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Evaluating the impact of COVID-19 on Educational system: Challenges, Modifications, and Future Directives

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Abstract: The World Health Organization proclaimed the COVID-19 pandemic in December 2019, and it has severely disrupted many industries globally, including education. In this study, it is shown that how the outbreak of COVID-19 had affected education system along with the others areas of life. Indefinite holidays molded the system into a new form that was new or unacceptable to the majority. Especially, how the technical difficulties encountered in online classes affected the students and teachers. In this research, we utilized six supervised machine learning techniques to forecast the impact on the annual system of education by using qualitative data obtained from a sample of 1280 in Punjab, rural and urban areas. The Random Forest algorithm had the maximum accuracy and execution time efficiency both in the presence and absence of Principal Component Analysis (PCA). This study also identified the association between educational disruption and other categorical factors such as course completion, delivery mode, technology use, and disparities.

Keywords: Chi Square; COVID-19; Decision Tree; K-Nearest Neighbour; Logistic Regression; Naïve Bayes; Principal Component Analysis; Random Forest; Support Vector Machine.

1. Introduction

In December 2019, the World Health Organization declared the COVID-19 coronavirus to be a globally health threat. The virus was initially discovered in China and [1, 2] then rapidly spread over the world, having detrimental effect on several cities in Asia, Europe, and America. The Chinese city of Wuhan is where the coronavirus pandemic started, but it has already spread to other parts of the world. Infection cases are still increasing at an exponential rate. As a result, employees start working from home, students start studying at home, conferences were postponed, store shelves were ruined, and the world economy was seriously threatened. There is no denying that coronavirus infection has permanently affected education. Since the virus's creation, practically every nation has enforced severe lockdowns in its major towns and other urban areas in an effort to prevent large crowds of people from congregating and lessen the virus's effect. More than 34 hundred million, or forty three percent of the world's population, have already been placed under lockdown. While this has helped individuals preserve social distance, it has also had a long-term detrimental effect on it. UNESCO recommends that nearly almost all colleges, universities and schools remain closed during third week of March. [3] Bhutan was first country in Asia to shorten business hours and close schools in the first week of March. The regular, partial or complete closure of institutes along with significant disruptions to both academic and extracurricular activity, plagued the whole education system. Academic and non-academic activities were closed even though the lockdown was implemented and maintained to stop the virus's spread.

Due to COVID-19, the most immediate and widespread impact was the closure of institutes to avoid the spread of virus. This decision creates the difficulties for both students and teachers. Due to closure of institutes student's academic was disturb almost in all the institutes. This disrupted traditional learning environments had led to the adoption of remote and online learning. Multiple circulars from Indian Ministry of Human Resource development have been produced, stating that exams and coursework cannot be resumed during the COVID-19 pandemic. They were also offered a very helpful recommendation regarding the implementation of online courses for all students, similar to those offered by their institution. Educational institutions rapidly shifted to virtual learning relying on videos, conferencing, online platforms, and digital resources. For both instructors and students, these signals start of a new chapter in education. This shift brought to light disparities in students' access to technology and the internet, which have an impact on their capacity to engage fairly in distance learning. COVID-19, exacerbated existing educational inequalities. Students from lower income families often faced challenges accessing necessary technology and a conducive learning environment, leading to potential learning loss.

Due to lack of on campus classes and opportunities for social interaction with peers and teachers, students' motivation declined. Some students struggled to stay in the center, had limited room, and had limited access to resources, as a result their living conditions weren't ideal for studying. The lack of physical resources and closing of libraries made it difficult for students to focus on the subject matter. Some students struggled to use their computerized learning skills, which made using online resources impossible for them. Numerous extracurricular activities and gathering were discontinued, depriving students of important opportunities for social interaction and personal growth.

In the previous study, Authors used different statistical tools for predict the effect of the online classes during COVID-19 on Education. But in this research, we are discussing the impact of COVID-19 on annual system of education. In previous study, authors just used basic variables like class, internet, online classes. But in this study, our main factor is Education loss or course. We will predict this issue by using machine learning algorithms. By using machine-learning algorithms, we will check the accuracy or time of algorithms with or without PCA.

2. Literature Review

Due to COVID-19, the most immediate and widespread impact was the closing of institutes to prevent the spread of virus. Different authors used different statistical and machine learning tools for evaluate the impact of COVID-19 on semester system of education students or predict the result of students in upcoming semester. But in this study, we are using the different classifier to evaluate the impact of COVID-19 on education.

[4] Due to closures of school in COVID-19, children stay at home for long duration which may increasing the parenting stress. [5] Moreover students mental wellness outbreak during the COVID-19. Physical classes shift into online classes, which change the psychological health of the students. During COVID-19, students' anxiety, depression rate increases. Due to closures of institutes students' diseases like anxiety 42.5%, 72.4% depression and 63.3% suicidal thoughts cases increases.[6] Moreover, lockdown and quarantine had also negative effect on the university students. Although, the immediate effects appear obvious, there were uncertainty about the long-term effects, and although the number of suicide thoughts has significantly increased, it was doubtful that this will lead to fatalities. [7] During epidemic, graduate and post graduate students also faced different problems related to anxiety sadness, poor internet connection, and opposed learning environment at home. During the pandemic, student from marginalized and distant places mostly confront significant obstacles in their academic pursuits. [8] Consequently, countries devise strategies for utilizing educational technology, including digital learning tools, free internet access, and live instruction. During closings, educational institutions develop curricula and post-

coronavirus teaching and learning strategies. When schools reopen, they make plans to welcome back students and make up for lost instruction. [9] Many of the schools shifted into online classes during the pandemic situation. This study primary goal was to assess the mental health of students who transitioned from traditional classroom instruction to online learning. [10] Furthermore, in the course of COVID-19, cell learning has become an essential platform in lots of instructional establishments. Using gadget studying strategies to forecast humans' propensity to apply cellular studying packages on epidemic days. [11] Mobile learning application play a crucial rule during the pandemic. Number of students were limited to accept the effectiveness of mobile learning application. [12] The cross section employed in this study to assess students' psychological effects following school reopening was utilized by the author. This cross-sectional observe aimed to assess the psychological effects of COVID-19 following the reopening of faculties and look into, via device studying, the factors influencing the kid's feelings of fear and despair. [13] Forecasting is one of the important statistical tools for predicting the outcomes. One of the most effective statistical techniques used worldwide in a variety of fields for identifying and evaluating patterns as well as projecting future results on which prompt and mitigating actions may be made is forecasting. To that purpose, a variety of machine learning and statistical approaches have been used, depending on the needed analysis and the data's accessibility. [14] COVID-19, several impact on those peoples which have weak immunes system. During COVID-19 most of those people has affected which are daily wage worker. In this paper different machine learning tools are used for evaluating the effect of COVID-19 on daily wageworker. [15] In order to lessen network congestion, multicast routing can be used to enable the idea of creating student communities within the edge network through the application of machine learning clustering methods, as presented in this study.

In this era, coding system become more popular to find the accurate result other than statistical system. [16, 20] Machine learning technique has opened the new venture in many areas by assembling nearly accurate estimates with precise forecasts. [21, 24] The machine learning systems have evolved to be capable of doing sophisticated algorithm-based data analysis on extracted data. In the context of education, machine learning has proven useful in assessing an institutions success. It has aided in selecting the finest products and testing, responding, making predictions and the results of various teaching techniques were evaluated.[25] in this research, author used both supervised and unsupervised machine learning techniques to evaluate the coronavirus diseases and the accuracy of machine learning algorithms were 92.9% and unsupervised machine learning accuracy were 7.1%.

[26] In this paper, researcher used statistical approaches like chi-square, analysis of variance, t-test and also used supervised machine learning algorithms to identifying the psychological impact of COVID-19 on students' academic performance. The accuracy of all algorithms is 100% except Random Forest and Ad boost. The value of chi square 0.70 and p-value is 9.51 which shows the use of technology for online education has no significance difference. [27] The researcher used the ML techniques for predicting mental stress of young student. In this research article, Support Vector Machine has 85% accuracy which is high as compare to other supervised Machine Learning algorithms. The specificity or sensitivity is 98% or 75% which is also high as compare to other supervised machine learning algorithms. [28] The researcher used different five supervised ML techniques for decision making at higher educational institutes. The accuracy of random forest machine learning algorithms is 99.29% which is high as compare to other like Decision Tree, SVM, and Naïve bayes. [29] In this paper, researcher used all the supervised ML classifiers to check the effect of COVID-19 on School closer. Decision tree accuracy were 90.75%, which was high accuracy as compare to other machine learning algorithms.

3. Methodology

3.1. Dataset

In this research, we have used qualitative data which was collected from different areas of colleges in rural or urban areas of Punjab in Sahiwal and Rawalpindi. We had collected total 1280 dataset from questionnaire.

3.2. Data Processing

Data pretreatment was done in phases in order to run Machine Learning algorithms efficiently. A non-numerical dataset has been imported once the required libraries have been imported.

3.3. Classifiers

We have used six distinct supervised Machine Learning classifier to check the effect of COVID-19 on annual system of Education**.**

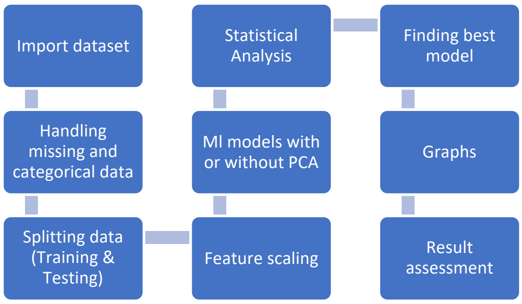

Figure 1. Data Processing

3.3.1. Decision Tree

The family of supervised learning algorithms includes decision tree as well. Decision trees are typically used for classifications, but they can also be utilized to tackle regression and classification problems [30-31].

3.3.2. Naïve Bayes

The Naïve Bayes model is a probabilistic graphical representation of information pertaining to random variables. Predicting class membership probabilities, the Naïve Bayes classifier is a statistical supervised machine learning system. [32] [40] Naïve Bayes applies to big dataset with a high speed and precision. Naïve Bayes is also called Gaussian distribution.

3.3.3. Random Forest

Similar to the Decision tree, Random Forest also generate tress. The ultimate output of the Random Forest classification technique combines the outcome classes of individual decision trees, based on ensemble learning [33] [41].

3.3.4. Support Vector Machine (SVM)

Supervised device gaining knowledge of methods make up Support Vector Machines. Although SVM is particular used for class, it could additionally be used for regression. Using a K-dimensional area wherein K is the overall wide variety of features and the fee of each function factor at a given coordinate, the Support Vector Machine technique affords information as factors [34] [39].

3.3.5. K-Nearest Neighbors (KNN)

In addition to being the most popular and straightforward classification technique, the KNN algorithm is also the simplest. The multiclass label classification problem has been validated using the KNN method, which also exhibits strong generalization capabilities. Every example that is available is stored by the algorithm, which then uses similarly metrics to categories fresh cases [35] [42].

3.3.6. Logistic Regression

The supervised machine learning technique known as logistic regression was created especially for classification applications. To ascertain the parameters of interest the maximum likelihood estimation approach is utilized.

3.3.7. F1 Score

When there is an imbalance in the distribution of classes, a classification model performance is evaluated using a statistic known as the F1 score. Being the harmonic mean of recall and precision, it offers a balance between the two.

3.3.8. Principal of Component Analysis (PCA)

One of the most basic methods for reducing dimensionality and extracting useful characteristics from high dimensional input data vectors is PCA. It is based on a mathematical concept that includes standard deviation, variance, covariance, covariance matrix, eigenvectors, and eigenvalues. In this section, our total 139 number of features we will see the practical application of dimensionality reduction of education dataset consisting on 80 features for making the classification problem more efficiently [36] [38].

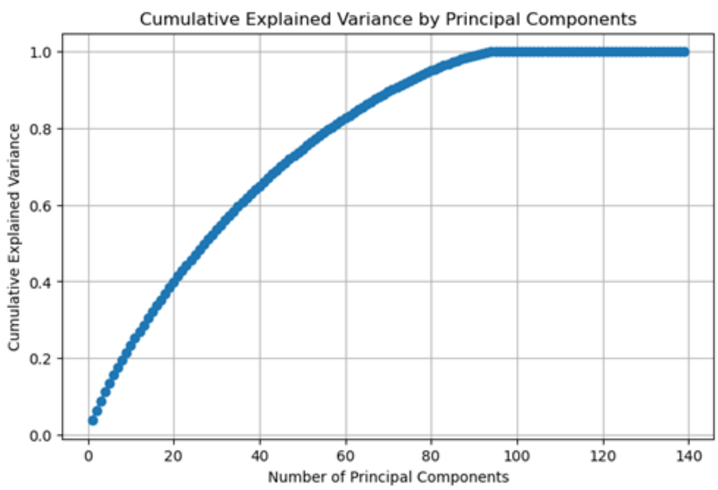

Figure 2. Principal Component Analysis

<u>Algorithms</u>

- PCA normalize the data if the dataset has different approaches and each feature have different scales.
- Calculate the mean from each dimension and deduct it from each value.
- Calculate the co variance matrix of the dataset.
- Calculate the eigen values and eigen vectors from covariance matrix.
- To calculate the PCA select the top K eigen vectors that correspond to the largest eigen values.

4. Results & Discussion

4.1. Comparison of Accuracy, Area Under Curve (AUC), & F1 Score

The Table 1 show the Accuracy and F1 score of six machine learning algorithms which are used on a dataset. The random forest is overall high Accuracy 75% with PCA and also high 77% without PCA. Naïve Bayes Accuracy is lowest 28% without PCA and on the other hand Niva Bayes Accuracy 68% percent with PCA. Logistic Regression and SVM maintained their performance in both cases. On the other hand, Decision tree has largest 0.47 F1 Score without PCA and also largest 0.38 F1 score with PCA. Figure 3 also show the accuracy performance of six machine learning classifiers graphically. In figure 1, two bars show on each classifier, one is blue and other is brown. In figure 3 Blue bar show Accuracy without PCA and Brown bar show Accuracy with PCA.

Table 2 or Figure 4 show the comparison of classifier AUC with or without PCA. SVM and Random Forest has the maximum 66% AUC score without PCA and KNN or SVM has the maximum 65% AUC score with PCA. Naïve Bayes has smallest AUC score in both with or without PCA cases.

Table 1. Represents the accuracy and F1 score of classifiers with or without PCA

Classifier Types	Measures			
	Accuracy (%) Without PCA	Accuracy (%) With PCA	F1 Sore Without PCA	F1 Score With PCA
Decision Tree	68	65	0.47	0.38
Logistic Regression	70	70	0.24	0.19
SVM	75	75	0.22	0.22
Naïve Bayes	28	68	0.44	0.30
KNN	72	71	0.34	0.29
Random Forest	77	75	0.29	0.18

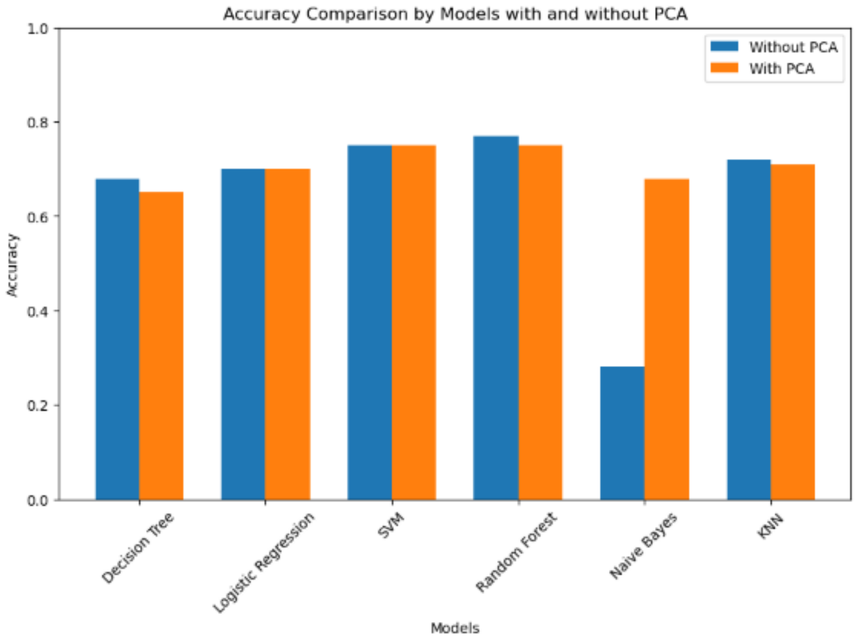

Figure 3. Comparison of Classification Accuracy with and without PCA

Table 2. Represent the area under ROC curve with or without PCA

Classifier Types	Measures	
	AUC Score Without PCA	AUC Score with PCA
Decision Tree	0.63	0.57
Logistic Regression	0.58	0.57
SVM	0.66	0.65
Naïve Bayes	0.55	0.54
KNN	0.64	0.65
Random Forest	0.66	0.64

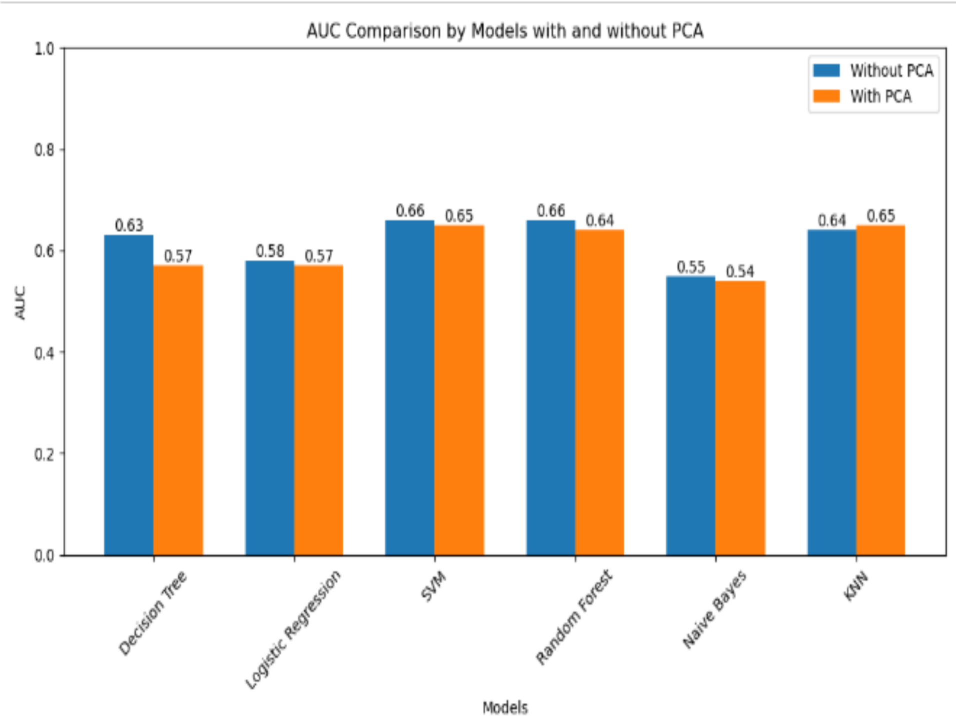

Figure 4. Comparison of Classification AUC with and without PCA

4.2. Execution of Time

Table 3 or Figure 5 shows the execution time of the classifiers with or without PCA. By using PCA, the computation time has decreased for all the classifiers. This is to be expected because PCA makes the data less dimensional which speeds up computations. The Random Forest is the exception in this case, as PCA significantly decrease computation time as compare to other classifiers. When PCA is applied, Decision Tree and Logistic Regression reduce the execution time is lowered 50% roughly. This suggest that these models benefit from the smaller feature space which expedites the training process even though they are not very sophisticated. As a result, the execution time drops by almost 173%, demonstrating how sensitive SVM are to feature density. During training, faster convergence is the result of the reduced dimensionality. Random Forest shows the biggest gain with an approximately 1258% reduction in execution time. In this research, the key aspects are execution time of different machine learning classifier with or without PCA. To formalize this, we can represent the execution time of classifier mathematically.

PCA dimensionality *reduction*

$$\text{PCA}_{compexity} = \text{O}\left(nd^2 + d^3\right) \tag{1}$$

Classifier execution time

$$\text{T}_{without\ \text{PCA}} = f\left(n,d\right) \tag{2}$$

$$\text{T}_{with\ \text{PCA}} = \text{O}\left(nd^2 + d^3\right) + g\left(n,k\right) \tag{3}$$

Where

$\text{T}_{with\ \text{PCA}}$ = Execution time of classifier with PCA

$\text{T}_{without\ \text{PCA}}$ = Execution time of classifier without PCA

n = No of samples

d = No of features

k = Reduced no of features after applying PCA ($k < d$)

4.3. Statistical Analysis

[37] The Chi Square test is used in this study to examine the relationship between the categorical variables (Age, Internet, deliver mode, Experience, seven days, educational disparities, Course completed, lecture satisfactory, continue online, Challenges faced, Impact std performance, Remote learning necessary, Edu quality, Technology importance, Disrupt Edu materials) with p-value=0.05 for testing and 95% confidence interval.

Table 3. The Time of classifiers with or without PCA

Classifier Types	**Measures**		
	Execution Time	**Execution Time**	**Percentage Difference**
	Without PCA Per second	with PCA Per second	
Decision Tree	0.0385	0.0192	-50.15
Logistic Regression	0.0385	0.0192	-50.05
SVM	0.1055	0.0385	-173.74
Naïve Bayes	0.0385	0.0000	-100.00
KNN	0.0385	0.0217	-43.70
Random Forest	0.5235	0.0385	-1258.46

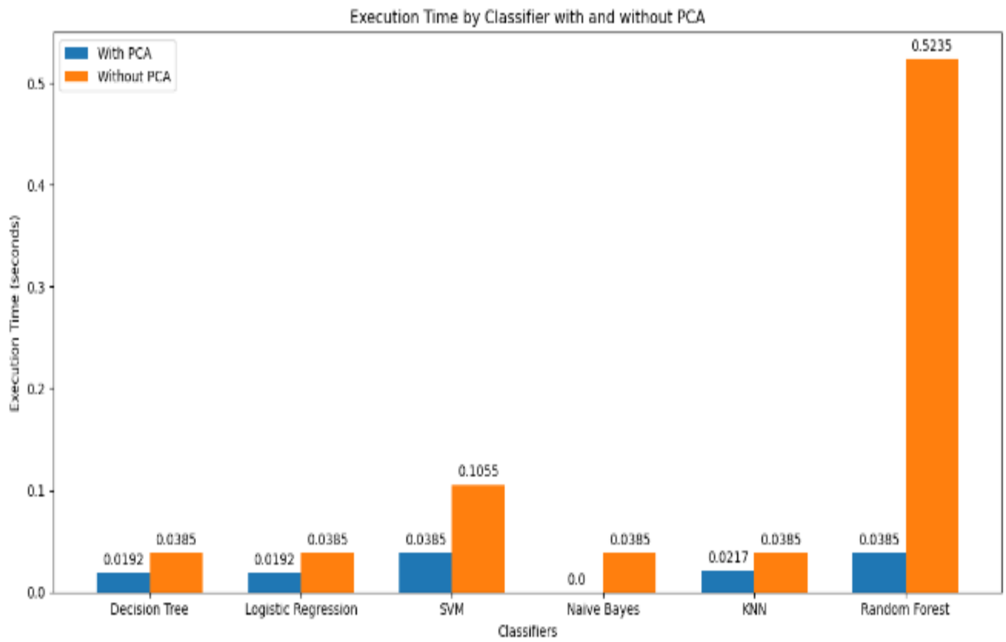

Figure 5. The execution time of classifiers with or without PCA

First independent variable Gender and value of $\chi^2 = 0.88$ and the value of $p = 0.3474$ which is greater than 0.05 so the null hypothesis is accepted. Its mean there is no association between Gender and Disrupted Education. Internet with $\chi^2 = 0.72$ and the value of $p = 0.39$ which is larger than 0.05 so the null hypothesis is true and show that there is no association between internet and Disrupted Education. Delivery mode with $\chi^2 = 2.94$ and value of $p = 0.02$ which is less 0.05 so null hypothesis rejected. Its mean there is association between Disrupted Education and Delivery mode.

Experience with χ^2 = 0.06 and value of p = 0.96 which support the acceptance of null hypothesis because value of p is larger than 0.05. Its mean there is no significant association between students experience and disrupted education. Online quality with χ^2 = 2.65 and the value of p = 0.44 which support the acceptance of null hypothesis because p is larger than 0.05. Technology with χ^2 = 2.83 and value of p = 0.03 which is smallest than 0.05 so null hypothesis false. This result shows a significant association between Technology and Education disrupted. Seven days with χ^2 = 0.16 and value of p = 0.68 which support the acceptance of null hypothesis because value of p larger than 0.05. Educational disparities with χ^2 = 7.72 and value of p = 0.005. The result of p value shows the rejection of null hypothesis because p value is smallest than 0.05. Its mean educational disparities have impact on students Education. Course completed with χ^2 = 5.61 and value of p = 0.02 which is smallest than 0.05 so null hypothesis false. This result show that course completion has strong association with education disruption. Lecture satisfactory with χ^2 = 0.48 and value of p = 0.48. The result of p shows the acceptance of null hypothesis because p value larger than 0.05. Continue online with χ^2 = 0.00 and value of p = 1.00. The value of p is larger than 0.05 so null hypothesis is accepted. Challenges faced with χ^2 = 3.66 and value of p = 0.30. The result pf p value shows the acceptance of null hypothesis because p value is larger than 0.05. Impact std performance with χ^2 = 1.46 and value of p = 0.48 which shows the acceptance of null hypothesis because value of p is larger than 0.05. Remote learning with χ^2 = 0.78 and value of p = 0.85. The result of p values is larger than 0.05 so null hypothesis is accepted. Edu quality with χ^2 = 0.51 and value of p = 0.92. The result of p value also indicates the acceptance of null hypothesis because p value is larger than 0.05. Technology importance with χ^2 = 0.67 and value of p = 0.88 which support the acceptance of null hypothesis because value of p is larger than 0.05. Disrupt Edu materials with χ^2 = 3.03 and value of p = 0.55 shows the acceptance of null hypothesis.

The findings suggest a substantial correlation between the COVID-19 impact on education and a number of variables including course completion, delivery style, the impact of technology, and educational inequities. This suggest that adjustment to these factors probably had an impact on the way that instruction was provided and received during the pandemic. However, other variables such as experience, gender, and internet availability did not exhibit significant relationships indicating that these factors were not as important in determining how COVID-19 affected schooling.

Table 4. Association between the variables

Variables	χ^2	P-value	Significant
Gender	0.88	0.34747	Accept
Internet	0.7182	0.3967	Accept
Deliver mode	9.47	0.0236	Reject
Experience	0.06	0.96	Accept
Online quality	2.65	0.44	Accept
Technology impact	8.37	0.04	Reject
Seven days	0.16	0.68	Accept
Educational disparities	7.72	0.005	Reject
Course completed	5.61	0.02	Reject
Lecture satisfactory	0.48	0.48	Accept
Continue online	0.0	1.0	Accept
Challenges faced	3.66	0.31	Accept

Impact std performance	1.46	0.48	Accept
Remote learning necessary	0.78	0.85	Accept
Edu quality	0.52	0.92	Accept
Technology importance	0.67	0.88	Accept
Disrupt Edu materials	3.02	0.55	Accept

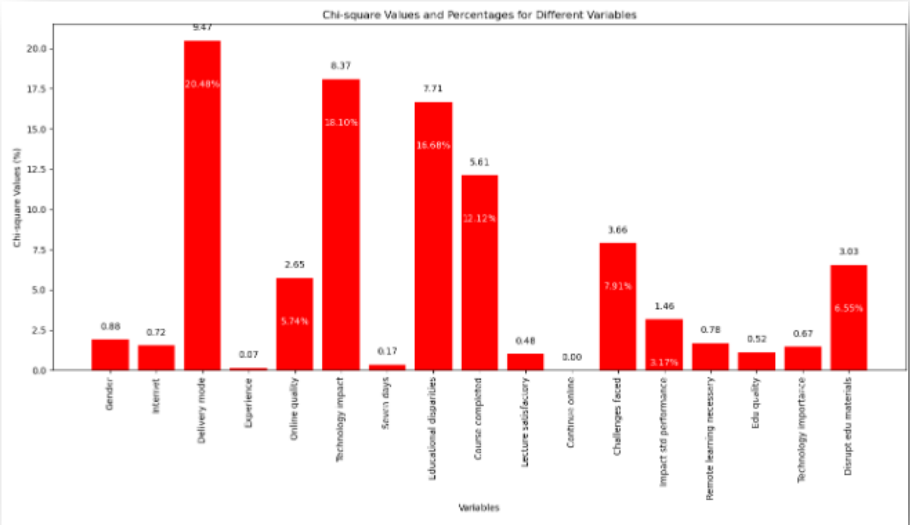

Figure 6. Association independents & dependent variable

5. Conclusion

In this research, we have used supervised machine learning techniques to exploring the impact of COVID-19 on education. In this research, we have used six supervised machine learning classifiers to check the accuracy or execution time of the classifier with or without PCA. Using PCA to reducing dimensionality, high dimensional data can be reduced to yield more useful feature which reduce the execution time of classifiers and raising its accuracy. Random Forest with or without PCA accuracy or execution time of the classifiers is high as compare to other classifiers and this research also show that delivery mode, Technology impact, educational disparities, course completed are associated with students disrupted education.

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