Impact Prediction of Online Education During COVID-19 Using Machine Learning: A Case Study

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Impact Prediction of Online Education During COVID-19 Using Machine Learning: A Case Study

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Abstract The transition from traditional to online education is challenging and has many obstacles in various situations. Due to the Covid-19 situation, we use digital blended education from the traditional system. However, in some cases, it can harm our student's academic performance. In this research, we aim to identify the factors that impact the student's academic performance in online education. On the other hand, this study also finds the student Cumulative Grade Point Average (CGPA) fluctuation using machine learning classifiers. To achieve this, we survey to gather data perspective of Bangladesh private university, and this data allows us to analyze and classify using machine learning techniques such as Logistic Regression (LR), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), Decision Tree (DT), and Random Forest (RF). This study finds Random Forest (RF) outperforms the other state-of-art classifiers.

Keywords Machine learning · Performance · Online education

1 Introduction

Approximately 1.5 billion students worldwide are affected by the closing of educational Institutions due to COVID-19 [1, 2]. With the emergence of online education in Bangladesh in March 2020, due to the government's decision to keep all the educational institutions closed from March 17, 2020 onwards, there has been a noticeable

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change in the student's academic performance [3]. The future of 37 million children in Bangladesh is in jeopardy, with the COVID-19 pandemic wreaking havoc on their schooling. The government's primary approach was to use television-based educational programs. However, after a few months of the school's closure, it is evident that student learning and academic performance were in jeopardy. This research conducted a study among private university students in Bangladesh to determine the pattern of change due to online education during this period. If the difference is negative and persists, it will be a severe setback for many Bangladeshi students. To find and prevent the potential negative impact of online education, we surveyed students from different private universities in Bangladesh. We conducted this survey through an online questionnaire. We prepossessed the data collected from this survey into a suitable format for the machine learning classifications.

Statistical and machine learning algorithms are used in various industries, including marketing, health, medical difficulties, weather forecasting, socioeconomic behavior analysis, and so on [4–7]. It has also been discovered in educational data. Different patterns can be generated from this data, which will be useful in making judgments [8, 9]. In the literature [10–14], this research approach has been discovered very few recorded works in which machine learning models were used to predict the student's academic performance. We also correlated a relation such as CGPA change versus comfortability with online exams, CGPA change versus the type of assignment submission, CGPA change versus comfortability with online classes, and CGPA change versus internet stability. The following is our contribution to this paper:

- We apply machine learning classifiers to predict fluctuation of CGPA using the attributes such as living area, family, devices, Internet type, Internet stability, loadshedding, studied more, CGPA before, submission type, mental health, online class, online exam, and online teacher.
- We compare the performance of the proposed Random Forest Classifiers with the state-of-the-art classifiers such as Logistic Regression (LR), K-Nearest Neighbor, Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), Decision Tree (DT).

The rest of the paper is organized as follows. In Sect. 2, we discuss some literature reviews of existing research. Research methodologies are stated in Sect. 3. In Sect. 4, the result and discussion are shown. Finally, the conclusion is discussed in section.

2 Related Work

Online education or distant learning has been used in Bangladesh for a while now. It always has its limitations that are different from the traditional education system [15–17]. Different studies have tried to provide insights into these shortcomings in front of us. Islam et al. argue that expansion of the utilization of ICT can directly enhance the condition for online education for Bangladesh [18]. Nevertheless, this study was done back in 2006, when numerous changes in the infrastructure of Bangladesh were made. In contrast, Hossain et al. highlight the critical steps that the government can take to improve the OE/DL in Bangladesh [19]. However, this work has not considered the direct and indirect impact of OE/DL on the students' academic performance. On the same note, Efta Khairul Haque et al. state in their study that the availability of gadgets and access to the Internet has been a significant element in online education and suggested some steps that the government should take to avoid the situation from being a tragedy [20, 21]. Research connected to the fear of academic delay and psychological distress among university students by Hossain et al. gave us an insight into the scene of mental health and its impact on the students' performance in online education [22]. On the other side, Tamanna et al. talk about the satisfaction level of students in Online education [23]. The author discovered the association between the living area and satisfaction levels with online education. Besides, some studies have also been conducted from the teacher's perspective, such as the one by Parvej et al., which sheds light on the scenario of teachers and online education facilities [24]. Bangladesh and other underdeveloped countries experience comparable hurdles during online education due to the infrastructural situation. This has been mentioned by S. Shrestha et al. in their research about practices of online education in Bangladesh and Nepal [25].

3 Research Methodology

3.1 Data Collection and Description

For the study, we used online forms and questions in both English and Bangla for the convenience of the respondents. A total of 1468 people responded to the questionnaire, and these responses were then saved for further analysis and classification. The questionnaire's questions were thought to be directly related to the student's performance during online education. Among these 1468 responses, 49% of the students' academic performance decreased during online education compared to traditional offline education. Table 1 represents the list of attributes in online education during Covid-19 pandemic.

3.2 Machine Learning Classifiers

To perform prediction based on the obtained data and further analyze, we utilized Logistic Regression classifier, K-Nearest Neighbors classifier, SVM Linear and Radial Basis Function classifier, Gaussian Naive Bayes classifier, Decision Tree classifier, and Random Forest classifier on our dataset. A classification analysis approach for estimating a data value based on past data set observations is called logistic regres-

Table 1 List of attributes in online education data set

Attribute	Type	Question	Response (%)
Living area	Qualitative	What would you describe your living area as? Rural area, Urban area	39.9, 60.1
Family	Qualitative	Are you currently living with your family? Yes, No	95.6, 4.4
Devices	Numeric	How many devices do you have available for online classes? 1, 2, more than 2	33.5, 52.7, 13.8
Internet type	Qualitative	What type of internet connection do you have? Broadband, Mobile Internet	66.1, 33.9
Internet stability	Numeric	How stable is your Internet connection? 0, 1, 2, 3, 4	5.3, 16.8, 36.4, 29.3, 12.1
Load-shedding	Numeric	How long are the usual hours for load shedding (power outage) in your area? 0, 1–3, 3–5 h, more than 5 h	13.6, 55.4, 19.8, 11.2
Studied more	Qualitative	When did you spend more time studying? Before online classes started, after online classes started	66.1, 33.9
CGPA before	Numeric	What was your CGPA before online classes started?	N/A
Submission type	Qualitative	Which one do you think is easier for you? Submitting assignments online, Submitting assignments offline	63.3, 36.7
Mental health	Qualitative	Do you think online education had any negative impact on your mental health? Yes, no	80.3, 19.7
Online exam	Numeric	Rate your experience with online examinations 0, 1, 2, 3, 4	14.2, 22.5, 40.6, 17.2, 5.5
Online class	Numeric	Rate your comfortability with online classes 0, 1, 2, 3, 4	16.7, 13.3, 35.1, 16.3, 18.6
Online teacher	Numeric	Rate the quality of communication with your teacher during online session 0, 1, 2, 3, 4	9.6, 24.9, 37.1, 18.0, 10.4
CGPA_change	Qualitative	What was the change in your CGPA after online classes started? Did not decrease, decreased	50.95, 49.05

sion. A k-nearest neighbor algorithm is a data classification approach that evaluates how possible a data point belongs to a group based on its closest data points. The Support Vector Machine (SVM) is a common Supervised Learning technique used to solve regression and classification tasks. To categorize non-linearly segregated data, non-linear SVM is utilized. Non-linear data refers to the information that cannot be classified using a straight line, and the model used is the non-linear SVM classifier. The Gaussian Naïve Bayes classifier is an alternate form of the Naïve Bayes classifier. Other functions may be employed to estimate the data distribution. However, the Gaussian (or Normal) distribution is the most elementary to deal with since it involves the calculation of the mean and standard deviation from the training data. A Decision Tree is a fundamental paradigm for categorizing occurrences, and it has supervised machine learning in which data is constantly divided according to a parameter. Random Forest is a machine learning technique used to solve regression and classification problems. It is an ensemble approach. A random forest model consists of many decision trees that we call estimators, producing predictions.

3.3 Implementation Procedure

This section explains how to put the plan into action. A functional prototype of the proposed model has been introduced in Fig. 6. Python and Scikit-learn libraries were utilized to conduct the research. The models are run on Google Colab Notebook, and the scikit-learn framework is used to create and analyze machine learning models. The datasets are loaded and cleaned using the Pandas and NumPy frameworks. For data visualization, the Matplotlib and Seaborn frameworks are used.

3.3.1 Dataset Preprocessing

To collect data, we opted in for google forms. We engineered a survey with specific questions that would yield data attributes related to our research. In the survey form, all data fields were mandatory. Thus, no response had incomplete data points. After completing the survey, the response data could easily be exported into a CSV format file for later preprocessing. For preprocessing the data, we imported all the responses as a CSV file into Google Colab. We used python code for all preprocessing and prediction analysis. We ensured no data entry was missing using the NumPy and pandas libraries. To make it easy for analysis, we labeled the entries using a Label Encoder function from the sklearn library. We have also assigned short attribute names to each data point at this stage.

3.3.2 Correlation Analysis

The results of Pearson correlation reveals the impact of source attributes on target attribute: Change in CGPA. By analyzing Pearson correlation we found out the important features in this study. It has been plotted in a Fig. 1. Based on these important features, we can make comparisons and visualize their impact on the change of CGPA (Figs. 2, 3, 4 and 5). We can quickly point out the factors that impact students' academic performance in online education with these comparative graphs. We have exhaustively studied the factors and observed that adaptability plays an essential role in increasing CGPA. Students who were not comfortable with the implementation of online classes, assignments, and exams were the ones who had the most impact on their academic outcomes. Besides this, the network infrastructure available to the

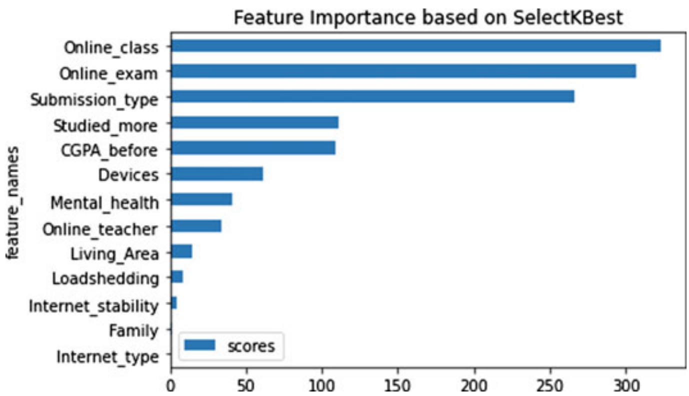

Fig. 1 Feature importance of attributes

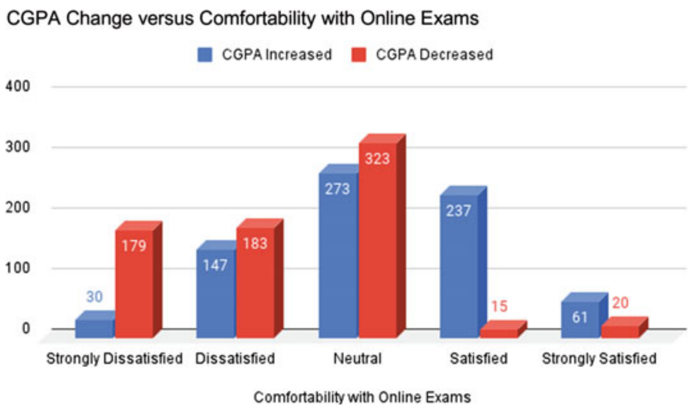

Fig. 2 CGPA change versus comfortability with online exams

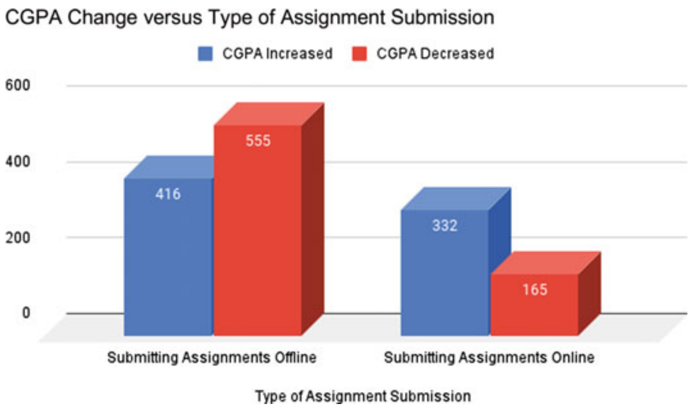

Fig. 3 CGPA Change versus type of assignment submission

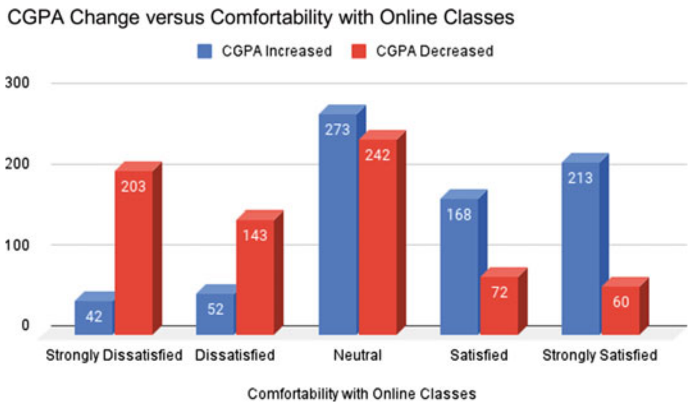

Fig. 4 CGPA change versus comfortability with online classes

student at the time of online education also affects how the student might perform academically. Thus we can state that students should adapt to change to do well in online education platforms.

3.3.3 Train-Test Splitting Data

We collected data as a numerical value, so there is no need to convert values, and all values were automatically normalized. After that, we split the total data into a 70–30% split for the train-test. The splitting was handled using a tool from the sklearn framework in python.

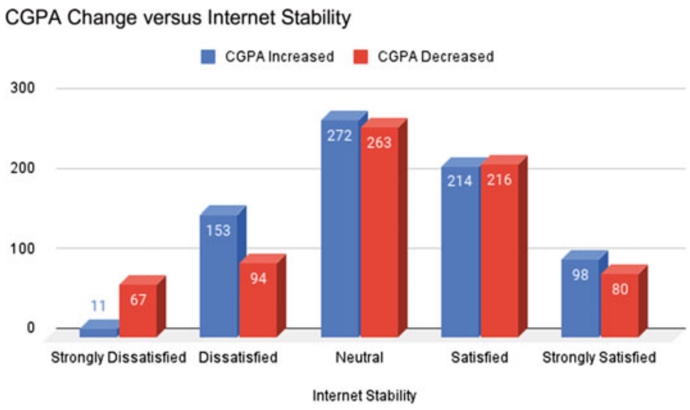

Fig. 5 CGPA change versus Internet stability

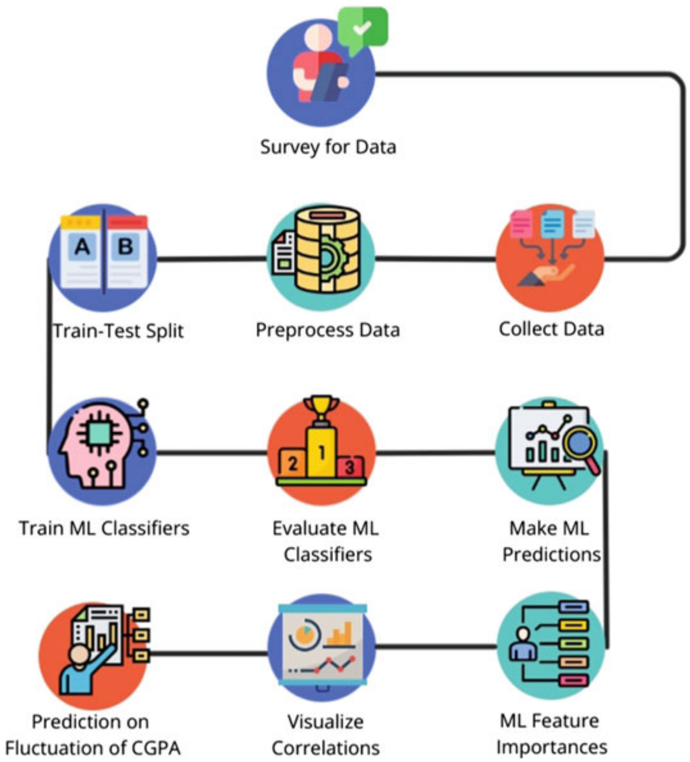

Fig. 6 A functional prototype of the proposed system

3.3.4 Train and Fit Model

Dataset was trained using the training data using six different classifiers in this step. The Fit model is then applied after this step is completed.

3.3.5 Performance Evaluation

In terms of the performance evaluation of the classifiers, we consider certain factors: accuracy, precision, recall, AUC Score, and ROC curve. In this study, we use a binary classifier, which can produce two types of errors: false positive (FP) and false negative (FN). True positives (TP) are vulnerable classes that have been accurately classified, while true negatives (TN) are non-vulnerable classes that have been correctly classified (TN).

4 Experimental Results and Discussion

This research used the classification models and considered Change in CGPA as the class attribute with binary values, ‘decreased’ and ‘did not decrease’ which were then encoded into 0 and 1. We classified the attributes into three groups. The first group is about demographic (living area, family, devices, Internet type, Internet stability,

Table 2 Features divided into different groups and top features

Serial	Group name	Features
1	group-1	‘Living-Area’, ‘Family’, ‘Devices’, ‘Internet-type’, ‘Internet-stability’, ‘Loadshedding’
2	group-2	‘Studied-more’, ‘CGPA-before’
3	group-1+group-2	‘Living-Area’, ‘Family’, ‘Devices’, ‘Internet-type’, ‘Internet-stability’, ‘Loadshedding’, ‘Studied-more’, ‘CGPA-before’
4	group-3	‘Submission-type’, ‘Mental-health’, ‘Online-exam’, ‘Online-class’, ‘Online-teacher’
5	group-1+group-2+group-3	‘Living-Area’, ‘Family’, ‘Devices’, ‘Internet-type’, ‘Internet-stability’, ‘Loadshedding’, ‘Studied-more’, ‘CGPA-before’, ‘Submission-type’, ‘Mental-health’, ‘Online-exam’, ‘Online-class’, ‘Online-teacher’
6	top-5	‘Online-class’, ‘Online-exam’, ‘Submission-type’, ‘Studied-more’, ‘CGPA-before’
7	top-9	‘Online-class’, ‘Online-exam’, ‘Submission-type’, ‘Studied-more’, ‘CGPA-before’, ‘Devices’, ‘Mental-health’, ‘Online-teacher’, ‘Living-Area’
8	top-13	‘Online-class’, ‘Online-exam’, ‘Submission-type’, ‘Studied-more’, ‘CGPA-before’, ‘Devices’, ‘Mental-health’, ‘Online-teacher’, ‘Living-Area’, ‘Loadshedding’, ‘Internet-stability’, ‘Family’, ‘Internet-type’

Table 3 Prediction performance of machine learning models with different groups

Serial	Classifier name	Train accuracy	Val accuracy	Accuracy	Precision	Recall	$F1$ score	FP rate	FN rate	AUC score
1	Logistic regression (group-1)	0.623	0.602	0.583	0.6	0.6	0.6	50	67	0.627
2	K-nearest neighbors (group-1)	0.914	0.874	0.819	0.88	0.88	0.87	7	30	0.932
3	SVM radial basis function (group-1)	0.769	0.714	0.657	0.75	0.75	0.73	14	70	0.832
4	Gaussian Naive Bayes (group-1)	0.560	0.527	0.582	0.52	0.52	0.52	77	62	0.589
5	Decision tree (group-1)	0.981	0.861	0.802	0.86	0.86	0.86	19	22	0.871
6	Random forest (group-1)	0.981	0.912	0.859	0.91	0.91	0.91	12	14	0.955
7	Logistic regression (group-2)	0.636	0.643	0.619	0.65	0.65	0.64	36	69	0.751
8	K-nearest neighbors (group-2)	0.818	0.738	0.714	0.74	0.74	0.74	34	43	0.838
9	SVM radial basis function (group-2)	0.635	0.626	0.620	0.63	0.63	0.63	40	70	0.75
10	Gaussian Naive Bayes (group-2)	0.641	0.626	0.627	0.65	0.64	0.62	30	80	0.713
11	Decision tree (group-2)	0.990	0.738	0.719	0.74	0.74	0.74	39	38	0.737
12	Random forest (group-2)	0.990	0.752	0.750	0.75	0.75	0.75	37	36	0.841
13	Logistic regression (group-1 + group-2)	0.720	0.707	0.684	0.720	0.710	0.710	28	58	0.763
14	K-nearest neighbors (group-1 + group-2)	0.945	0.918	0.834	0.920	0.920	0.920	5	19	0.965
15	SVM radial basis function (group-1 + group-2)	0.812	0.779	0.715	0.8	0.790	0.780	13	52	0.844
16	Gaussian Naive Bayes (group-1 + group-2)	0.641	0.653	0.654	0.660	0.660	0.650	34	68	0.710
17	Decision tree (group-1 + group-2)	1.000	0.891	0.812	0.890	0.890	0.890	12	20	0.893
18	Random forest (group-1 + group-2)	1.000	0.942	0.887	0.940	0.940	0.940	6	11	0.989
19	Logistic regression (group-3)	0.789	0.830	0.782	0.83	0.83	0.83	19	31	0.895
20	K-nearest neighbors (group-3)	0.956	0.956	0.848	0.95	0.96	0.96	4	9	0.987
21	SVM radial basis function (group-3)	0.819	0.874	0.805	0.87	0.87	0.87	16	21	0.936
22	Gaussian Naive Bayes (group-3)	0.713	0.759	0.768	0.76	0.76	0.76	26	45	0.826
23	Decision tree (group-3)	0.991	0.939	0.877	0.94	0.94	0.94	8	10	0.939
24	Random forest (group-3)	0.991	0.956	0.904	0.96	0.96	0.96	6	7	0.991

(continued)

Table 3 (continued)

Serial	Classifier name	Train accuracy	Val accuracy	Accuracy	Precision	Recall	*F*1 score	FP rate	FN rate	AUC score
25	Logistic regression (group-1 + group-2 + group-3)	0.820	0.864	0.856	0.87	0.87	0.86	11	29	0.916
26	K-nearest neighbors (group-1 + group-2 + group-3)	0.986	0.973	0.905	0.97	0.97	0.97	0	8	0.997
27	SVM radial basis function (group-1 + group-2 + group-3)	0.917	0.939	0.864	0.94	0.94	0.94	1	17	0.985
28	Gaussian Naive Bayes (group-1 + group-2 + group-3)	0.745	0.789	0.792	0.8	0.8	0.79	17	45	0.857
29	Decision tree (group-1 + group-2 + group-3)	1.000	0.956	0.894	0.95	0.96	0.96	4	9	0.957
30	Random forest (group-1 + group-2 + group-3)	1.000	0.983	0.965	0.98	0.98	0.98	1	4	0.998

Table 4 Prediction performance of machine learning models with top features

Serial	Classifier name	Train accuracy	Val accuracy	Accuracy	Precision	Recall	*F*1 score	FP rate	FN rate	AUC score
1	Logistic regression (top-5)	0.756	0.810	0.830	0.81	0.81	0.81	21	35	0.875
2	K-nearest neighbors (top-5)	0.941	0.932	0.871	0.93	0.93	0.93	8	12	0.984
3	SVM radial basis function (top-5)	0.790	0.816	0.830	0.82	0.82	0.82	14	40	0.88
4	Gaussian Naive Bayes (top-5)	0.758	0.806	0.819	0.81	0.81	0.81	18	39	0.865
5	Decision tree (top-5)	0.999	0.932	0.884	0.93	0.93	0.93	8	12	0.933
6	Random forest (top-5)	0.999	0.956	0.904	0.95	0.96	0.96	5	8	0.992
7	Logistic regression (top-9)	0.804	0.844	0.840	0.84	0.85	0.84	18	28	0.903
8	K-nearest neighbors (top-9)	0.974	0.969	0.923	0.97	0.97	0.97	0	9	0.993
9	SVM radial basis function (top-9)	0.874	0.881	0.826	0.89	0.89	0.88	5	30	0.954
10	Gaussian Naive Bayes (top-9)	0.752	0.793	0.812	0.8	0.8	0.79	17	44	0.854
11	Decision tree (top-9)	1.000	0.932	0.900	0.93	0.93	0.93	9	11	0.932
12	Random forest (top-9)	1.000	0.980	0.928	0.98	0.98	0.98	2	4	0.998
13	Logistic regression (top-13)	0.820	0.864	0.856	0.87	0.87	0.86	11	29	0.916
14	K-nearest neighbors (top-13)	0.986	0.973	0.905	0.97	0.97	0.97	0	8	0.997
15	SVM radial basis function (top-13)	0.917	0.939	0.864	0.94	0.94	0.94	1	17	0.985
16	Gaussian Naive Bayes (top-13)	0.745	0.789	0.792	0.8	0.8	0.79	17	45	0.857
17	Decision tree (top-13)	1.000	0.956	0.894	0.95	0.96	0.96	4	9	0.957
18	Random forest (top-13)	1.000	0.983	0.965	0.98	0.98	0.98	1	4	0.998

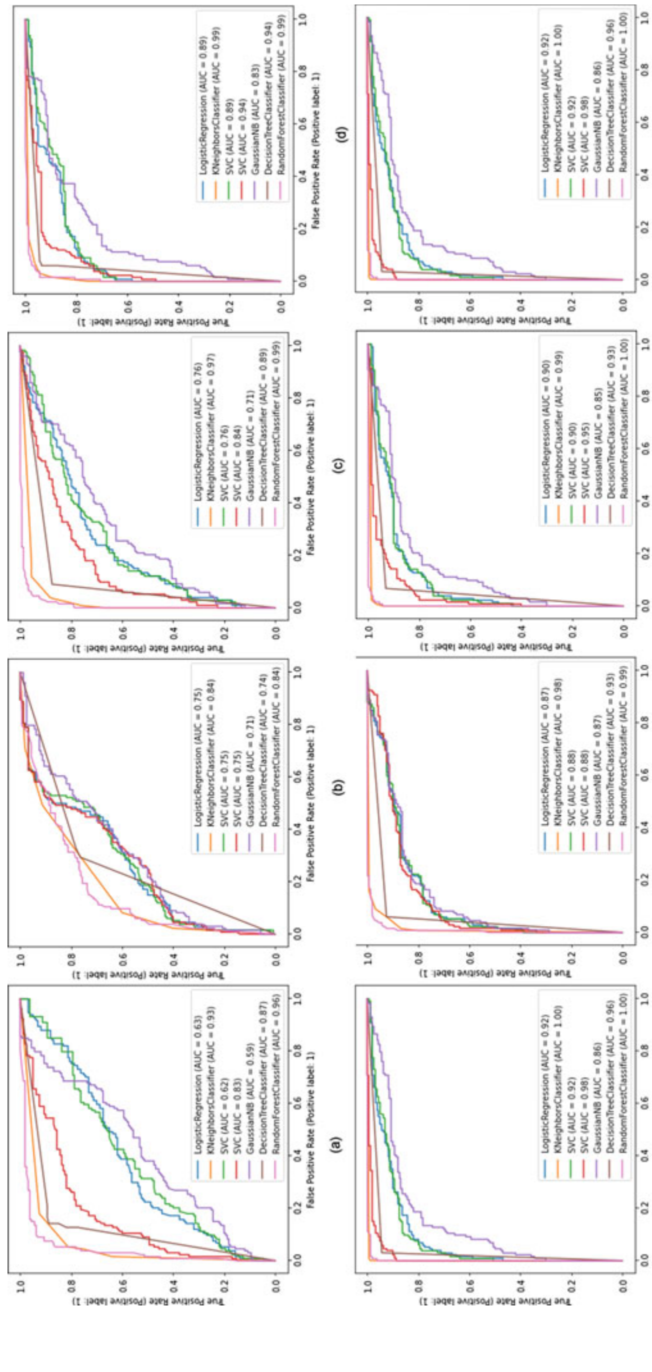

Fig. 7 Area under the curve (AUC) for different classifiers with different Groups and top features. **a** group-1, **b** group-2, **c** group-1 + group-2, **d** group-3, **e** group-1 + group-2 + group-3, **f** top-5, **g** top-9, **h** top-13

and load-shedding). The second group is about previous performance (Studied more and CGPA before). The third group is about online learning experiences (submission type, mental health, online exam, online class, and online teacher) that are the main focus. Therefore, the first and second groups serve as benchmarks in machine learning models to reveal the predictive power of the third group. Based on significant features, we also take into account top features. We also trained the model by looking at the top 5, then the top 9, and ultimately all 13 features (Table 2). We also measured the classification report of machine learning techniques with predicting student performance.

Tables 3 and 4 represents the prediction performance of machine learning models with different groups as well as top features. Based on these group and top features analyses, We will choose the random forest classifier because it performed better than a few other machine learning classifiers. We also test it using multifold cross-validation. From our random forest classification, we achieved the highest accuracy of 0.85, 0.75, 0.90, 0.88, and 0.96 with group-1, group-2, group-3, group-1 + group-2, and group-1 + group-2 + group-3 attributes to predict the Change in CGPA of a student. In random forest classification the AUC-ROC score has been 0.955, 0.841, 0.991, 0.989, 0.998 with group-1, group-2, group-3, group-1 + group-2 and group-1 + group-2 + group-3 attributes and also compared to others algorithm (Fig. 7).

5 Conclusions

This study aimed to predict the student's academic performance during the Covid-19 pandemic. In this research, we applied machine learning classifiers to predict the fluctuation of CGPA using several attributes such as living area, family, devices, Internet type, Internet stability, load-shedding, studied more, CGPA before, submission type, mental health, online class, online exam, and online teacher. In addition, we compared the performance of the proposed Random Forest Classifiers with the state-of-the-art classifiers such as Logistic Regression (LR), K-Nearest Neighbor, Support Vector Machine (SVM), Gaussian Naive Bayes (GNB), Decision Tree (DT). We found that the Random Forest classifiers performed well in this case and examined how a random forest classifier performs better than the other algorithms.

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