Classification of Student's Confusion Level in E-Learning using Machine Learning

Bikram Kumar, Deepak Gupta, Rajat Subhra Goswami

***Abstract:** With the advancement of technology, the traditional mode of teaching-learning pedagogy has evolved into online education system as it is easily accessible. But, it is very difficult to detect whether the students are 'confused' or 'not confused' while watching online videos. Getting confused while watching online videos is one of the root causes of less performance of the students. Keeping in mind the above statements, we would like to investigate whether the students are 'confused' or 'not confused' while watching Massive Open Online Course (MOOC) videos. There are a lot of studies that prove electroencephalogram (EEG) signals behave differently as we are in different conditions such as happy, sad, angry, etc. So, in this paper, we have applied several supervised learning algorithms to detect if the students are 'confused' or 'not confused' while watching MOOC videos using EEG data. The results of this paper show that machine learning is a potential technique, for the analysis of EEG data that can detect the confusion level of the students which is comparable to human observation for predicting the confusion level of the students that can improve the quality of online education system.*

***Keywords:** Confusion, EEG, Machine Learning, MOOC, Supervised Learning*

I. INTRODUCTION

Unlike classroom education, MOOC is a non-campus, large scale, online education platform where any number of students can access any number of online courses via the Internet and this is increasing day-by-day [1]. But, it comes with its own pitfalls. Thompson showed the behavior of the students who were not fully attentive toward the correspondence-based distance education program [2]. There is a huge difference between classroom education and online education. In a classroom education, the educator can judge whether the students could understand the topics or not by verbal questioning, body language, etc and make them understand where this is a serious issue in online education. Sharma suggests some guidelines for the stakeholders in e-learning for better online course design [3]. Sublett showed the known fact about online courses and the impacts of the online courses on the community college students with respect to course completion, persistence, transfer and degree completion [4]. Now, these days MOOC providers provide interactive sessions where the instructor and the students can discuss several things and also provide feedback form to the students to get the student's review. No one can deny that online education provides ample amount of benefits to the students. But, still, the lack of a classroom is a big concern. But, detection of the students confusion level while watching MOOC videos is a key idea to make online education system more efficient.

EEG is typically a non-invasive medical diagnostic technique, where electrodes are put on the scalp of the subject to record the electrical activity of the brain [5]. The variation of the voltage between the neuron of the brain is measured by the EEG signal. EEG estimates both frequency and amplitude of electrical activity produced from the brain [6]. EEG can give millisecond range temporal resolution which is not possible with any high-resolution imaging technique [7]. Because of this, many researchers use EEG data to solve brain-related problems. H. Berger, the German physiologist recored the EEG of a human for the first time in 1924 [8]. EEG data is normally used to diagnose epilepsy. It can likewise be utilized to recognize sleep disorders, coma, encephalopathy, brain death, emotions like anger, disgust, happy, sad, fear and many more. EEG signal varies from situation-to-situation. So, we assumed that the EEG signal of a student who is 'confused' will differ from a student who is 'not confused'. So, in this paper, we use EEG data to determine the student's confusion level while watching MOOC videos.

II. RELATED WORK

There are many researchers who are using different Machine Learning algorithms along with EEG data to perform different tasks like detection of emotion, Alzheimer, drowsiness of car driver, etc. Yeo et al. used the support vector machine (SVM) for detecting car driver's drowsiness during car driving using EEG data [9]. Wang et al. gathered EEG from 10 college students to check the confusion level of the students while watching online videos using Gaussian Naive Bayes classifier [10]. Mampusti et al. used EEG data for measuring academic affective states of the students using three supervised learning algorithms namely K-Nearest Neighbors, SVM and Multilayer Perceptron (MLP) respectively [11]. Subasi and Gursoy used EEG data along with PCA, ICA and LDA to extract features and SVM to predict epileptic seizure or not [12]. Ni et al. used EEG data and bidirectional LSTM recurrent neural network to check whether a student is 'confused' or 'not confused' while watching online course videos [13]. Edla et al.

Revised Manuscript Received on December 15, 2019.

***** Correspondence Author

Bikram Kumar, M.Tech scholar of CSE Dept, NIT Arunachal Pradesh, Naharlagun, India. Email: biikramkumar@gmail.com

Deepak Gupta*, Assistant Professor of CSE Dept., NIT Arunachal Pradesh, Naharlagun, India. Email: deepak@nitap.ac.in

Rajat Subhra Goswami, Assistant Professor of CSE Dept., NIT Arunachal Pradesh, Naharlagun, India. Email: rajat@nitap.ac.in

lead an investigation to gather EEG data from 40 human brains and used techniques to extract features with random forest classifier for the classification of mental state of human into two classes those were concentration and meditation [14]. For emotion detection, Mangalagowri and Raj used EEG data and extract features using 'db4' wavelet using multilevel decomposition and used Feed Forward Backpropogation algorithm [15]. Hajinoroozi et al. used Deep Belief Networks (DBN) to extract features and dimensionality reduction from EEG data to predict the cognitive states of the driver [16]. The results showed that DBN-C is a potential technique to extract features. Petrosian et al. showed that using long-term EEG signals recurrent neural networks can recognize Alzheimer disease symptoms [17]. Abdulla et al. performed EEG signal analysis with extreme machine learning algorithm to develop a technique to detect the sleep stages based on EEG signals [18]. Hussain et al. used five different supervised learning algorithms and performed k-fold cross-validation to detect the student difficulties using session data [19]. Lin and Kao used machine learning algorithms to perform mental effort detection in e-learning using EEG data [20]. Bacos explored human-centered techniques of using technology in education [21]. Raheel, Majid, and Anwar used EEG data and from the data thirteen different features were extracted to classify five different expressions namely looking up, looking down, smile, eye-wink and eye blink using four different classifiers namely K-nearest neighbor, naïve bayes, SVM and MLP [22]. Zhou et al. used EEG data and proposed an end-to-end method for the analysis of EEG data to detect the confusion state of student in learning [23].

III. PROBLEM STATEMENT

Online education has become a new means in the field of education as multiple number of students can access a huge number of courses through the internet. It is emerging day-by-day as students can learn new things, gain knowledge and skill from different sources. But, there is a drawback of online education. There is no absolute way for the instructor to know whether the participant students are fully 'attentive' or 'confused'. Because, if the students are 'confused' while watching the videos they would not be able to gain knowledge. But, if the instructor would be able to know that the student is 'confused', he would be able to make the student understand the topic and there would be many more chances for making the online education platform more effectively efficient.

To detect the confusion level of the students while watching the MOOC videos, here we have used the EEG data. Since the confusion levels (pre-defined and user-defined) are either true or false, this is a binary class classification problem. So, we have applied several supervised learning algorithms like Decision Tree, Random Forest, Boosting algorithms, Bagging algorithms, SVM with different kernels, etc. to detect both pre-defined confusion level and user-defined confusion level. Figure 1 represents the confusion detection framework.

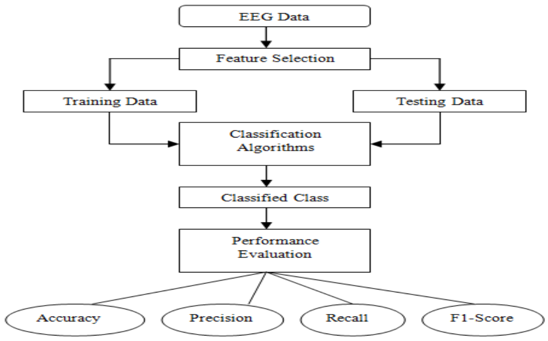

Fig. 1. Student's Confusion detection framework

IV. DATASET DESCRIPTION

The EEG data were gathered from 10 college students while they were watching MOOC videos. 20 videos were prepared, 10 of each category i.e. 10 pre-labeled as "easy", where 10 were pre-labeled as "difficult". Duration of each video was 2 minutes. The dataset "Confused student EEG brainwave data" is available at Kaggle [24].

Students were put on Mindset EEG devices. These devices were single-channel wireless devices and are used to measure the functioning of the frontal lobe. The devices operate by measuring the voltage between an electrode fixed on the forehead and two electrodes each of which are connected with an ear. Students gave their rating about their confusion level on a 1-7 scale, where 1 corresponds to least confusing and 7 corresponds to most confusing. These levels were quantified into two classes of which whether a student is 'confused' or 'not confused'. In the dataset 0 represents 'not confused' students and 1 represents 'confused' students. There are two labels: the pre-defined level has been assigned as per the experiment design and user-defined level has been assigned as per the students' review.

V. CLASSIFICATION FEATURES

For each student watching the videos, features were extracted at the sampling frequency of 2 Hz. There is total of 13 features in the dataset out of which 2 features are "Subject id" and "Video id" that range from 0 to 9 and we don't use them for classification. "Attention" measures the focus of the students and "Meditation" measures the calmness and "Raw" is the average of the original EEG signal. Table I shows the features that we have considered to classify class labels for 'confused' or 'not confused' students classification.

Table I: Feature's description of the dataset

Feature	Sampling Rate	Statistic
Attention	1Hz	Mean
Meditation	1Hz	Mean
Raw	512 Hz	Mean
Delta	8 Hz	Mean
Theta	8 Hz	Mean
Alpha1	8 Hz	Mean
Alpha2	8 Hz	Mean
Beta1	8 Hz	Mean
Beta2	8 Hz	Mean

Gamma1	8 Hz	Mean
Gamma2	8 Hz	Mean

VI. EXPERIMENTAL SETUP

To identify the class label of the students whether the students are 'confused' or 'not confused' while watching MOOC videos, we have evaluated 32 classifiers of different category. The experimental environment is an Intel (R) Core (TM) i5-4590 CPU 3.30 GHz, 4 GB RAM, a desktop running Windows 8 (64-bit), Python 3.7.3, Pandas 0.25.1, NumPy 1.17.3, Scipy 1.3.1, Scikit-learn 0.21.3, Matplotlib 3.1.1.

Here, we have evaluated 32 supervised machine learning algorithms to predict if the students are 'confused' or 'not confused' while watching MOOC videos. As state before, we have two different levels i.e. one is pre-defined level which has been assigned according to the experiment design and another is user-defined level which has been assigned as per the students review, we have applied 32 classifiers to predict both the confusion level.

Classification of pre-defined level: We take 70% of the dataset to train the classifiers and the remaining 30% to test the classifiers. So, it has 3844 test cases out of which 2016 are 'not confused' students and 1828 'confused' students. 5-fold cross-validation is performed to find the optimum parameter of each classifier. For each 5-fold cross-validation, we randomly divided the entire dataset into 5 folds, out of which 4 folds are used to train the classifier and remaining 1 fold is used to evaluate the classifier's performance.

Classification of user-defined level: We take 70% of the dataset to train the classifiers and the remaining 30% to test the classifiers. So, it has 3844 test cases out of which 1882 are 'not confused' students and 1962 'confused' students. Similarly, we perform 5-fold cross-validation to find out the optimum parameters for each classifier.

Table II: Performance of classifiers for detection of pre-defined confusion level

Classifier	Parameter	Accuracy	Precision	Recall	F1-Score
KnearestNeighbor	n_neighbors=1	54.86	0.55	0.55	0.55
Logistic Regressoion	C=1e-02	53.75	0.53	0.54	0.51
Logistic RegressoionCV	solver='liblinear', penalty='l1'	53.88	0.54	0.54	0.52
Linear Discriminant Analysis	solver='svd'	53.38	0.53	0.53	0.5
Quadratic Discriminant Analysis	reg_param=1, store_covarience='True'	53.38	0.53	0.53	0.53
Ridge Classifier	alpha=1e-05	53.38	0.53	0.53	0.5
Ridge ClassifierCV	alphas=[1e-04,1e-03,1e-02,1e-01,1,1e+01,1e+02,1e+03]	53.38	0.53	0.53	0.5
Decision Tree	splitter='random',criterion='entropy'	56.32	0.56	0.56	0.56
Gaussian Naive Bayes	var_smoothing=10	52.44	0.28	0.52	0.36
Perceptron	alpha=1e-05,tol=1e-05	49.11	0.62	0.49	0.35
Linear SVM	C=1e-03	52.52	0.75	0.52	0.36
SVM (Kernel='linear')	C=1e-05,gamma=2^-5	52.11	0.52	0.52	0.52
SVM (kernel='rbf')	C=1,gamma=2^-5	55.18	0.76	0.55	0.42
SVM (Kernel='sigmoid')	C=1e-05,gamma=2^-5	52.44	0.28	0.52	0.36
Passive Aggressive Classifier	C=1e-05,validation_fraction=0.1	50.62	0.5	0.51	0.51
Gaussian Process	Default	55.18	0.76	0.55	0.42
NuSVC	Gamma=0.03125,nu=0.3	55.18	0.76	0.55	0.42
SGD Classifier	Alpha=10,penalty='l1'	52.18	0.52	0.52	0.52
Multi Layer Perceptron	Alpha=10^5,hidden_layer_sizes=9	52.47	0.52	0.52	0.47
Random Forest	n_estimators=64	61.29	0.61	0.61	0.61
Extra Tress	criterion='gini',max_depth=19,n_estimators=80	60.4	0.6	0.6	0.6
Ada Boosting	learning_rate=1,n_estimators=58	54.85	0.55	0.55	0.55
Gradient Boosting	learning_rate=0.05,max_depth=24,n_estimators=200,sub sample=0.1	59.21	0.59	0.59	0.59
XG Boosting	colsample_bytree=0.7,gamma=0.1,learning_rate=0.05,m ax_depth=15,min_child_weight=5	60.33	0.6	0.6	0.6
Bagging with Decision Tree	n_estimators=250	61.78	0.62	0.62	0.62
Bagging with Random Forest	n_estimators=55	**61.89**	0.62	0.62	0.62
Bagging with Extra Trees	n_estimators=50	61	0.61	0.61	0.61
Bagging with Logistic Regression	n_estimators=15	53.46	0.53	0.53	0.52
Bagging with SVM(kernel='linear')	n_estimators=10	48.23	0.49	0.48	0.46
Bagging with SVM(kernel='rbf')	n_estimators=30	54.84	0.76	0.55	0.41
Bagging with SVM(kernel='sigmoid')	n_estmators=1	52.44	0.28	0.52	0.36
Voting Classifier	estimators=[LogisticRegression, RandomForest, GaussianNB]	60.15	0.6	0.6	0.6

Table III: Performance of classifiers for detection of user-defined confusion level

Classifier	Parameter	Accuracy	Precision	Recall	F1-Score
KnearestNeighbor	n_neighbors=19	57.41	0.58	0.57	0.57
Logistic Regressoion	C=100	59.21	0.59	0.59	0.59
Logistic RegressoionCV	solver='liblinear',penalty='l1'	59.83	0.6	0.6	0.6
Linear Discriminant Analysis	solver='svd'	59.44	0.6	0.59	0.59
Quadratic Discriminant Analysis	reg_param=1,store_covariance='True'	56.76	0.57	0.57	0.56
Ridge Classifier	alpha=1e-05,solver='auto'	59.47	0.6	0.59	0.59
Ridge ClassifierCV	alphas=[1e-04,1e-03,1e-02,1e-01,1,1e+01,1e+02,1e+03]	59.44	0.6	0.59	0.59

Decision Tree	splitter='random',criterion='entropy'	59	0.59	0.59	0.59
Gaussian Naive Bayes	var_smoothing=1	55.85	0.57	0.56	0.54
Perceptron	alpha=1e-05,tol=1e-05	53.77	0.56	0.54	0.48
Linear SVM	C=0.0001	53.02	0.54	0.53	0.52
SVM (Kernel='linear')	C=1e-05,gamma=2^-5	52.11	0.52	0.52	0.52
SVM (kernel='rbf')	C=1e-05,gamma=2^-5	51.04	0.26	0.51	0.34
SVM (Kernel='sigmoid')	C=1e-05,gamma=2^-5	51.04	0.26	0.51	0.34
Passive Aggressive Classifier	C=1e-05,validation_fraction=0.1	53.59	0.54	0.54	0.52
Gaussian Process	Default	53.12	0.76	0.53	0.41
NuSVC	Gamma=2^-5,nu=0.1	51.04	0.26	0.51	0.34
SGD Classifier	Alpha=0.1,penalty='l1'	51.24	0.51	0.51	0.51
Multi Layer Perceptron	Alpha=10^5,hideen_layer_sizes=8	58.38	0.59	0.58	0.58
Random Forest	n_estimators=93	65.89	0.66	0.66	0.66
Extra Tress	max_depth=28, n_estimators=77	64.2	0.64	0.64	0.64
Ada Boosting	learning_rate=1, n_estimators=45	61.13	0.61	0.61	0.61
Gradient Boosting	learning_rate=0.01,max_depth=29,n_estimators=200,sub sample=0.1	64.07	0.64	0.64	0.64
XG Boosting	colsample_bytree=0.7,gamma=0.3,learning_rate=0.05,m ax_depth=12	65.01	0.65	0.65	0.65
Bagging with Decision Tree	n_estimators=120	61.63	0.62	0.62	0.62
Bagging with Random Forest	n_estimators=20	**66.6**	0.67	0.67	0.67
Bagging with Extra Trees	n_estimators=100	65.69	0.66	0.66	0.66
Bagging with Logistic Regression	n_estimators=15	59.2	0.59	0.59	0.59
Bagging with SVM(kernel='linear')	n_estimators=50	48.93	0.63	0.49	0.35
Bagging with SVM(kernel='rbf')	n_estimators=20	54.63	0.76	0.55	0.41
Bagging with SVM(kernel='sigmoid)	n_estimators=100	52.44	0.28	0.52	0.36
Voting Classifier	estimators=[LogisticRegression, RandomForest, GaussianNB]	64.41	0.65	0.64	0.64

Table IV: Classifier's rank to detect user-defined level

Classifier	Rank	
	Accuracy	F1-score
KnearestNeighbor	18	18
Logistic Regression	14	13.5
Logistic RegressionCV	10	10
Linear Discriminant Analysis	12.5	13.5
Quadratic Discriminant Analysis	19	19
Ridge Classifier	11	13.5
Ridge ClassifierCV	12.5	13.5
Decision Tree	16	13.5
Gaussian Naïve Bayes	20	20
Perceptron	22	25
Linear SVM	25	22
SVM(kernel='linear')	27	22
SVM(kernel='rbf')	30	31
SVM(kernel='sigmoid')	30	31
Passive Aggressive Classifier	23	22
Gaussian Process	24	26.5
NuSVC	30	31
SGD Classifier	28	24
Multi Layer Perceptron	17	17
Random Forest	2	2.5
Extra Tress	6	6
Ada Boosting	9	9
Gradient Boosting	7	6
XG Boosting	4	4
Bagging with Decision Tree	8	8
Bagging with Random Forest	1	1
Bagging with Extra Trees	3	2.5
Bagging with Logistic Regression	15	13.5
Bagging with SVM(kernel='linear')	32	29
Bagging with SVM(kernel='rbf')	21	26.5
Bagging with SVM(kernel='sigmoid')	26	28
Voting Classifier	5	6

Table V: Classifier's rank to detect pre-defined level

Classifier	Rank	
	Accuracy	F1-score
KnearestNeighbor	13	10.5
Logistic Regression	17	17.5
Logistic RegressionCV	16	14.5
Linear Discriminant Analysis	20.5	20
Quadratic Discriminant Analysis	20.5	12
Ridge Classifier	20.5	20
Ridge ClassifierCV	20.5	20
Decision Tree	9	9
Gaussian Naïve Bayes	26	29.5
Perceptron	31	32
Linear SVM	23	29.5
SVM(kernel='linear')	29	14.5
SVM(kernel='rbf')	11	25
SVM(kernel='sigmoid')	26	29.5
Passive Aggressive Classifier	30	17.5
Gaussian Process	11	25
NuSVC	11	25
SGD Classifier	28	14.5
Multi Layer Perceptron	24	22
Random Forest	3	3.5
Extra Tress	5	6
Ada Boosting	14	10.5
Gradient Boosting	8	8
XG Boosting	6	6
Bagging with Decision Tree	2	1.5
Bagging with Random Forest	1	1.5
Bagging with Extra Trees	4	3.5
Bagging with Logistic Regression	18	14.5
Bagging with SVM(kernel='linear')	32	23
Bagging with SVM(kernel='rbf')	15	27
Bagging with SVM(kernel='sigmoid')	26	29.5
Voting Classifier	7	6

ISSN: 2278-3075, Volume-9 Issue-2S, December 2019

VII. PERFORMANCE EVALUATION METRICS

For classifier's performance evaluation we have used 4 difference matrices: accuracy, precision, recall and F1- score.

A. Accuracy: It is the ratio of correctly labeled points and the total number of points. Accuracy is given by the following:

$$Accuracy = (TP+TN)/(TP+TN+FP+FN)$$

where,
TP: True Positive
TN: True Negative
FP: False Positive
FN: False Negative

B. Precision: It refers to the percentage of results which are relevant. High precision means that an example labeled as positive is positive. It is given by:

$$Precision = TP/(TP+FP)$$

C. Recall: It refers to the total relevant results correctly classified by our algorithm. High recall means class is identified correctly. It is given by:

$$Recall = TP/(TP+FN)$$

D. F1-Score: It gives the weighted mean of precision and recall. It is given by:

$$F1\text{-}Score = (2*Precision*Recall)/(Recall+Precision)$$

VIII. RESULTS AND DISCUSSIONS

A. User-defined Confusion Level Detection: Table III represents the results of the different classifiers we have used to detect the user-defined confusion level of the students. We found out that for user-defined confusion level detection Bagging with Random Forest, Random Forest and Bagging with Extra Trees classifier gives the best result- their accuracy scores are 66.6%, 65.89% and 65.69% respectively and their F1-scores are- 0.67, 0.66 and 0.66. On the other hand, Bagging with SVM (kernel='linear'), NuSVC, SVM (kernel='sigmoid') and SVM (kernel='rbf') shows the worst performance, their accuracy scores are- 48.93%, 51.04%, 51.04% and 51.04% respectively and their F1-scores are- 0.35, 0.34, 0.34 and 0.34 respectively. Table IV shows the ranks of the different classifiers based on accuracy and F1-score. Table VI represents the confusion matrix for the best two classifiers i.e. Bagging with Random Forest and Random Forest to detect user-defined confusion level. Figure 2 (a) and (b) represents the Receiver Operating Characteristic (ROC) curve for the above two classifiers.

B. **Pre-defined Confusion Level Detection:** Table II represents the results of the different classifiers we have used to detect the pre-defined confusion level of the students. Among all the 32 classifiers, we found that Bagging with Random Forest, Bagging with Decision Tree and Random Forest shows the best performance – their accuracy scores are 61.89%, 61.78% and 61.29% respectively, and F1-scores are 0.62, 0.62 and 0.61 respectively.

Table VI: Confusion Matrix to detect user-defined level

Classifier	Confusion Matrix			
	TP	*TN*	*FP*	*FN*
Bagging with Random Forest	1226	1334	628	656
Random Forest	1224	1309	653	658

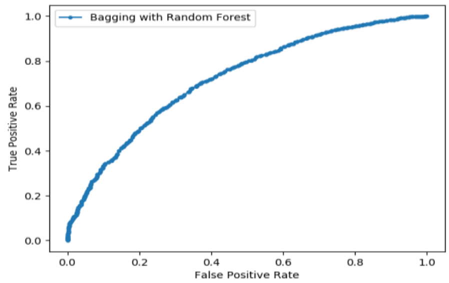

Fig. 2. (a) ROC curve of Bagging with Random Forest

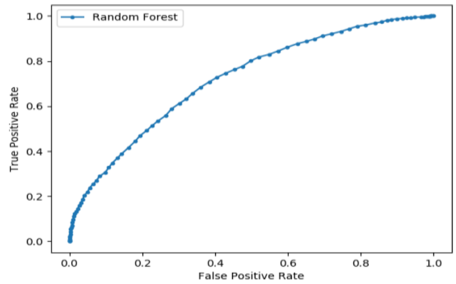

Fig. 2. (b) ROC curve of Random Forest

On the other side, Bagging with SVM(kernel='linear'), Perceptron and Passive Aggressive Classifier shows the worst performance- their accuracy scores are 48.23%, 49.11% and 50.62% respectively and their F1-scores are- 0.46, 0.35 and 0.51. Moreover, SVM (with different kernels) and Decision Tree do not show good performance either. Table V shows the ranks classifiers of the different algorithms based on accuracy and F1-score. Table VII represents the confusion matrix for the best two classifiers i.e. Bagging with Random Forest and Bagging with Decision Tree. Figure. 3. (a) and (b) represents the ROC curve for the above two classifiers.

Table VII: Confusion Matrix to detect pre-defined level

Classifier	Confusion Matrix			
	TP	*TN*	*FP*	*FN*
Bagging with Random Forest	1285	1094	734	731
Bagging with Decision Tree	1303	1072	756	713

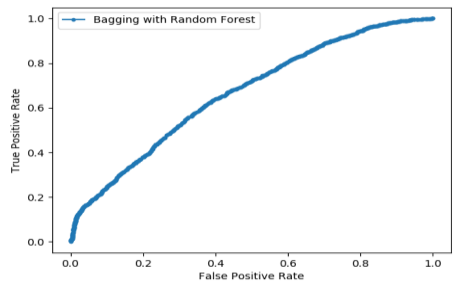

Fig. 3. (a) ROC curve of Bagging with Random Forest

Retrieval Number: B10921292S19/2019©BEIESP
DOI: 10.35940/ijitee.B1092.1292S19

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

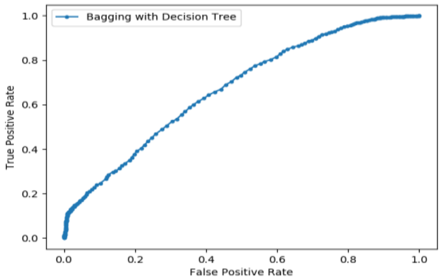

Fig. 3. (b) ROC curve of Bagging with Decision Tree

IX. CONCLUSION

In this paper, we have used EEG data of students to predict the confusion level while watching the MOOC videos in order to improve the quality and effectiveness of online education system. We have applied 32 supervised learning algorithms with various parameters setting to detect whether a student is 'confused' or 'not confused' while watching MOOC videos. It can be seen from the results that bagging with Random Forest gives an accuracy of 61.89% for pre-defined confusion level detection and 66.6% for user-defined confusion level detection. So, we can observe that these computational approaches may use to identify the confusion level of the students. Since, the computed accuracy is less so, in future we can apply Universum based models to improve the performance.

REFERENCES

1. Allen, I. Elaine, and Jeff Seaman. *Going the distance: Online education in the United States, 2011*. Sloan Consortium. PO Box 1238, Newburyport, MA 01950, 2011.
2. Thompson, Gordon. "How can correspondence-based distance education be improved?: a survey of attitudes of students who are not well disposed toward correspondence study." *International Journal of E-Learning & Distance Education/Revue internationale du e-learning et la formation à distance* 5.1 (1990): 53-65.
3. Sharma, Ramesh C. "Innovative Applications of Online Pedagogy and Course Design." *International Journal of Information and Communication Technology Education* 15.2 (2019).
4. Sublett, Cameron. "What Do We Know About Online Coursetaking, Persistence, Transfer, and Degree Completion Among Community College Students?." *Community College Journal of Research and Practice* 43.12 (2019): 813-828.
5. Teplan, M. "Fundamental Of EEG Measurement‖ Measurement Science Review." (2002).
6. Niemic, Christopher. "Studies of Emotion: A Theoretical and Empirical Review of Psychophysiological Studies of Emotion." (2004).
7. Chernecky, Cynthia C., and Barbara J. Berger. *Laboratory Tests and Diagnostic Procedures-E-Book*. Elsevier Health Sciences, 2012.
8. https://en.wikipedia.org/wiki/Electroencephalography (Accessed 4th Nov, 2019).
9. Yeo, Mervyn VM, et al. "Can SVM be used for automatic EEG detection of drowsiness during car driving?." *Safety Science* 47.1 (2009): 115-124.
10. Wang, Haohan, et al. "Using EEG to Improve Massive Open Online Courses Feedback Interaction." *AIED Workshops*. 2013.
11. Mampusti, Ella T., et al. "Measuring academic affective states of students via brainwave signals." *2011 Third International Conference on Knowledge and Systems Engineering*. IEEE, 2011.
12. Subasi, Abdulhamit, and M. Ismail Gursoy. "EEG signal classification using PCA, ICA, LDA and support vector machines." *Expert systems with applications* 37.12 (2010): 8659-8666.
13. Ni, Zhaoheng, et al. "Confused or not confused?: Disentangling brain activity from eeg data using bidirectional lstm recurrent neural networks." *Proceedings of the 8th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics*. ACM, 2017.
14. Edla, Damodar Reddy, et al. "Classification of EEG data for human mental state analysis using Random Forest Classifier." *Procedia computer science* 132 (2018): 1523-1532.
15. Mangalagowri, S. G., and P. Cyril Prasanna Raj. "EEG feature extraction and classification using feed forward backpropogation algorithm for emotion detection." *2016 International Conference on Electrical, Electronics, Communication, Computer and Optimization Techniques (ICEECCOT)*. IEEE, 2016.
16. Hajinoroozi, Mehdi, et al. "Feature extraction with deep belief networks for driver's cognitive states prediction from EEG data." *2015 IEEE China Summit and International Conference on Signal and Information Processing (ChinaSIP)*. IEEE, 2015.
17. Petrosian, A. A., et al. "Recurrent neural network-based approach for early recognition of Alzheimer's disease in EEG." *Clinical Neurophysiology* 112.8 (2001): 1378-1387.
18. Abdulla, Shahab, et al. "Sleep EEG signal analysis based on correlation graph similarity coupled with an ensemble extreme machine learning algorithm." *Expert Systems With Applications* 138 (2019): 112790.
19. Hussain, Mushtaq, et al. "Using machine learning to predict student difficulties from learning session data." *Artificial Intelligence Review* 52.1 (2019): 381-407.
20. Lin, Fu-Ren, Chien-Min Kao. "Mental effort detection using EEG data in E-learning contexts." *Computers &Education* 122 (2018): 63-79.
21. Bacos, Catherine A. "Machine Learning and Education in the Human Age: A Review of Emerging Technologies." *Science and Information Conference*. Springer, Cham, 2019.
22. Raheel, Aasim, Muhammad Majid, and Syed Muhammad Anwar. "Facial Expression Recognition based on Electroencephalography." *2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*. IEEE, 2019.
23. Zhou, Yun, et al. "Confusion State Induction and EEG-based Detection in Learning." *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2018.
24. https://www.kaggle.com/wanghaohan/confused-eeg

AUTHORS PROFILE

Bikram Kumar is pursuing M.Tech in Computer Science and Engineering of National Institute of Technology, Arunachal Pradesh. He has completed B.Sc from Gour Mahavidyalaya and M.Sc from University of Gour Banga in Computer Science. His area of interests include Machine Learning, Data Science and Data Mining.

Dr. Deepak Gupta is currently working as Assistant Professor in Computer Scinece and Engineering of National Institute of Technology, Arunachal Pradesh. He has completed MCA from Jawaharlal Neheru University. He has also completed M.Tech and Ph.D in Computer Science and Engineering from Jawaharlal Neheru University. His research fields include Machine Learing, Support Vector Machine, Extreme Learning Machine for Classification and Regression Problems. In 2017, he received the SERB-Early Career Research Award in Engineering Sciences.

Dr. Rajat Subhra Goswami is currently working as Assistant Professor in Computer Science and Engineering of National Institute of Technology, Arunachal Pradesh. He has completed B.Tech in Information Technology from West Bengal University of Technology, M.Tech in Multimedia Development from Jadavpur University and Ph.D in Computer Science and Engineering from National Institute of Technology, Arunachal Pradesh. His research fields include Information Security, Cryptography, Image Processing, Big Data, Network Traffic Classification.