Framework for Thought to Text Classification

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Abstract--- *People with neurological disorders are unable to communicate their basic requirements because they lost the ability to speak. Designing a brain-computer interface that could convey their basic needs would make their lives easier. This article presents a system to determine the patient's imagined words in the brain without him/her physically expressing by EEG signal and machine learning. The imagined words in the mind to text mapping is converted into a classification problem among a predesigned set of words and classified by using machine learning algorithms. The decoding/classification of EEG signals to identify imagined words is carried out KNN classifier, and Random forest classifier. The classification accuracy shows that the random forest classifier achieved better classification accuracy in comparison with KNN.*

Keywords--- *EEG Signals, Machine Learning, Imagined Words, KNN Classifier, Random Forest Classifier.*

I. Introduction

Many individuals suffer from the locked-in condition due to diseases like amyotrophic lateral sclerosis, a brain stem stroke or a spinal cord injury. This situation disconnects them from society. Even for primary requirements, they were unable to communicate to the caretaker. A brain-computer interface (BCI) for detecting a few necessary needs can be a better solution for such patients for communication .We aim to determine the patient's imagined words without him/her physically expressing them. The aim of our work is to decode patterns in electroencephalography (EEG) for soundless communication. Imagined speech is a process where a subject tries to actually say the word without making any sound or moving any muscles, that is the person thinks of the sound of words.

EEG (Electroencephalography) is typically a non-invasive method used to measure the electrical activity of the brain. From EEG measurements, it may be possible to uncover patterns invisible to the human eye and extract information about this brain activity. In this work, we identify the imagined words by using two different machine learning algorithms-KNN classifier, which is a linear algorithm and Random forest classifier, which is a non-linear algorithm. In this paper, we discuss the various accuracies achieved using two algorithms. Data recorded over various time periods and also from the number of words the model is trying to classify. From the accuracy achieved we will be able to deduce whether the imagined words EEG signal is a valid basis for detecting the words said in mind.

In the works of [1], emotion recognition was tried despite there not being much physiological indication in EEG signals with changes in emotion. Feature extraction and classification methods like KNN and SVM have resulted in some level of accuracy, implying the possibility of emotion recognition from processing of EEG signals. In [5], identification of imagined syllables was tried. The syllables 'ba'and 'ku'were experimented on. These syllables have

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very little semantic content and therefore its EEG recording too would naturally be unlikely in reflecting any semantic contribution. In [4], suggested feasibility of usage of EEG to classify the imagined speech. Filters were designed from envelopes based on the experimental data collected through electrodes to determine the syllable in the trial, In [2] to find out whether it has some information about the imagined syllable. In [8], accuracy of detecting twenty emotional Chinese words using SVM and LDA was found to be 48.78% and 57.04% respectively. Using ANN , average accuracy obtained to classify "yes" and "no" was 75.7%. In the works of [3] it was found that word-based classification from EEG signal of imagined speech has not been as successful as the syllable based counterpart although there does exist some differentiating components that can aid in classifying into different categories . Classification of two words from 5 subjects was tried: "yes" and "no" using MelFrequencycepstral Coefficients (MFCC) and k-Nearest Neighbor (k- NN). Maximum accuracy of 63% was obtained using KNN classifier. We aim to further this work using a different approach to classify more words and from more subject

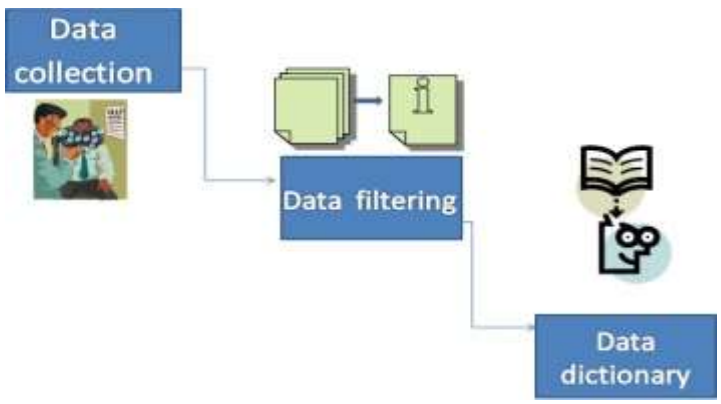

Figure 1: Flow of the Experiment

II. DATA COLLECTION

Our project work can be divided into two major parts: Collection and processing of data and use of appropriate Machine learning algorithm to predict result. Machine learning is a division of artificial intelligence (AI). Machine learning is a model that learns by itself and improve itself without being explicitly programmed.

Collection of data involves use of headgear that can record single channel Electroencephalography signals or EEG signals from the subject. We use the Neurosky Mindwave Mobile 2 Brainwave starter kit for our project. It is an all-in-one wearable package that consists of adjustable rubber sensor arms, forehead sensor and wide ear clip contacts. It is comfortable and easy to use.

Mindwave Mobile 2 is a device that safely measures EEG through a single channel and transfers the voltage values via Bluetooth through iOS or android device. One can measure the levels of attention and relaxation too. The systems also include built-in noise reduction mechanism, and use embedded (chip level) solutions for signal processing to deduce other parameters and provide a vast range of output. The headset's ground electrodes are on the ear clip and the EEG measuring electrode is on the sensor arm, in contact with the center of the forehead. It can work for 8 hours with the help of a single AAA battery. Python programming language was used to view, plot and analyze the recorded EEG data.

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The data can be collected by connecting through any third party application or by directly interfacing to the computer. Third party applications provide more data that are derived from the raw EEG value which the headset primarily measures. We use the raw EEG values for our purpose. The idea is to collect data from the brain when the subject is thinking about saying certain words. Using that data , one would train a machine learning categorization algorithm and use the resulting system to then deduce the subject's brainwaves in real time and classify them into words they may be trying to say. The expected outcome will be to predict the word the subject is trying to say.

The brain waves consist of signals that belong to distinct frequency bands. The connection between these values and our implementation is that these categories of brain waves are used to interpret different states of the brain, as described in the right column of the figurebelow. More importantly, it could pass these values to a machine learning algorithm to have it predict what a person is thinking when it identifies a certain pattern in these values.

We decided on four words, namely- YES, NO, FOOD, WATER. 15 subjects were from among our family and friends aged between 19-20 and 45-50. The subject was made to understand the entire experiment and consent was taken before the readings were collected. Data was collected in a calm and confined environment.

The subject was required to make an attempt to say the words, but not utter any sounds, that is to say those words in their minds. This is the tricky bit as the readings recorded are subjective and dependent on the state of the mind of the subject. One might use external stimuli (auditory or visual) or pre-training like meditation to obtain better EEG recordings. For our experiment, audio signals of the words to be imagined were made to be heard through headphones to the subjects.

Delta	0.5-2.75 Hz	Deep sleep
Theta	3.5-6.75 Hz	Meditating or sleeping
Alpha low	7.5-9.25 Hz	Relaxed or Thinking normally
Alpha high	10-11.75 Hz	
Beta low	13-16.75 Hz	Focusing or thinking intently
Beta high	18-29.75 Hz	
Gamma low	31-39.75 Hz	Conscious and perceptive thinking
Gamma mid	41-49.75 Hz	

Figure 2: Frequencies of EEG Readings

The subject was asked to think of saying a particular word while the readings were collected as the audio stimuli of the same word played in the headphones. A recording duration of one, five and ten seconds was selected. Each duration was then re-recorded with different sampling rates of one, five and ten milliseconds. Thus in total nine readings were collected from one individual for one word. This process was continued for four words in total and for fifteen subjects.

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The recordings obtained were in CSV format and contained values of different components of the EEG brain signal like delta, theta, alpha high, alpha low, beta high, beta low, gamma low, gamma mid, blink strength, attention, meditation , raw EEG value etc. Raw EEG value was chosen as the variable to be parsed in the algorithm.

	A	B	C	D	E	F	G	H	I	J	K	L	M	
1	timestam	eegRawV	eegRawVa	attention	meditatio	blinkStrer	delta	theta	alphaLow	alphaHigh	betaLow	betaHigh	gammaLo	ga
2	1.58E+12	-302	-6.64E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
3	1.58E+12	-331	-7.27E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
4	1.58E+12	-362	-7.95E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
5	1.58E+12	-362	-7.95E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
6	1.58E+12	-331	-7.27E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
7	1.58E+12	-299	-6.57E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
8	1.58E+12	-300	-6.59E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
9	1.58E+12	-293	-6.44E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
10	1.58E+12	-258	-5.67E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
11	1.58E+12	-264	-5.80E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
12	1.58E+12	-266	-5.84E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
13	1.58E+12	-263	-5.78E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
14	1.58E+12	-275	-6.04E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
15	1.58E+12	10	2.20E-06	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
16	1.58E+12	-269	-5.91E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
17	1.58E+12	-263	-5.78E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
18	1.58E+12	0	0	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
19	1.58E+12	-273	-6.00E-05	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
20	1.58E+12	20	4.39E-06	67	53	41	118181	16745960	8073	2825	4990	4292	1947	
21	1.58E+12	26	5.71E-06	67	53	95	118181	16745960	8073	2825	4990	4292	1947	
22	1.58E+12	35	7.69E-06	67	53	95	118181	16745960	8073	2825	4990	4292	1947	
23	1.58E+12	56	1.23E-05	67	53	95	118181	16745960	8073	2825	4990	4292	1947	

1sec 1ms

Figure 3: Sample of EEG Data Collected

III. METHODOLOGY

Our experiment aims to find if imagining words can cause some specific cortical activity recognized in the single channel EEG recordings that can be classified to indicate the word. Machine learning is used for signal analysis , image analysis and decision making[9]. Here, the raw EEG value was fed to KNN (K nearest neighbor) algorithm and Random Forest Algorithm, and their accuracies measured.

KNN for two word classification had provided average accuracy of 58% in [3] as mentioned in the introduction, KNN is a non-parametric pattern recognition machine learning technique for classification. The implementation primarily requires training the model with labelled data and specifying the number of neighbors. If the number of neighbors are specified as 'n', the data to be classified selects its nearest 'n' neighbors by calculating distance to each of the data points, then predicts the class of the unknown data as the average of the classes of the 'n' nearest

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neighbors. The distance between the data points can be of three types: Euclidean, Manhattan and Minkowski.

KNN classification for four word classification was attempted. The words were: ‘yes’, ’no’, ’food’ and ’water’

Nearestneighbors was set at 10. An accuracy of around 40% was achieved.

Random Forest algorithm was also implemented as a novel technique for the same data to classify the imagined word among the four specified words. The Ensemble method was used in our random forest algorithm. The goal of ensemble methods is to put together the predictions of several estimators built with a given learning algorithm in order to improve robustness and accuracy as compared to a single estimator. A random forest creates various decision tree classifiers on different sub-samples of the dataset and calculates average to improve the predictive accuracy. The accuracy obtained was around 50%- 60%.

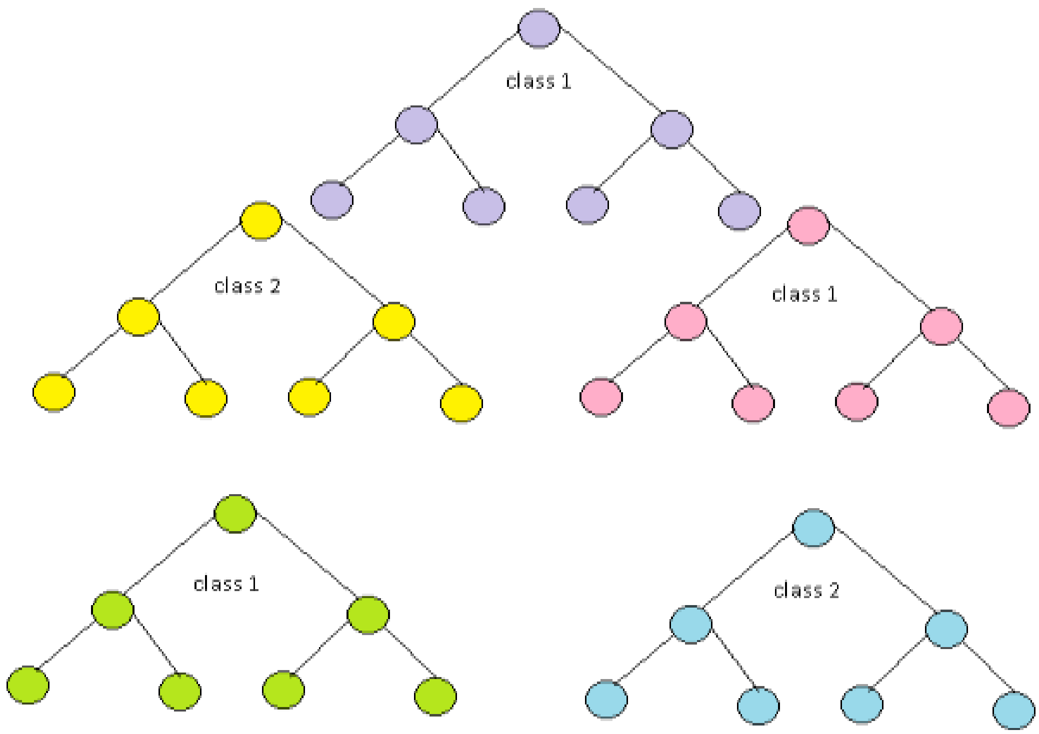

Figure 4: No. of Decision Trees Making Up RANDOM FOREST

IV. Results And Discussions

In our work, we tried to classify four words by parsing their data in two Machine Learning algorithms. The KNN Classifier and Random Forest Classifier was implemented. Data collected over various sampling rates were used in the experiment to check for the differing accuracies. The different sampling rates of EEG data used are: 1ms, 5ms and 10ms.

Table 1: Accuracy Achieved from Data of 10 Subjects with KNN

Sampling Rate	No. of words=4
1ms	40%
5ms	45%
10ms	50%

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Table 2: Accuracy Achieved from Data of 10 Subjects with Random Forest

Sampling Rate	No. of words=4
1ms	62.5%
5ms	75%
10ms	63%

Table 3: Accuracy Achieved from Data of 15 Subjects with KNN

Sampling Rate	No. of words=4
1ms	42.8%
5ms	46%
10ms	40%

Table 4: Accuracy Achieved from Data of 15 Subjects with Random Forest

Sampling Rate	No. of words=4
1ms	54%
5ms	63%
10ms	50%

In our work, we tried to classify four words by parsing their data in two Machine Learning algorithms. The KNN Classifier and Random Forest Classifier was implemented. Data collected over various sampling rates were used in the experiment to check for the differing accuracies. The different sampling rates of EEG data used are: 1ms, 5ms and 10ms.

As shown in Table 1, 40% accuracy was achieved using KNN classifier with EEG data of 10 subjects with sampling rate 1ms. With sampling rate of 5ms, accuracy obtained was 45%, and with sampling rate of 10ms, again accuracy was 50%. Comparing to previous works done,[3],maximum accuracy achieved for two words using KNN was 63%. When we increase the number of words, the accuracy, naturally decreases', meaning it becomes more difficult for the model to differentiate and classify into four words than into two words. While observing accuracies of different sampling rates, we see that the accuracy achieved using 5ms is more than that of accuracy achieved for 1ms. Accuracy of 5ms and 10ms sampling rates are more or less equal.

With Random Forest Classifier, higher values of accuracies were achieved. For data of 10 subjects, and sampling rate equal to 1ms, accuracy obtained was 62.5%, accuracy for 5ms sampling rate was the highest amongst all resulting in 75%. For 10ms sampling rate, the accuracy resulted in 63%. The difference in accuracies over different sampling rates could indicate about over fitting and under fitting in the model. When the number of subjects was increased, the data for training fed to the model was increased and an overall decline in accuracy was observed. This could be explained by high variability and low bias achieved when taking bigger datasets.

The accuracy for 15 subjects, when KNN was used was 42.8% for 1ms sampling rate. For 5ms sampling rate,

accuracy increased to 46% and it again decreased to 40% for 10ms sampling rate EEG data.

With random forest , accuracy achieved was more than that of KNN of 15 subjects, but less than that of random forest for 10 subjects. Accuracy was 54%, 63% and 50% for 1ms, 5ms and 10ms sampling rate respectively. Here as we see, accuracy is more for 5ms sampling rate EEG data.

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In general we can conclude that:

- Random forest performs better than KNN
- Accuracy falls for dataset of 15 subjects than that of 10 subjects
- Accuracy is more for 5ms sampling rate than for 1ms and 10ms sampling rate.

V. FUTURE WORKS

With single channel EEG data, maximum accuracy attained is 75% for classification of four words. As the number of channels will be increased, the quality of EEG data will improve and accuracy achieved will be more.

With increase in number of subjects in the dataset, the variability increases and the accuracy fall. Different subjects have different response times and different thinking patterns. It becomes difficult for model to train with this widely variable data. Fine tuning and feature extraction could improve the accuracy obtained.

Our experiment was conducted with data of sampling rates 1ms, 5ms and 10ms, out of which 5ms sampling rate data provided the maximum accuracy. Further experiments can be done by using other sampling rates , which optimally align with the neural response time and thus help in providing better results.

The raw EEG data is highly variable and non-linear in nature. Hence a non linear ensemble classifier like Random Forest will perform better than a linear classifier like KNN. Other non linear methods like neural networks and SVM can be used to improve the accuracy of the system.

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