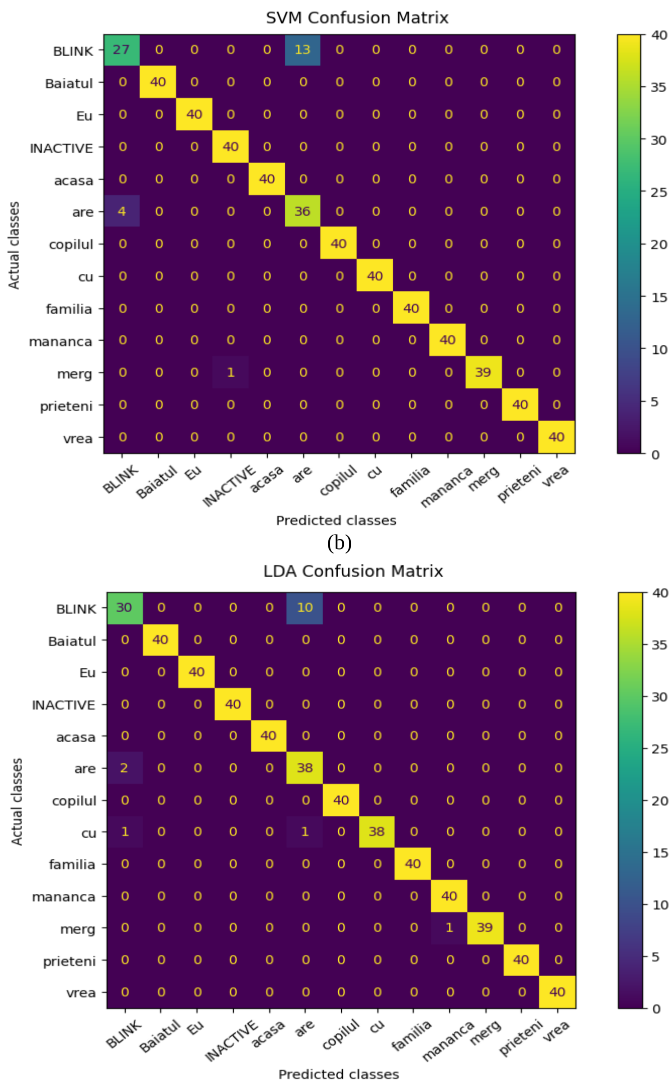


(c)

Fig. 8. Confusion Matrix of KNN- English, (b). Confusion Matrix of SVM-English, (c). Confusion Matrix of LDA- English.



(a)



(b)

(c)

Fig. 9. (a). Confusion Matrix of KNN- Romanian, (b). Confusion Matrix of SVM- Romanian, (c). Confusion Matrix of LDA- Romanian.

In Table III and Table IV, True Positive Rate (TPR) or recall computes the ability of the model to detect positive samples which must be close to one for better results, and precision or “positive predictive value” is the ratio of positive samples that are correctly classified to the total number of classified positive samples where precision value must be close to one also for better results. Precision helps to find the machine learning model’s reliability to positively classify the model. It can be noticed from the Tables that the KNN is the best classification algorithm for the English dataset while LDA is the best classification algorithm for the Romanian dataset.

The system testing is conducted using the pre-trained model with real-time EEG data streamed from the subject’s brain through the headset. Fig. 10 shows different execution screenshots for English and Romanian words. The subject was asked to think of the previously trained words where the desired word should be printed on the screen. The BLINK word in the figure refers to blink status when the subject blinks her eyes, while the red words present a misclassification status. The results may be affected by limitations like the mood of the subject, ability of focusing, or whether is he/she patient. Although some miss classifications occurred during the execution, a limited group of words have been used in this work, and the study is conducted on one person only, the system has successfully decoded thoughts which are a necessary step toward human interaction with computers or the surrounding environment through speech imagery.

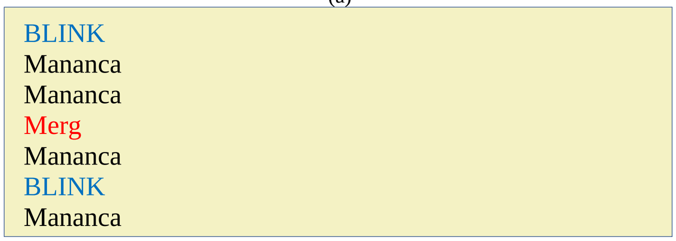
TABLE III. PRECISION AND RECALL OF ENGLISH CLASSIFICATION

Classifier / Class	KNN		SVM		LDA	
	Precision	Recall	Precision	Recall	Precision	Recall
BLINK	0.7	0.35	0.68	0.62	0.65	0.28
I	0.93	0.97	0.95	0.97	0.93	0.93
INACTIVE	0.98	0.97	1	1	1	1
Boy	0.97	0.97	0.98	1	0.74	1
Child	0.95	0.9	0.89	0.85	0.87	0.85
Eats	1	1	0.93	1	0.77	0.9
Family	0.87	0.97	0.97	0.97	0.8	0.7
Friends	0.62	0.62	0.6	0.65	0.6	0.6
Go	0.84	0.93	0.8	0.82	0.8	0.82
Has	0.62	0.57	0.61	0.55	0.59	0.6
Home	0.87	0.97	0.87	0.85	0.69	0.62
Wants	0.93	1	1	0.97	0.93	1
With	0.89	1	0.88	0.93	0.85	1

TABLE IV. PRECISION AND RECALL OF ROMANIAN CLASSIFICATION

Classfier / Class	KNN		SVM		LDA	
	Precision	Recall	Precision	Recall	Precision	Recall
BLINK	0.82	0.7	0.87	0.68	0.91	0.75
baiatul	1	1	1	1	1	1
eu	1	1	1	1	1	1
INACTIVE	0.95	1	0.98	1	1	1
acasa	0.95	0.97	1	1	1	1
are	0.77	0.93	0.73	0.9	0.78	0.95
copilul	1	1	1	1	1	1
cu	0.89	0.85	1	1	1	0.95
familia	0.97	0.97	1	1	1	1
mananca	0.97	0.97	1	1	0.98	1
merg	1	0.95	1	0.97	1	0.97
prieteni	1	1	1	1	1	1
vrea	1	0.97	1	1	1	1

(a)



(b)

Fig. 10. (a) Real-time Words on Execution Screen-English, (b). Real-time Words on Execution Screen-Romanian.

V. Conclusion and Future Work

There is always a necessity for a new natural approach to control and communicate with electronic devices and machines than the usual digital input approaches like touchscreens and buttons which may be limited to healthy people more than people with disabilities and diseases. Brain-to-text is a very modern field of research, and more research and gaps can be achieved and fulfilled in this field, especially in the medical domain. In this study, a brain-to-text BCI system is presented to mentally predict the word in English and Romanian languages. The system can help the disabled who cannot write or mute people to communicate with others or machines in writing in real-time. It will translate the neural activity into text using algorithms for feature extraction and classification. The three algorithms used in this system show promising results like high accuracy and prediction speed, especially KNN in English and SVM in Romanian.

In future work, more feature extraction and classification techniques like Fast Fourier Transform (FFT), neural networks, etc. may be used to enhance the accuracy and prediction of the system, considering increasing the collected EEG signals and samples. In addition, more languages like Arabic, which is written from right to left and its script is totally different from Latin script may be involved to target different language speakers.

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