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Brain-Computer Interfacing based Classification of Brain Activities via Machine Learning

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Abstract: *Human mind can be directly connected with the computers through a new technology known as BCI (Brain-Computer Interface). Electroencephalography (EEG) based BCI enables to interact the people with the surrounding world through brain signals noninvasively. This method of reading the mind through physiological signals by EEG sensors has made significant progress in neurological science and motor control research. The BCI system can record, analyze and translate the system input, acquired from the brain in terms of commands. These commands can further be used to actuate external devices of choice according to the user's mind. The BCI is emerging as one of the powerful tools in realistic biomedical applications such as rehabilitation, cognitive processes, prosthetics and many neuro-feedback functional activities. However, the functionality of BCI relies upon the recognition and classification of brain signals for discriminating task and resting activities of the brain. We have developed an algorithm for classification of EEG signals recognizing brain activities under the given tasks. We have tested our classifier from open source EEG dataset. The dataset is consisting of EEG recordings acquired from twenty-six healthy participants during word generation (WG) tasks. By implementing our algorithm which is based on SVM (Support Vector Machine) method, the signals of rest and task events were classified more precisely. In this work, we have achieved an average classification accuracy peak of 85.27 % with the dataset.*

Keywords: *EEG, Brain Computer Interface, SVM and Classification.*

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I Introduction

Brain based cognitive activities are human's ability to perform various mental tasks associated with learning and problem-solving skills. The task could be from the simplest to the most complex. The cognition relies upon inner speech and visual imagery. Assessment of these two components indicates the cognitive level of the person which is a measure of neuronal activity of the brain. Virtually, all kinds of jobs require workers to exercise their cognitive skills efficiently. Particularly in students, it is very important to know their cognition level that helps to adapt effective method of teaching. According to literacy statistics of United States, about 14% of youths remain high school dropouts due to the difficulties in understanding basic subjects involving text reading and mathematical problem solutions [1]. Aptitude for mathematics among youngsters is normally tested by their skill at solving arithmetic, algebra and fractions which are domains of mathematics. Most of the students struggle in solving numerical problems in their classes. Commonly, the skills of individuals are evaluated by questionnaire which is not much accurate because the cognitive skills are driven by neural mechanism of the brain in individuals. Despite of considerable advances in understanding cognitive and behavioral mechanisms through various models, little is known about the brain dynamics by experimental techniques. Therefore, it is important to understand and monitor the brain dynamics while performing simple assigned tasks.

Brain Computer Interfacing (BCI) is a technique that provides communication between human brain and machine or a device that can be activated without involvement of muscular activity. Several applications of BCI have been explored including rehabilitation [2], cognition, diagnosing neurological disorders and activation of gadgets. Researchers have also developed commercial and non-medical BCI systems with novel analysis algorithms and signal processing techniques. Among the many possible modalities for measuring brain activity in BCI systems, EEG and fNIRS (functional near infrared spectroscopy) have been popular; since they are non-invasive, simple and comparatively user friendly. EEG has been popular as a modality for applications such as BCI and measuring cognitive levels [3].

Typically, BCI system comprises of measurement of brain activity, processing of the brain waves, extraction of prominent features from the signals and categorization of the signals to transform as commands required in operating the desired device through interfacing protocol. Acquisition and measurement of signals are possible by suitable sensors and associated circuitry which determines the sensitivity and SNR (signal to noise ratio) while the processing, feature extraction and classification of the signals greatly influences the performance accuracy of the BCI. In the past, considerable progress has been made towards high performance hardware development and the researchers achieved maximum possible output from the hardware. It is now therefore, necessary to select an appropriate method for classification of the signals which can enhance the performance accuracy. Many classifiers are available in the literature to group EEG signals in groups and then, recognize significant differences between these groups. In recent years, Machine Learning (ML) algorithms are becoming focus of attraction among researchers to do similar tasks over the traditional classifiers. ML is a subset of artificial intelligence (AI) which makes machines to learn specific tasks through its input data, statistical parameters and trial and errors optimizing the process at faster rate. ML has capability to learn like humans and has potential to solve any complicated problem. Thus the BCI facilitates to connect human mind with artificial intelligent devices like computers and robots through ML technology. Broadly, three types of algorithms are available in ML to make the machines to learn. They are; supervised learning, un-supervised learning and reinforcement learning. In most of the practical machine learning applications, supervised learning is implemented due to its versatility, high accuracy and simple in coding. Researchers found that supervised learning algorithms are best satisfactory in the classification of EEG signals. Many algorithms are available in supervised learning, but support vector machine (SVM) algorithms are very popular in the classification of signals.

A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyper-plane. Given labeled training data, the algorithm outputs an optimal hyper-plane which categorizes new examples. In two-dimensional space, this hyper-plane considering as line that divides a plane in two parts, wherein each class lay on either side. The SVM approach emphasizes the idea of maximizing the margin in the training data.

II Methodology

The main purpose of our research is to develop a simple and accurate machine learning algorithm to help the mentally disabled people in assessing their speech and cognitive capabilities. Further, an assistive method can be developed based on artificial intelligent (AI) method as a tool for them. So, we considered EEG signals acquired during the speech tasks and classified them as responsive and non-responsive categories at higher accuracy. Towards this, the first step of our work is the design of BCI for data acquisition.

EEG data acquisition and protocol for the signal measurement An open source EEG raw dataset [4] was used in this work. The data was collected using a multichannel BrainAmp EEG amplifier (Brain Products GmbH, Gilching, Germany) at 1 KHz sampling rate. Thirty EEG electrodes were placed on an EEG cap with 10-5 configuration system [5]. The configured EEG electrodes are Fp1, Fp2, AFF5h, AFF6h, AFz, F1, F2, FC1, FC2, FC5, FC6, Cz, C3, C4, T7, T8, CP1, CP2, CP5, CP6, Pz, P3, P4, P7, P8, POz, O1, O2, TP9 (reference) and TP10 (ground)). Positions of electrodes are shown in Fig 1. The dataset consists of EEG recordings acquired from twenty-six healthy participants during word generation (WG) tasks. During the recording of EEG, the participants were asked to sit comfortably on an armchair. A 24 inch LCD monitor was placed in front of the chair such that the distance between the monitor and eyes of participant was maintained 1.2 m. On the right armrest of the chair, a numeric key pad was fixed and the participants were allowed to operate 7 and 8 numbers on the keypad by their index finger and middle finger respectively.

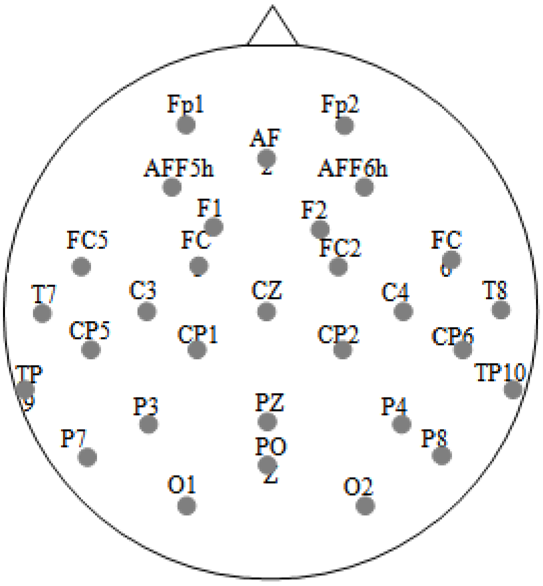

Fig 1. Positions of EEG electrodes

There are three sessions of dataset for each participant. Each session contains ten trials of WG and ten trials of baseline (BL), thus twenty trials in a session for each participant. For WG, a single letter was shown on the monitor for 2 s for baseline fixation and 10 s for the task. The paradigm is explained in detail by Shin J, et al.
Classification Algorithm

EEG is noninvasive, portable and cost-effective methods with potential applications in neuroscience. The signals acquired from the brain activities during the cognitive tasks and it was preprocessed used MATLAB 2019b. EEG signals are classified by SVM algorithm. Below Fig 2 shows the block diagram of each stage of operation on the EEG database. EEG features were calculated using a sliding window, which was window size 5 s and step size 1 s, moved from the beginning to the end of the period (−5 to 25 s). Common spatial pattern (CSP) filtering was then applied to decompose the EEG data to decide the most discriminative CSP components. Features were finally extracted using the variance; then applied logarithm. SVM was used as a predictive classifier. A 5 × 5-fold cross-validation was performed to evaluate the classification performance for each sliding window. At training phase, feature extraction was used to convert each train data to a feature set. These feature sets were used to classify the signals. Feature sets and labels were fed into the SVM algorithm to generate a classifier model. In second phase of the algorithm, the same feature extraction was used to convert unknown test data to feature sets. These feature sets were then fed into the classifier model, which generates predicted labels.

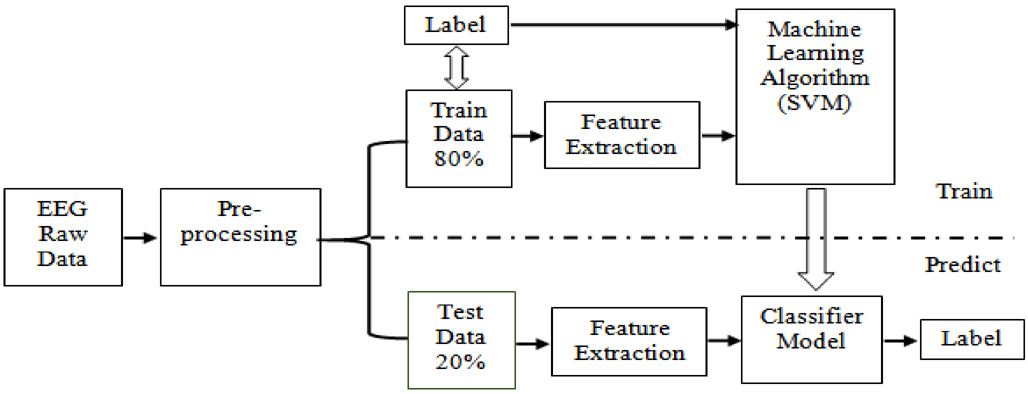

Fig. 2: Block diagram of the proposed SVM based classifier for brain activities.

III Results And Discussion

Fig. 3 shows SVM classifier performance accuracy with respect to time. The x-axis represents the right end of the sliding window. The y-axis indicates the classification accuracy of SVM. EEG classification accuracy starts to increase earlier to the onset of the task period. It can be understood that the initial task condition was given at t =0 s, then the participants recognized the beginning of the task and began to think what to do in the task period. The classification accuracy peaks at t = 7 s, scoring 81.3 % accuracy and slightly decreases after t = 10 s at which the task completes.

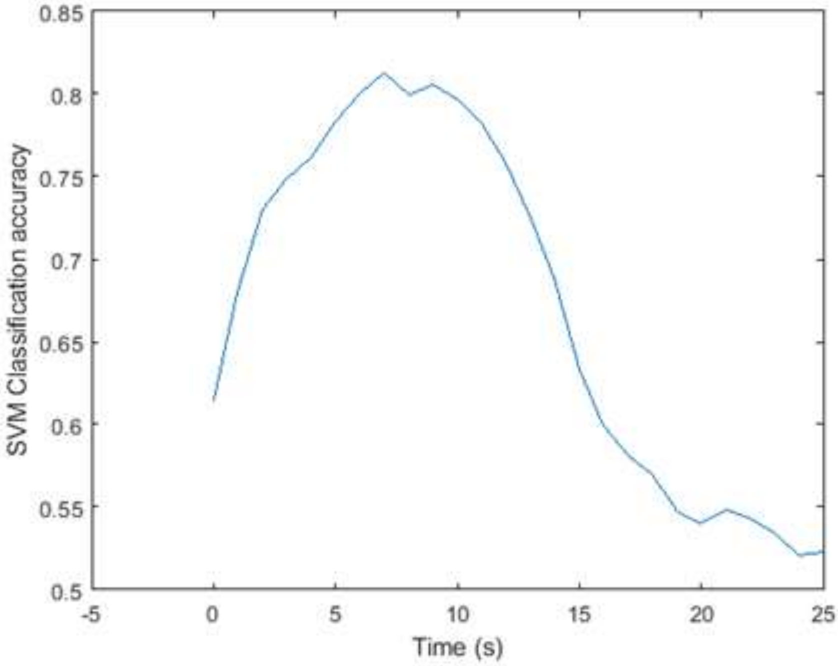

Fig 3. EEG classification accuracy over the time calculated by the sliding window (averaged over 26 participants)

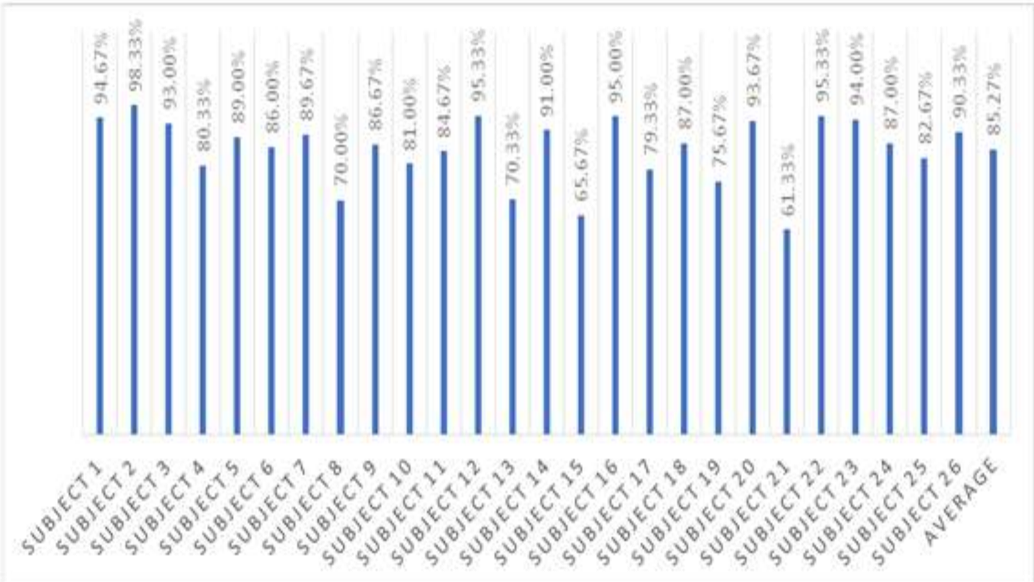

Fig 4. EEG classification accuracy peaks of each participant

In Fig 4, the classification accuracy for each participant is shown. Each vertical bar in the figure represents a participant and its height represents accuracy peak. The last bar in the figure shows average value of classification accuracy which is taken over twenty six participant. Thus, the SVM classification algorithm achieved an average accuracy of 85.27% during the WG task.

IV Conclusion

SVM algorithm applied to EEG signals of rest and task events were classified more precisely. In this work, we claim that an average classification accuracy peak of 85.27 % is achieved with the SVM classifier which is found to be higher than the previously reported results by the researchers for the same EEG dataset of

WG task. We proposed a simple SVM algorithm forward with optimizations parameter done and getting a higher accuracy comparing to other methods used for this EEG classification without any complex.

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