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Cognitive State Classification Using a single-channel Headset: An EEG Analysis Approach

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Abstract-A growing number of people are using electroencephalography (EEG) as a noninvasive way to record and monitor their brainwaves. An EEG is a technique that captures the electric signals generated by the brain using tiny metal discs connected to the scalp. The goal of this paper is to classify the cognitive state into two categories using information from the Neurosky headset, namely maths and relax label. In this paper, we have used logistic regression, linear SVM, non-linear SVC, random forests, XG boosting, MLP, gradient boosting, and neural network to make accurate predictions about the subject's cognitive state. The performance of the machine learning models were analyzed on the basis of various evaluation parameters like accuracy, precision, recall and F-1 score. The random forest algorithm had the highest accuracy rate of 89%, followed by the XG boosting algorithm, which had an accuracy rate of 87%. After tuning the hyper parameters, the XG boosting algorithm's accuracy increased by 3 and as a result, XG boosting model emerged as the best model, with a 90% prediction accuracy.

Keywords – EEG, Cognitive State, Machine Learning, Deep Learning, Classifiers, Accuracy

I. INTRODUCTION

EEG can be defined as the graphical recording of electrical impulses of the brain. It measures the potential difference that is caused by electrolytes within the brain's neurons. Brain computer interfaces (BCI) are devices that directly observes brain activity in order to manage machines and automaton [1]. An EEG can help the doctor to diagnose the type of epilepsy, pinpoint possible causes of seizures, and prescribe the most effective treatment for patient[2]. Electroencephalography (EEG) devices are frequently used to capture EEG signals because they are non-invasive, have good temporal resolution, and have a comparatively low acquisition cost. Motion pictures EEG signals, which capture brain activity during user-imagined motions, are currently the subject of ongoing research due to their numerous applications in the fields of neuro-rehabilitation [3], game control [4], and motion restoration for the paralyzed people. The purpose of an EEG is to detect abnormalities in brain electrical activity, also known as brain waves [5]. Electrodes—tiny metal discs connected by flimsy wires—will be positioned all over the scalp throughout the process. Electrodes detect the minute electrical charges that brain activity generates [6]. The amplified charges can be viewed on a computer monitor graph or even a recording which can be copied on paper. Physician will analyze the findings.

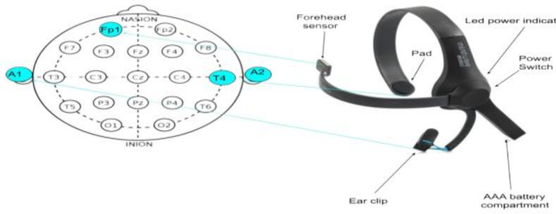


Figure 1: Neurosky Mindwave Mobile 2 headset and its components

Figure 1 shows the working of Neurosky Mindwave mobile 2 headset .The Mindwave mobile 2 is a secure device that is composed of a headset, a sensor arm, and an ear clip. The headset's reference and ground electrodes are situated on the ear clip (A1), while the EEG electrode is placed on the sensor arm, positioned above the eye (FP1 spot). This equipment is capable of measuring EEG power spectrums, Neurosky eSense meters (which calculate levels of attention and meditation), and eye blinks. Electrical voltages that oscillate within the brain and measure only a few millionths of a volt are called brain waves.

The summary of our work can be defined as follows:

- We have used Fast Fourier Transform for extracting the features from the raw EEG data.
- We develop models using various Machine Learning and Deep Learning algorithms to predict the subject's action into two categories i.e., math’s or relax.
- We have tried to tune the hyperparameters of XG Boosting and Random Forest and as a result its prediction accuracy become better than all other models available on the internet on MIDS Dataset.

The rest of the paper is organized as follows: The second section addresses the related work, while section three describes the experimental set-up, which includes data collection, data preprocessing, and exploratory data analysis. Section four represents the proposed methodology that includes feature extraction, training machine learning and deep learning models. Results and discussions are presented in Section five. Section six contains the conclusions.

II. LITERATURE REVIEW

Liang et al. [7] state that current deep learning-based methods in the area of EEG Signal processing require a lot of labelled data. Their approach is based on the consistency regularization principle, which says a resilient model should produce consistent results for the same inputs despite perturbations. Using stochastic augmentation and dropout, they consider the neural network as a whole as a stochastic process, and they impose a consistency constraint to minimize present prediction discrepancies. N.C. et al. [8] proposed that most multivariate machine learning research has focused on identifying children with psychiatric conditions among typically developing children. Most kids with a clinical diagnosis have multiple psychiatric diseases (multi-morbidity), so this study doesn't reflect reality. A clinician must choose between multiple diagnoses or combinations. The current benchmark predicts mental multi-morbidity in children and teens. They used two machine learning benchmarks to do this. The initial problem is to predict the seven most common DSM-V psychiatric disorders, of which each person may have more than one. The second method involves predicting the severity of psychiatric symptoms using behavioral and cognitive measure.

Ma et al. [9] suggest that with the development of brain science and biomedical engineering, as well as EEG signal analysis techniques, the use of EEG signals to monitor human health has become a prominent research area. In this study, they used wavelet technology to extract EEG features before developing a depths factorization machine model (FM+LSTM). The suggested model outperforms previous classifier methods when tested on real data. The approach in this research can also be used to determine interactive features (user weariness) for a recommendation system. Bhardwaj et al. [10] proposed feature extraction and classification of EEG data using hybrid genetic programming (HGP). Thirty videos were shot in Hindi and English and added to an existing database. Fifty individuals' brain signals were voluntarily collected for this study. Using this data, they constructed four HGP classifiers, each with two classes (HGP1, HGP2, HGP3, and HGP4), and one for each of the four MBTI trait categories. The overall classification accuracy of the HGP classifier was 82.25 percent for a 10-fold cross-validation partition.

Thakare et al. [11] argue that during brain illness attacks, brain areas and neural networks are ineffectively decoupled, resulting in low signal strength, noise, and non-stationary EEG data Using a convolutional neural network (CNN), an online EEG categorization system was created. The method identifies sad states accurately and quickly without preprocessing or feature extraction. In trials using publicly available data, the depression control group and healthy control group had 99.08, 98.77, and 99.42 percent accuracy, sensitivity, and specificity, respectively.

III. EXPERIMENTAL SET-UP

A. Data collection

The MIDS class at UC Berkeley's School of Information collected this dataset in one day. Two groups of 15 subjects saw a 5-minute film in this experiment. Each group observed their particular stimuli with their 15-person group, and EEG activity was assessed. During these movies, the Mind Wave headset recorded their brainwaves at one-second intervals. The tasks in the two movies were blinking, relaxation, instruction, mental math, listening to music, watching a Doritos commercial (comedy), thinking of stuff, and color counting.

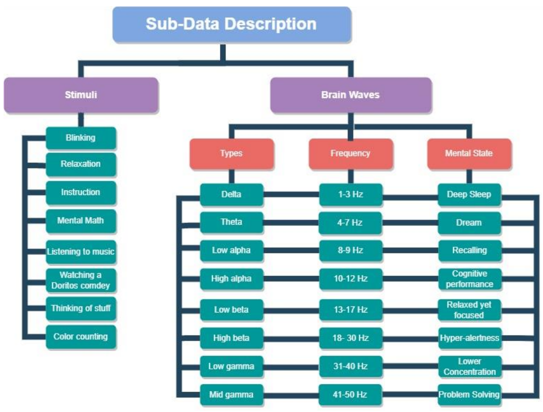


Fig. 2.Sub-data description

Both groups performed the same tasks, with just minor variations, such as math questions or music. The entire experiment lasted an hour, and the Mind Wave gadget recorded everything, including raw data and programmatically derived data like attention and relaxation sensor data. The EEG data table contains 30,000 rows of data. Each row of data represents one second of Neurosky Mindwave Mobile EEG recordings. Fig. 2 shows the various list of the stimuli's and different types of brainwaves along with their frequencies and mental state associated with them.

B. Data preparation and preprocessing

The EEG data table was first cleared of unwanted data. Since the dataset's developers have already completed time synchronization calculations, we eliminated any unnecessary date and time columns (apart from "Indra time"). Given that these data packets are meaningless, we deleted rows with signal quality 100 or greater (a lower signal quality is better). Finally, we removed all unlabeled data from the table; these rows were collected when the participant wasn't participating.

Everyone was given a headset at the same time, and group 1 watched stimulus 1 while group 2 waited outside. This leads to unlabeled data that cannot be used. Each stimulus begins with a baseline setting activity, so establishing a baseline won't be a problem even without this data. EEG-data and subject-metadata were joined on the basis of ID column in one big data frame, and it leads to 20 columns in the dataset. Unnecessary labels were dropped and the problem was converted to binary classification problem i.e. math vs relax, and as a result dataset was having 1870 samples and 15 columns.

C. Exploratory Data Analysis

Exploratory data analysis (EDA) is a set of techniques for examining, evaluating, and summarising data. It is used to discover patterns and trends in data, as well as locate connections among variables and identify outliers [12]. EDA serves as the first step in the data analysis phase and aids in the decision-making process while developing predictive models .EDA involves the use of a variety of techniques, including visualizations, descriptive statistics, and inferential statistics [13].

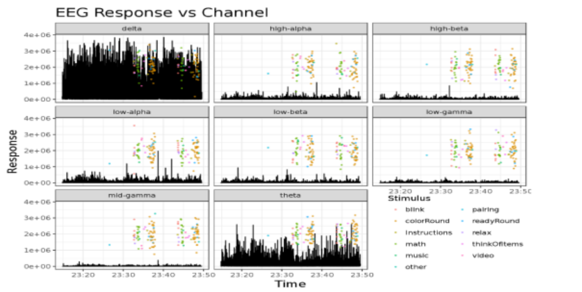


Fig.3. Frequency Channel as a function of time with respect to various brain waves (delta, theta, low alpha, high alpha, low beta, high beta, low gamma, mid gamma)

The frequency channel as a function of time is a mathematical function that describes the rate at which a signal changes over time [14]. This function can be used to determine a signal's frequency, which can be used to determine the type of signal being transmitted. It can also be used to calculate signal power and signal-to-noise ratio. Figure 3 shows trends in different frequency channels as a function of time to see how people responded to the different stimuli, i.e., blink, Instruction, math, music, other, pairing, ready round, relax, think of objects, and video. Initially, the frequency of each label (math and relax) were checked in order to know whether the dataset is balanced or not and as a result below observation was obtained.

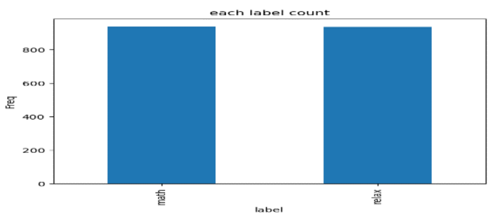


Fig.4.Frequency of each label

Fig.4 shows that dataset is balanced as it contains 936 samples for math against 934 samples for relax, hence there is no need to use sampling techniques. Then the frequency for each category with respect to categorical features was checked and the distribution of each numerical features was also examined which is shown in figure 4.

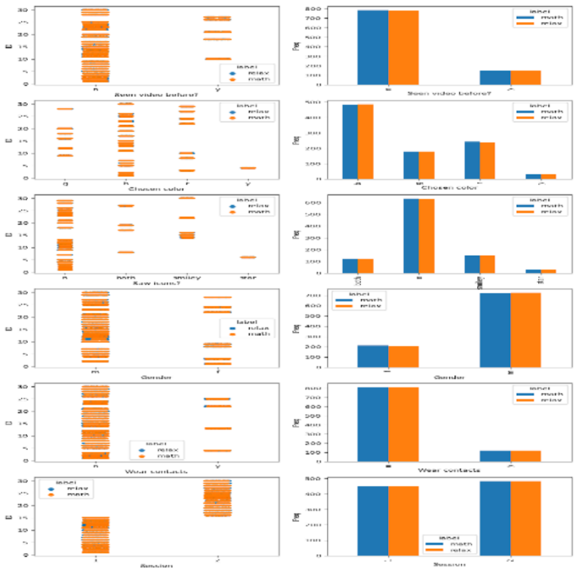


Fig.5. The frequency of each categorical variable (math and relax) with respect to each categorical feature (Have you seen the video before? What color did you choose during the color counting exercise? Did you see the hidden icon displayed during the color counting exercise? What is your gender? Do you wear contacts?)

Fig.5 indicates that the number of samples from each category within each feature are equal for each label. For example, if there are 100 females and 200 males, then there would be 50 females doing math and 50 females relaxing, and the same would be true for the males with 100 doing math and 100 relaxing. It means that each of the categories in the data set have an equal sample size associated with each label. This is important in data analysis as it helps to ensure that the data is balanced and that the results are more reliable.

IV. PROPOSED METHODOLOGY

This paper first introduces the proposed flow chart as shown in Fig.6 and then discusses about the various machine learning models used in this research work for predicting the subject's action. The models evaluated include logistic regression, linear SVM, non-linear SVC, random forests, XG boosting, MLP, gradient boosting, and neural network. To enable the use of precise measurements early in the process, accurate and quick models for predicting the user's activity are desired.

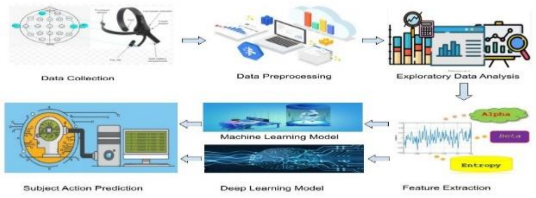


Fig. 6.Proposed process flow diagram

A. Features extraction

Features extraction process is very important technique that is used for EEG data analysis as its absence decreases the performance of the model, but if the proper features engineering steps are included then the accuracy get doubled [15]. First, the values of the browser_latency feature was converted to float, and the values of the categorical features was converted to categorical from object. After this the categorical features were taken and their values were converted to one hot encoded data (n -> 0.1), and labels were stored into new variable, their values got converted to 0 and 1, and the label feature from the dataset was dropped. And for the egg_power, the median for each list was taken and it was saved as a new feature in the data frame called egg features mean. And for the final object feature, which is raw values, some better feature vectors were build. Each group of 512 raw values produced by the device were taken roughly, and FFT was applied on them to produce a power spectrum. The

FFT is a mathematical algorithm that converts raw values into a power spectrum [16]. The power spectrum is a graph that shows how much power is present at each frequency [17]. This is used to analyse the device's data and gain insights into the data. Then, the result was logarithmically bind to produce feature vectors of 1870 vector and the median of each vector was taken and it was added as a new feature in the dataset, and at the last, the raw values feature was dropped from the dataset. All unnecessary features were also dropped which will not be used in the training process i.e., 'id', 'raw values', 'egg_power', 'unnamed: 0', 'indra_time', 'reading_time', 'updatedAt', 'createdAt'. Finally, all the values were scaled based on the mean and standard deviation.

B. Machine learning models

Machine learning models are algorithms based on math designed to spot the connections and trends in data [18]. The dataset was divided into two parts: training data (80% of the data) and testing data (20% of the data). Logistic regression with saga solver, Linear support vector classifier, Non-linear support vector classifier, Random forest classifier, XG boosting classifier ,Multi-layer perceptron classifier with Adam optimizer and ReLU activation function and three hidden layers (64 neurons, 32 neurons, 18 neurons),Gradient boosting classifier were used to create machine learning models. All these models were trained on the training dataset, and then they were evaluated on the basis of evaluation parameters like accuracy, precision, recall and F-1 score. To find the optimal hyper parameters for the top two classifiers, Random Forest and XG boosting classifiers, were used.

The Random Forest classifier's hyper parameters were max leaf nodes criterion, min samples split, min samples leaf, max features, and min weight fraction leaf. The hyper parameters that were tuned for the XG boosting classifier were max depth, gamma, reg alpha, reg lambda, colsample bytree, learning rate, min child weight, and max leaves. Both the Random Forest classifier and the XG boosting classifier were trained using their randomly chosen hyper parameters, then they were evaluated on the testing data. These steps were repeated for 1000 times, and at the last, best hyper parameters combinations were chosen on the basis of the highest accuracy generated on the testing data.

C. Deep learning model

Deep learning focuses on developing multi-layered artificial neural networks, also referred to as deep neural networks [19].Deep learning has been effective at recognizing brain sate, voice and recognizing images [20]. A neural network model with three hidden layers and one dropout layer following the first hidden layer was created as shown in figure 7. All the hidden layer has the Relu as activation function and the model was optimized using Nesterov Adam for 200 epochs and 64 batch size, and Keras tuner was used to choose the best hyper parameters.

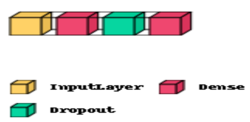


Fig.7.Neural Network Model

Hyperband is the search method that was used to find the best combination of hyper parameters. It outperforms Bayesian search and random search [21]. After conducting numerous trials in search of the best hyper parameters, we chose the best hyper parameters combination with the highest validation accuracy score. The tuned hyper parameters were the number of neurons in the first hidden layer, the number of neurons in the second hidden layer, the number of neurons in the second hidden layer, the value of the dropout in the first hidden layer, and the number of neurons in the third hidden layer. l1 penalty in the first hidden layer, l2 penalty in the first hidden layer, l2 penalty bias in the first hidden layer, l1 penalty in the second hidden layer, l2 penalty bias in the second hidden layer, l1 penalty in the third hidden layer, l2 penalty bias in the third hidden layer, and learning rate.

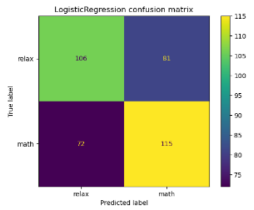
V. RESULT AND DISCUSSION

The MIDS dataset was classified using Logistic regression, Linear SVM, Non-linear SVC, Random forests, XG boosting, MLP, Gradient boosting, neural network. Random forest and XG boosting led to a surprising accuracy in the upper 80s, but closer examination showed that majority of the models were accurately predicting the user's action. Unlabeled data were removed and many of labels were poorly classified so all labels for same activity were merged. All 12 math variables were also merged into one single label.

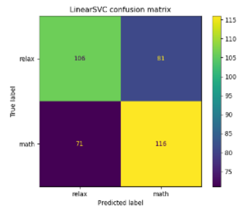
Table 4: Model performance evaluation

Model	Accuracy	Precision	Recall	F1-score
Logistic regression	59%	59.5%	59%	59%
Linear support	59.35%	60.5%	60.5%	59.5%
Non-linear SVC	59.35%	65%	59.5%	55.5%
MLP	59%	59%	58%	58.5
Neural Network	60%	59%	59.5%	59.5%
Gradient boosting	81%	81%	81%	81%
XG boosting	87%	87.5%	87.5%	87.5%
Random forest	89%	88.5%	88.5	89%

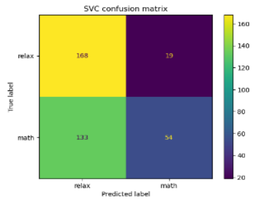
Table 4 shows the evaluation metric for Logistic regression, Linear SVM, Non-linear SVC, Random forests, XG boosting, MLP, Gradient boosting and neural network. It can be seen from the table that Random Forest algorithm has got maximum accuracy of 89 % followed by XG boosting with an accuracy of 87%.On the other hand, logistic regression has got the worst accuracy of 59% followed by linear SVC and Non-linear SVC. Thus it can be said that the Random forest and the XG boosting models were able to predict the subject's action more accurately than all the other existing models in the table. Precision, recall, and F-1 score are low for logistic regression, linear SVM, non-linear SVC, MLP, and neural networks. Low accuracy indicates that these ML models are not producing reliable predictions. It implies that these models' predictions are not very accurate, and in order to increase their accuracy, the models need to be retrained. Low precision values indicate that there is a significant percentage of false positives. This indicates that there is a higher chance that these models are misclassifying the positive cases as negative ones. Low recall values indicate that these models are not accurately predicting or recognizing true positives. This means that models are not able to accurately identify all the positive instances of a given class. A low F1-score suggests that models are not accurately predicting the target labels and need more tuning or optimization. Gradient boosting, XG boosting, and random forests are functioning well in terms of correctly forecasting the outcome, as the accuracy, precision, recall, and F1 score are all high. High recall means that models are able to correctly identify every positive observation; high accuracy means that models are able to classify the majority of the observations correctly; high precision means that models are able to classify the desired result correctly; and a high F-1 score means that models are able to classify both positive and negative observations correctly.



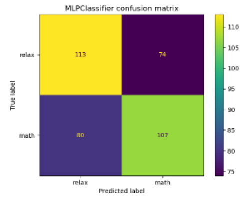
a) Logistic regression classifier confusion matrix



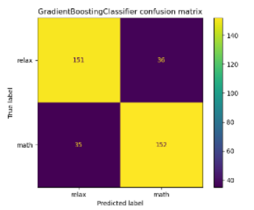
b) Linear SVC Confusion Matrix



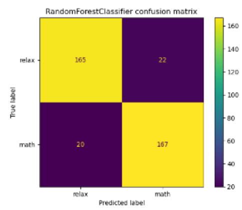
c) SVM classifier confusion matrix



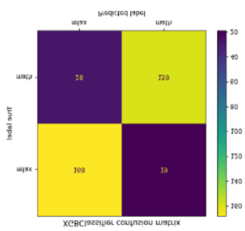
d) MLP classifier confusion matrix.



e) GB classifier confusion matrix



f) RF classifier confusion matrix



g) XG boosting classifier confusion matrix

Figure 10: - [a] Logistic regression classifier,[b] Linear SVC, [c] Non-linear SVC,[d] MLP Classifier ,[e] Gradient boosting classifier,[f] Random Forest Classifier and [g] XG boosting classifier confusion matrix

In figure 10[a], the logistic regression classifier only predicted 221 labels out of 374 labels, 106 for relax and

115 for math, with an accuracy of 59%. In figure 10[b], linear support vector classifier predicted 222 labels out of 374 labels, with an accuracy of 59.35%, which is similar to the Logistic regression classifier. In figure 10[c], Non-linear support vector has 222 labels out of 374 labels, so its accuracy is same as linear support vector classifier. In figure 10[d], the multi-layer perceptron classifier predicted only 220 true labels (113 for relax and 107 for math) out of 374 labels, with an accuracy of 58%. In figure 10[e], Gradient boosting classifier performed well, predicting 303 true labels (151 for relax and 152 for math) out of 374 labels with an accuracy of 81%.

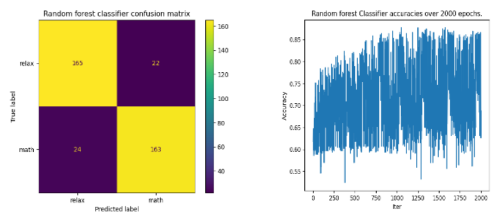
In figure 10[f], the random forest classifier predicted 332 labels (165 for relax and 167 for math) out of 374 labels, with an accuracy of 89%. In figure 10[g], the XG boosting forest classifier predicted 327 true labels (168 for relax and 159 for math) out of 374 labels with an accuracy of 87%.From above results, we can say that the random forest classifier is the best model in correctly predicting the labels while XG boosting classifier is the second best model.

At last we again tried to increase the accuracy of Random Forest Classifier and XG boosting classifier by tuning their hyper parameters. The results were as follows:-

Table 5: Model performance evaluation parameters values after tuning their hyper parameters

Model	Accuracy	Precision	Recall	F1-score
Random forest	88.5%	88%	89.5	88.5%
XG boosting	90%	88.5%	88.5%	89%

Table 5 displays the values of the performance evaluation parameters for the Random Forest algorithm and the XG boosting algorithm after tuning their hyper parameters. It can be seen here that after tuning the hyper parameters of these two algorithms, the prediction accuracy of XG boosting surpasses the accuracy of Random Forest, and thus XG boosting becomes the best prediction model for accurately predicting the user's action.

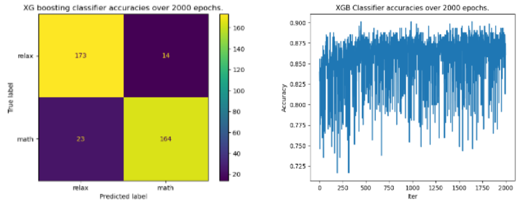


a)Tuned RF classifier confusion matrix

b)RF accuracies over each iteration

Figure 11: [a] Tuned Random Forest classifier confusion matrix and [b] Random Forest accuracies over each iteration.

In figure 11[b], over 2000 iterations, we tried different hyper parameters to improve the accuracy of the Random Forest Classifier, and it was able to predict 328 true labels (156 for relax and 163 for math) out of 374 labels, with an accuracy of 88% as shown in figure 11[a]. It can be seen here that the Random forest classifier accuracy doesn't improve after randomly tuning its hyper parameters.



a) Tuned XGB classifier confusion matrix

b) XGB accuracies over each iteration

Figure 12: - [a] Tuned XGB classifier confusion matrix and [b] XGB accuracies over each iteration

After randomly tuning its hyper parameters, XG boosting classifier prediction accuracy improved by 3%. In figure 12[b], we tried different hyper parameters over 2000 iterations and found that it could predict 337 true labels (156 for relax and 163 for math) out of 374 labels with an accuracy of 90% as shown in figure 12[a], making it the best model among all models.

VI. CONCLUSION

In this paper, we proposed an effective prediction model to precisely classify the user's activity into two labels, namely math or relax. Models were trained using various machine learning and deep learning algorithms. After tuning the hyper parameter, the XG boosting algorithm gave the highest prediction accuracy of 90%, and thus our proposed model outperforms all existing models on the internet in terms of accuracy. One of the major limitation of this paper is that Fast Fourier Transform has been used for feature extraction but there are much better feature extraction techniques like Independent Component Analysis and Principal Component Analysis which could have increase the prediction accuracy much more. In the future, we will experiment with different machine learning and deep learning algorithms, tuning their hyper parameters to improve prediction accuracy even more. Class labels other than maths or relax can also be considered for classification.

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