

Social Media And Students Cognition : A Machine Learning Approach Using Random Forest Classifier

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ABSTRACT

Social media networks have become a major communicator in today's modern world. The main objective of the study is to find out how social networks affect students' behavior. Consideration is also given to whether trust, social media participation, and social media behaviors are positively linked. In order to collect primary data, a general sweep model was used to observe the attitude of undergraduate and post-graduate students aged 18 to 21. 95% of respondents responded to the questionnaire for which descriptive statistics were applied to analyse data. Random Forest, Boosting, Voting, and Bagging have been used as a standard set of techniques in this work. Using these ensemble methods researchers got good results that demonstrated the reliability of the proposed model. For greater productivity, the different classifiers are brought together and subsequently added to the overall ensemble method using the Voter procedure. The findings suggest that the impact of social media can be positive or negative, as this research narrowly identifies the real impact of social media sites. The goal of this study is to identify the reasons why students today suffer from mental illnesses such as depression, anxiety, stress, and the cognitive-behavioral changes of the students. Social media websites such as Instagram, Google+, Facebook, and WhatsApp draw students' attention to their studies and have a positive or negative impact on their grade points. The results of the implementation show that the bagging method improved the existing model, where the precision of the bagging algorithm with bagging is 92.6%. Recall outcomes of prediction 1 to prediction 2 are improved from 0.90 to 0.97 and accuracy results also increased from 0.60 to 0.72.

keywords: Random Forest, Boosting, Bagging, Ensemble methods, students, social media.

I. INTRODUCTION

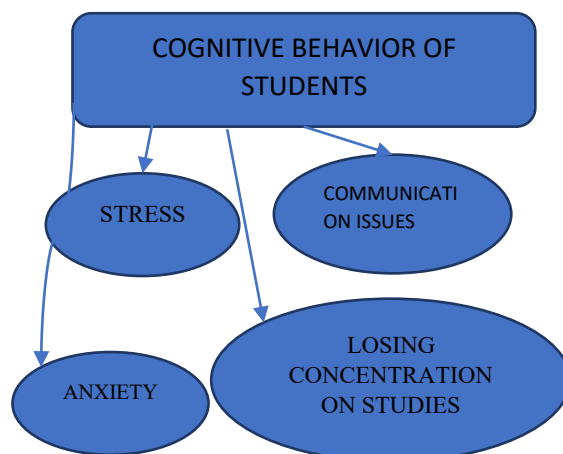
The prediction of student achievement is extremely important in today's education system. These days, students' performance prediction encourages the bearer and the future of students. The goal of the study is to determine the impact of the growing use of social media websites on student academic achievement and cognitive behaviour. Usage of social media influences student behavior and academic performance. The negative influence is more compared with the positive effect on student behavior aged between 18-21. Results cannot be disseminated throughout the student community as they are specific to individual respondents [5]. This learning grants a connection between the anti-thetic and creative attributes of social media and stands insights for future research by enabling an improved consideration of the use of social networks [3][4] on the Web.

A selection of 300 students was randomly selected. The questionnaire was used as a tool for collecting data. Spending lots of time in social media leads to several changes in the student's behavior such as emotionally strong or weak, questioning, and significant behavioral changes that differ from other behavioral changes are observed.

Some of the behavioral changes in the students are categorized as not having the ability to communicate with people whom they don't know very well, can't speak up at a meeting with crowded people, may shout at people more than usual, will be angry at small things, will lose interest in the things which they enjoyed earlier after a stressful [7][8] involvement, feeling startled or jumpy when unexpected noise are heard, cannot

get to sleep within 30 minutes, wake up in the middle of the night unawarely, etc., The below figure 1 shows some of the cognitive behavior of students. The ensemble model [1] used in this work are random forest classifier [2], bagging [6], and voting classifier [9][10].

Figure 1 Cognitive behavior of undergraduate/ postgraduate students



The main objective of this work is categorized as follows

- Develop a questionnaire based on the consequence of social media usage for undergraduate or post-graduate students.
- Identify the usage of social networks having an impact on student behavior.
- Determining the cognitive behavior of students causes mental diseases such as stress, lack of sleep, anxiety, depression, mood disorders [11].
- Usage of Random Forest classifier, bagging, voting, and opinion mining techniques for the reliability of work on metric accuracy, recall, and accuracy.
- Assess the positive and negative impact of student performance using social media sites [12] with a confusion matrix.

The paper is organized as follows: the literature review of the preceding articles is referred to in Section II. In Section III, the theoretical context of classifiers and processes used in the study are set out. Section IV describes the proposed methodology and Section V details the implementation and results. Finally, section VI discusses the conclusions and future work of the research.

II. RELATED WORK

This section provides general research information for the purposes of this study. To this end, we looked at past studies related to student performance prediction and attempted to display entry attributes that affect student behavior [15]. All prediction algorithms and their measures of accuracy are determined.

H. Sahlaoui et al., [1] describe the various factors of student performance such as personal factors, academic factors [12][13][14], financial, family, and institutional factors. The behavior challenges faced by students are categorized through these factors. Upgrading the structure of education must depend on the characteristics that interfere with students' academic success [16][17]. Personal factors include how students conduct themselves, such as thoughts, feelings, or gestures, and student demographics. [18]. Researchers have examined how psychometric aspects incline to impact student achievement [19][20].

Academic factors follow the points in order to determine the failure [21][22] or success [23][24] of students. Characteristics similar to those of this group relate to the educational connection and income that the organization distributes for the best academic performance of its students. The author observed the psychological factors that influence the performance of students.

S. Jayapraksh et al.,[2], in their work student data are analyzed for academic, psychological factors, cognitive factors, and socioeconomic factors. Random forest classifier ensemble model used for prediction student academic performance. Enhancement of reliability, efficiency, and accuracy of the work.

Kaur et al.,[8] Conduct student performance prediction using evaluation scales. To identify the classification voter classifier are used. This allows the categorized columns to be modeled [31] based on likelihood ratings.

M. Naseem et al.,[9] focus on selecting university students through the ensemble model for classification and cross-validation are performed. Feature selection helps to determine the most influencing factors among the students. Cross-validation is intended to confirm that representations are not over-adjusted.

J.M. Carrillo et al.,[19] deals with the random forest classifier to predict the student's academic success or failure. Classification of students is made through three categories good, excellent, and acceptable.

D. Petkovic et al.,[20] focused on predicting the learners of educators through software engineering teams. A random forest classifier is used for predicting [27] the learners in the entire team.

X.Li et al.,[15] use a bagging classifier to improve the accuracy [25] [26] of the classified data. After the classification of random forest, bagging classifiers are modeled.

F.T. Guintine et al., [12] focuses on users suffering from depression through social media and emotionally validated features by users' email specialists. Opinion mining [34] techniques, discover models to predict depressive user behavior. This methodology makes it possible to determine the emotions [30] and cognitive behavior of users.

R.K.Bakshi et al.,[35] predict the positive and negative aspects of users through the opinion mining of each word. This system automatically combines a supervised [27] learning process that extracts, learns [28], and classifies tweets with expressions of opinion [13]. The core concept is to use subject-specific training data [29] to develop a generic classification template using social media data to improve performance. The pretest and posttest scores were compared to determine if there was a significant difference in students' performances before and after the intervention[36].

III SYSTEM ARCHITECTURE AND ALGORITHMS

A. SYSTEM ARCHITECTURE

Figure 2 illustrates the architecture of the proposed system. This model is the tree structure, classification model. Here, the data is divided into 80 per cent for training and 20 per cent for testing. The sample data

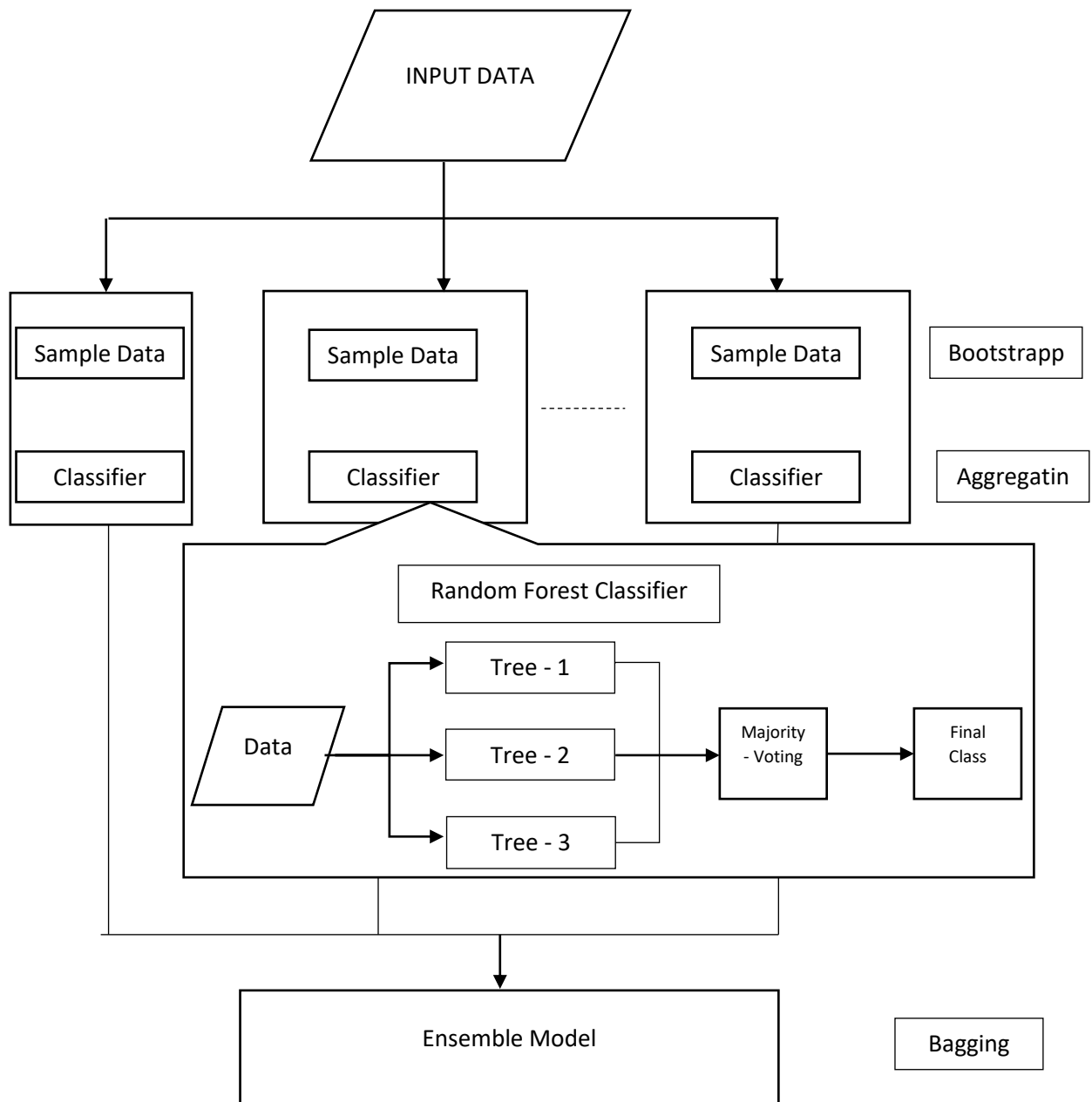
related to the psychology of the students. Initially, a decision tree was used to fit the model for accuracy. Sample data is the questionnaire collected from students. The classifier used for modelling is Random Forest Classifier and Bagging classifier. Classification of questionnaires is made through Bootstrapping [33] and Aggregation [32].

Basic Decision Tree Classifier

A decision tree classifier is a directional tree made up of a leaf and the root node. The decision tree will split the data into the train of 80 percent and 20 percentage of the test.

After the collection of input data, the sample data will be divided into root nodes and leaf nodes. Random forest consists of multiple decision trees, which will be trained on many parts of the similar training dataset with the average of reducing variance [34]. This model helps in boosting the performance of the model.

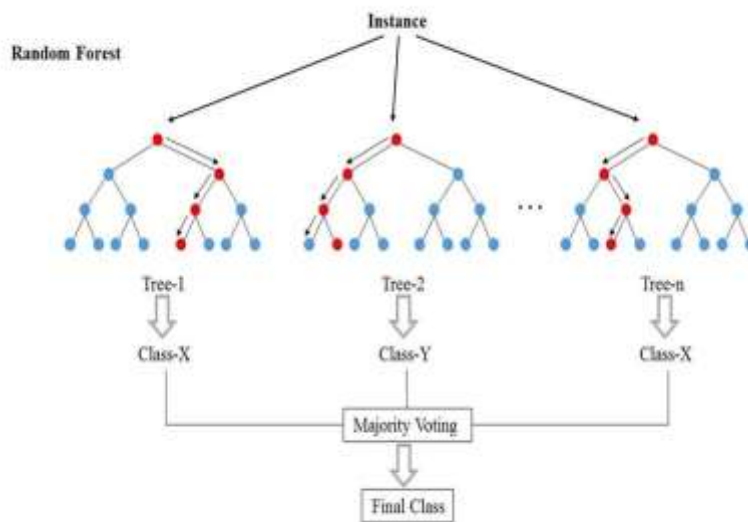
FIGURE 2 SYSTEM ARCHITECTURE OF PROPOSED SYSTEM



B. RANDOM FOREST CLASSIFIER

A Random Forest (RF) [35] classifier algorithm can be used for both regression and classification problems. This model helps to attain the accuracy of the sampled data. The model creates numerous decision trees corresponding to a forest with randomized attribute values. The degree of accuracy depends on how many trees are built. The algorithm selects at random the root node and the characteristic node for tree construction. Besides the regression problem, it also makes it possible to classify the categorical and multivariate variables. The data are collected as numerical and nonnumerical. The Random Forest classifier model is shown in figure 3. The data column is classified as x and y.

Figure 3 Random Forest Classifier Structure



The classification mechanism is categorized as the tree classifier randomly obtaining the characteristic input vector, the class with each tree in the forest, and producing the class label that received most of the "votes". RF classification algorithm reduces the risk of exceedance by including randomness. The flowchart of the Random Forest algorithm is determined through steps followed in Algorithm 1.

Algorithm 1: Random Forest Classifier

- 1 *Begin*
- 2 Keep the number of training cases on Y and the number of variables in the testing is X.
- 3 the number x of input variables is used to decide the decision at a structure node m far less than X.
- 4 *Select* one set of training data for this tree by selecting N times with additional replacement in all Y training cases.
- 5 For each tree node, randomly select the variables m on which to make the decision at that node.
- 6 *Finally*, every tree is entirely grown and not trimmed.
- 7 *End*

C. BAGGING CLASSIFIER

Bagging classifier is also called bootstrap aggregation which is used for fixing the instability in the model classification. This model is related to the majority of votes for classification or the average is calculated for regression. Bagging classifier algorithm is determined through the Algorithm 2.

Algorithm 2: Bagging Classifier

- 1 Input: Training data S with correct labels $\omega_i \in \Omega = \{\omega_1, \dots, \omega_C\}$ representing C classes
- 2 Weak learning algorithm WeakLearn (Random Forest),
- 3 Integer T stating the number of iterations.
- 4 Percentage (or fraction) F for generating bootstrapped training data.
- 5 Do $t = 1, \dots, T$
 1. Take a bootstrapped replica S_t by randomly drawing F percent S .
 2. Call WeakLearn with S_t and accept the hypothesis (classifier) h_t .
 3. Add h_t to the ensemble, E .
- 6 End the algorithm.

IV. PROPOSED METHODOLOGY

A. DATA

Data are collected from the student of undergraduate and postgraduate students of BCA/MCA aged between 18-21. Questionnaire is the method used for collecting data from the students. Sample data was collected from 300 students. The data used for researches are related to academic, extracurricular activities, entertainment basis, and the personal information of the students.

The data are imported normally then pre-processing carried out for unwanted columns to be dropped. Some of the columns are renal for encoding works. Duplicate values are removed through this pre-processing and the features with missing values will be removed from the dataset. Table 1 illustrates the summary of all the features present in this proposed system. We are converting a nominal value to a numeric value for the purpose of processing. We define the features of numeric data as $X1$ --- $X9$ are independent variables and non-numeric data as $Y1$ and $Y2$ dependent variables. For occurrence, $X1$ feature (Time Spent for using social media for academics per day) has the numeric values of (0,1,2,3,4,5) represents 1 - 2 hours, less than an hour, more than 2 hours, more than 3 hours, and more than 4 hours. Lastly, the dataset used in tests has a total of 950 occurrences conforming to the cognitive behavior of students affecting the academic performances by using social sites.

Table 1 Data used for experiments

FEATURE	DESCRIPTION	VALUES
x1	Time Spent for using social media for academics per day	0-5
x2	You can't communicate with people you don't know very well	0-5
x3	Can't speak up at a meeting with crowded people	0-5
x4	I shout at people any more than usual	0-5
x5	I am all that angry about things	0-5
x6	Lose interest in the activities you	0-5

	loved until you had a stressful experience.	
x7	A sense of nervousness or surprise when an unexpected noise is heard.	0-5
x8	Cannot get to sleep within 30 minutes	0-5
x9	Wake up in the middle of the night unawarely	0-5
y1	Is usage social media has affected your physical and mental health positively or negatively?	0-5
y2	The usage of social media for education purpose has made a negative impact on affecting the student's behavior. Do you agree on it?	0-5

B. CLASSIFICATION TASK

Random forest classifier solves the classification and regression problem. Graphical analyses are determined. To execute the classification, we study the input variables of nine features are denoted as $\{X_1, \dots, X_6\}$ which are independent variables and as prediction class, the feature of dependent values as Y_1 and Y_2 which has values in them. For each and every first category total number counts are checked. Word count and count plots are used for visualization. In this psychology-related data, last two columns have a t-factor. For these two columns, the word count will be the representation. A decision tree was used to fit the model initially. To determine the learning process, 80 percent of data is split for train and 20 percentage of data is split to test. Time complexity of run time is checked then the space complexity of how much memory is consumed will be determined. Once checked into the decision tree, the model will try using a Random Forest classifier. Below the ensemble model, Random Forest Classifier will be fitted and checked. Output model will be given through Bagging Classifier which comes under Random Forest Classifier.

Figure 4 Label Encoding for instance x1

Time spent on social media per day in social media non-numerical values	Time spent on social media per day in social media (Label Encoding)
1-2hours	0
Less than a hour	1
More than one hour	2
More than two hours	3

V. IMPLEMENTATION AND RESULTS

A. CORRELATION HEAT MAP

Correlation heatmap labels the heat map which is the measurement of x and y axis calculated as matrix. This matrix method displays the cognitive behavior of students using the label encoded values shown in table 2.

Table 2 Values of x and y-axis upon likelihood ratings

	x1	x2	x3	x4	x5	x6	x7	x8	x9	y1_rate	y2_rate
1	0	20	20	10	20	10	10	20	20	0	0
2	1	40	40	50	10	20	20	10	10	1	0
4	0	20	20	40	20	20	40	10	20	0	0
5	1	20	10	50	40	30	50	10	10	1	0
6	0	20	20	20	30	40	30	30	20	0	0

The values of cognitive behavior categorical data are converted into numerical data are visualized using different colors are shown in figure 5.

Figure 5 Correlation heat map



B. MODEL EVALUATION

OPINION MINING

After label encoding, opinion mining concepts of study-related data from the last columns of the feedback form will be collected. To convert into numerical, opinion mining techniques are used. This process is carried out by word count and count plots. Word counts are collected and combined with the columns data count1 and data count2. With the word count, the collected data will be split for positive or negative. Through the given question positive words are listed and are compared for negative or positive prediction. After replacing of last two columns text will be converted into numeric binary. Finally, classification of positive or negative feedback are determined.

CONFUSION MATRIX

Evaluation of model is determined through comparison of confusion matrix with prediction1 and prediction2. Comparison is carried out within the same proposed model since there is no model done through complete numeric data till now. The confusion matrix gives the accuracy and performance of the model. Statistical measures of precision, F1-score, accuracy, True Positive rate, and False Negative rate are analyzed and interpreted through this model. Table 3 illustrates the prediction of positive or negative feedback where the attributes are mentioned as True Positive (TP), False Positive (FP), False Negative (FN), True Negative (TN). TP denotes the model prediction is correct. TN denotes the total number of instances that are predicted correctly. FP refers to the total number of instances that are predicted wrongly.

Table 3 Prediction of Positive or Negative

	PREDICTIVE POSITIVE	PREDICTIVE NEGATIVE
ACTUAL POSITIVE	TP	FN
ACTUAL NEGATIVE	FP	TN

PRECISION, RECALL, ACCURACY, F-SCORE

Precision is also known as predictive positive value fixes the segment of related instances in contrast to the retrieved instances. Precision is measured by the given formula of eqn 1.

$$\text{Precision Rate}(PR) = \frac{TP}{(FP+TP)} \text{-----}(1)$$

A recall is calculated based on the below equation 2. Where the number of true positive values are counted with the total number of TP and FP values. Measurements are based on the right instances with the instances retrieved.

$$\text{Recall Rate}(RR) = \frac{TP}{(TP+FP)} \text{-----}(2)$$

F-score produces the accuracy of the test. The performance of model and their accuracy can be computed using F-score formula 3.

$$F - \text{Score} = 2 \times \text{Precision Rate}(PR) \cdot \text{RecallRate}(RR) / (\text{precision} + \text{recall}) \text{-----}(3)$$

Accuracy of the model is computed with the below equation 4.

$$\text{Accuracy} = \frac{TN+TP}{(TP+FP+TN+FN)} \text{-----}(4)$$

The calculation of precision, recall, f-score and accuracy of the bagging and random forest classifier are tabulated for prediction 1 is shown in table 4.

TABLE 4 Performance Metrics of prediction1

	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.62	0.90	0.73	29
1	0.40	0.11	0.17	18

ACCURACY			0.60	47
MACRO AVG	0.51	0.50	0.45	47
WEIGHTED AVG	0.54	0.60	0.52	47

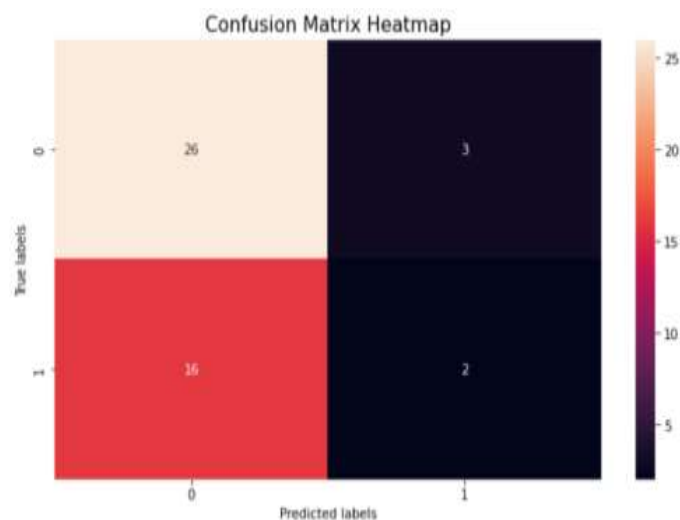
TABLE 5 Performance Metrics of prediction2

	PRECISION	RECALL	F1- SCORE	SUPPORT
0	0.79	0.97	0.87	35
1	0.75	0.25	0.38	12
ACCURACY			0.79	47
MACRO AVG	0.77	0.61	0.62	47
WEIGHTED AVG	0.78	0.79	0.74	47

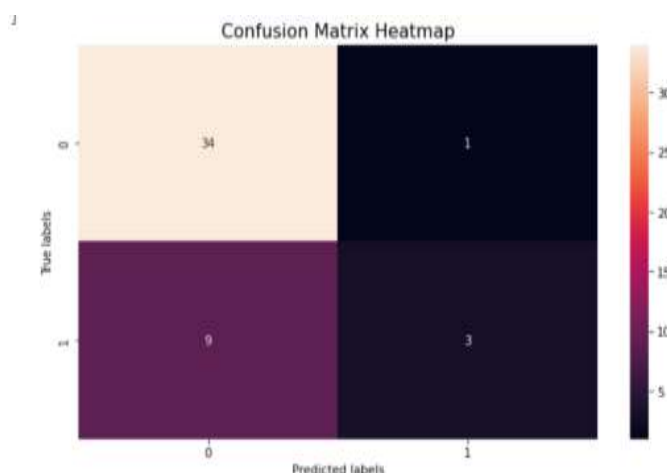
The prediction2 of the random forest classifier with bagging computation are made and listed in the below table 5.

Confusion Matrix Prediction 1

The overall accuracy of the bagging and random forest classifier is computed using confusion matrix shown in figure 6. True labels and predicted labels are predicted for the words determined from the opinion mining.

Figure 6 Confusion Matrix of Prediction 1

The next prediction of labels will be determined by the confusion matrix shown in below figure 7. The overall random classifier achieved accuracy on the bagging method increased from 0.60 to 0.72. The confusion matrix produces better understanding through class and provide insight for recall and precision efficiency.

Figure 7 Confusion Matrix of Prediction 2

The insights can be determined through confusion matrix of the ensemble model with the accuracy of 92.6%.

VI. CONCLUSION AND FUTURE WORK

Cognitive behaviour of students using social media are analyzed and determined through the random forest classifier and bagging model. The accuracy is obtained by comparing the prediction1 and prediction2 from 91.3% to 92.6%. Recall consequences of prediction 1 to prediction2 are upgraded from 0.97 to 0.90, and accuracy results also improved from 0.60 to 0.72. Solutions to the problems faced by students are given below:

- Increase time duration spent for academic/educational purpose through educational social network rather than spending in entertainment purpose.
- Prefer offline entertainment than online entertainment to lessen stress caused by physically and mentally.
- From our studied analysis, around 40% of students utilize social media only 1-2 hour for study purpose and around 71% of students utilize social media below 2 hr/day for academic.
- Offline mode of study is much more preferred by the students since most of the students' behaviour has been negatively impacted due to the online mode of study.

Classification is made for the positive or negative feedback of the student behavior are determined. Till now, many researches are not carried out in numeric data alone. In future, the accuracy rate of the different classifiers for the numeric data alone can be computed.

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