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Prediction of Student Adaptability Level in e-Learning using Machine and Deep Learning Techniques

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***Abstract**: E-learning is an educational model in which the lectures can be taught at the same time using technical material without time and space barriers. E-learning has gained its popularity during the Covid-19 pandemic era and has been applied as a valid educational model in all educational levels. Due to the sudden pandemic measures, e-learning has brought about a lot of technical problems at unprepared educational institutions against the pandemic. It is important for the decision makers of educational institutions to get feedback about the effectiveness of e-learning so that they can take further steps to make it more beneficial for the students. In this paper, a dataset was collected from Kaggle depository for the adaptability level in e-Learning. In order to find how effective e-learning, a group of machine and deep learning algorithms were applied to predict the adaptability level of the students to e-learning. The best machine-learning algorithm was Decision Tree Classifier with Accuracy (92.00%), Precision (92.00%), Recall (92.00%), F1-score (92.00%); however, the proposed deep learning algorithm achieved Accuracy (94.67%), Precision (94.80%), Recall (94.70%), F1-score (94.61%).*

Keywords: e-learning, Education, Deep Learning, Machine Learning, Prediction, Adaptability Level

Introduction

Machine learning is a subset of artificial intelligence (AI) [1-15]. It is focused on teaching computers to learn from data and to improve with experience – instead of being explicitly programmed to do so [16-20]. In machine learning, algorithms are trained to find patterns and correlations in large data sets and to make the best decisions and predictions based on that analysis [21-25]. Machine learning applications improve with use and become more accurate the more data they have access to [26-30]. Applications of machine learning are all around us –in our homes, our shopping carts, our entertainment media, and our healthcare [31-35].

Deep learning networks are neural networks with many layers [36-40]. The layered network can process extensive amounts of data and determine the "weight" of each link in the network; for example, in an image recognition system, some layers of the neural network might detect individual features of a face, like eyes, nose, or mouth, while another layer would be able to tell whether those features appear in a way that indicates a face [41-45]. Like neural networks, deep learning is modeled on the way the human brain works and powers many machine learning uses, like autonomous vehicles, chatbots, and medical diagnostics [46-50]. The more layers one have, the more potential one have for doing complex things well [51-55]. Deep learning requires a great deal of computing power [56-60], which raises concerns about its economic and environmental sustainability [61-65].

E-learning is widely applied due to the Covid-19 worldwide pandemic these days [66]. Due to the international pandemic measures, many educational institutions had to compulsorily pass to e-learning [67]. E-learning has gained more attention after the Covid-19 pandemic situation all over the world and it has been implemented as a legal educational model in all educational institutions [68]. Overall educational institutions have been affected by the pandemic situation and cancelled all the face-to-face classes. While e-learning offers a non-physical learning environment to more students, the students have to come together in a narrow learning environment such as a classroom in face-to-face education [69]. In this worldwide crisis, UNESCO has recommended e-learning and online learning platforms for student-instructor communication away from a pandemic danger at closed schools due to the worldwide pandemic [70]. It is claimed that an explicit-hybrid learning model will become long-lasting in life due to the education requirements after the Covid-19 era [71]. It was also defended that the problems such as future infectious diseases, war, regional conflicts, and other types of natural disasters can restrict real-time education again [72].

Many educational institutions have started e-learning in order not to interrupt education. The e-learning environments have been quickly arranged for the continuity of education by the educational institutions. All institutions have started to research quality of virtual learning environments in terms of hardware and software due to the Covid-19 pandemic concern. According to [73], e-learning environments are web-based platforms that provide management and teaching the courses in online learning. These platforms provide interactive learning facilities by their online features such as blackboards, surveys, chat rooms, online exams, home works, and discussion forums. During the pandemic era, the most widely used online learning environments in different countries are Zoom, Microsoft Teams, Google Meet, Skype, Adobe Connect, and similar others [74]. While the e-learning platforms have been used by instructors that teach different science branches, these instructors have to also learn and use technical materials that they have not practiced before [75]. Due to the unexpected pandemic measures, the online educational model has brought about a lot of problems at educational institutions that were not ready against the pandemic [76]. According to [77], many instructors had to lecture in less time at online education due to technical problems such as insufficient bandwidth and file upload limits. Moreover, according to [78], the assessment and evaluation are other important online education problems at online exams. As it is specified in the literature, technical problems of online education should be solved for quality interactive learning.

The aim of the study is to determine the factors that can play a significant role to ensure the smooth execution of the online education. So, predicting the student's adaptability level based on these factors helps the decision-makers in taking the necessary steps to alleviate the issues.

We used a group of machine learning algorithms: Gaussian Mixture, Perceptron, Nu SVC, Nearest Centroid, Multinomial NB, Logistic Regression CV, Linear SVC, Linear Discriminant Analysis, Label Propagation, Extra Tree Classifier, SGD Classifier, Calibrated Classifier CV, Quadratic Discriminant Analysis, SVC, Gaussian NB, Random Forest Classifier, Complement NB, MLP Classifier, Bernoulli NB, Bagging Classifier, LGBM Classifier, Ada Boost Classifier, KNeighbors Classifier, Logistic Regression, Gradient Boosting Classifier, Decision Tree Classifier to predict the student's adaptability level in e-learning. Furthermore, a deep learning model was proposed to predict the student's adaptability level in e-learning.

Literature Review

E-learning is an educational model that gets more members for its courses. All members can participate in the courses from different locations due to online learning environments. Owing to the global pandemic, most students have to attend courses via online platforms in recent years. Although e-learning has a lot of advantages for learning, it has also a lot of disadvantages such as technical infrastructure, momentary synchronization, exam problem, and the inadequacy of experiments in technical sciences.

Many researches have wrote about online education, particularly during the pandemic era and last decades, with structured research methods such as surveys, one-on-one meetings, and social experiments. The online education problems were categorized and defined by making a literature review in another study that was performed in 2011 on teachers and students in different locations [81]. The researcher in [82] has performed a comparative study by analyzing undergraduate students who took courses and studied in the computer science department with the distance education and full-time education model in the last two decades.

In [83, 84] the researchers have studied enhancement of the e-learning education model. The study in [83] showed an outstanding difference concerning students' performances, satisfaction and firmed many benefits of e-learning education for students. It exhibited similar performances and it showed similar offers and student satisfaction both off-campus and on-campus. The study in [84] was dedicated on formative assessment for enhanced learning and the exploratory results showed 85% of students replied they learn more in online education. Essentially the researchers tried to enhance the assessment system for students and instructors, also self and peer assessment for students and instructors.

Researchers in [85] used a Supervised Machine Learning algorithm to identify the existence of satisfactory practices, they focused on feedback that they collected from the Learning Management System (LMS) courses. Researchs in [84] studied the improvement of the e-learning education model with the integration of Machine Learning and Data Analysis in LMS. Researchers in [86] concentrated on academic performance of students by applying Machine Learning. That paper presented the results and evolution of the project which aimed to prepare and measure the performance of some Machine Learning algorithms for the analysis purposes and prediction of the academic performance of student in the course. Researchers in [87] studied that education is moving on online and course content available on digital platforms. So their analysis was based on Neural Networks, Support Vector Machine (SVM), Decision Tree, and Cluster Analysis. Their prediction accuracy of Blended Learning was not satisfactory. The exploratory results showed Online education is better than blended education.

Researches in [88] studied how much machine learning is effective in education. The aim of that paper was to assess the potential of applying machine learning in the education sector. They identified four main categories:

1- Grading students: Machine learning is able to grade students by detaching human biases. They tried to improve the assessment of problem-solving in education.
2- Improving student retention.
3- predicting student performance and t
4- Testing students.

Researches in [89] studied selecting student features to predict student pass rates in e-learning education. That paper tried to predict student pass rates and tried to discover the most effective machine learning algorithm to find out more important student features affecting learning. They used three algorithms DT, SVM, DNN to construct a feature model.

Researches in [90] studied that the dropout rate is a serious problem in online education or E-learning courses. They tried to predict a workable solution to stop dropout students.

In [91], the researchers have studied COVID-19 in concern with the global education systems. For Corona disease, approximately 100 countries closed their schools. They showed in the study that the effects of coronavirus on education was very horrible and they found many obstacles that obstruct students and instructors' interaction in e-learning education in order to continue learning during COVID-19 era. Also, they found rural areas have technological barriers, individual barriers, domestic barriers, institutional barrier, communication barrier, poor electricity, have network issues, lack of proper training, absence of finance, resistance to change, etc. are the extensive barriers for e-learning education during the COVID-19 pandemic.

Therefore, in our study, we tried to find out the student's adaptability to e-learning education during this pandemic situation.

METHODOLOGY

This section we will present the methodology of our study which includes Data Collection, Data Preprocessing, Description of Models used for prediction and analysis.

A. Data Collection

Dataset used in this study was collected from Kaggle depository [92]. It has 1205 records as a result of a survey (from December 10, 2020, to February 5, 2021) of students enrolled in university, colleges, and schools. The dataset has 14 features:
Gender, Age, Education Level, Institution Type, IT Student, Location, Load-shedding, Financial Condition, Internet Type, Network Type, Class Duration, Self LMS, Device, and Adaptively Level. A brief description of the dataset features can be found in Table 1.

Table 1: Dataset Description

Features	Feature Type	Possible Values
Gender type	Input	Girl(0), Boy (1)
Age range of the student	Input	Around 1 to 5 (0), 6 to10 (1), 11 to 15 (2),16 to 20 (3), 21 to 25 (4), 26 to 30 (5), 30+(6)
Education institution level	Input	School (0), College (1), University (2)
Education institution type	Input	Non-Government Ins (0), Government Ins (1)
Studying as IT student	Input	No (0), Yes (1)
Is student location in town	Input	No (0), Yes (1)
Level of load shedding	Input	Low (0), High (1)
Financial condition of family	Input	Poor (0), Mid (1), Rich (2)
Internet type used mostly in device	Input	2G (0), 3G (1), 4G (2)
Device used mostly in class	Input	Tab (0), Mobile (1), Computer (2)
Network connectivity type	Input	Mobile Data (0), Wi-Fi (1)
Daily class duration	Input	0 (0), 1 to 3 Hours (1), 3 to 6 Hours (2)
Institution's own LMS availability	Input	No (0), Yes (1)
Adaptability level of the student	Output	Low (0), Moderate (1), High (2)

B. Data Analysis

1. How gender impacts e-learning education?

   Even though in negligible quantities, **Male** students tend to show higher adaptability to e-learning education in comparison to **Females** as can be seen in Figure 1.

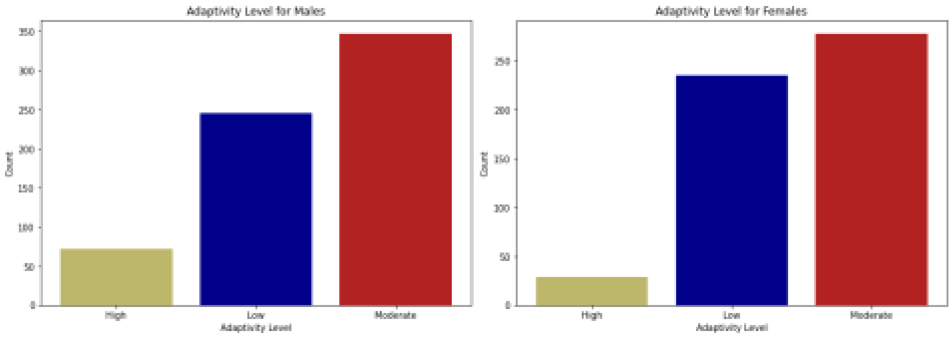

Figure 1: Gender adaptability level to e-learning education

2. How Age Group impacts e-learning Education?

The majority of the surveyed students has Moderate adaptability showing moderate effectiveness of the e-learning education. Age groups 6-10, 16-20 and 26-30 showed large Low adaptability as well. The former age group belongs to instructor led Schools or Colleges while the latter mostly belongs to higher education as show in Figure 2.

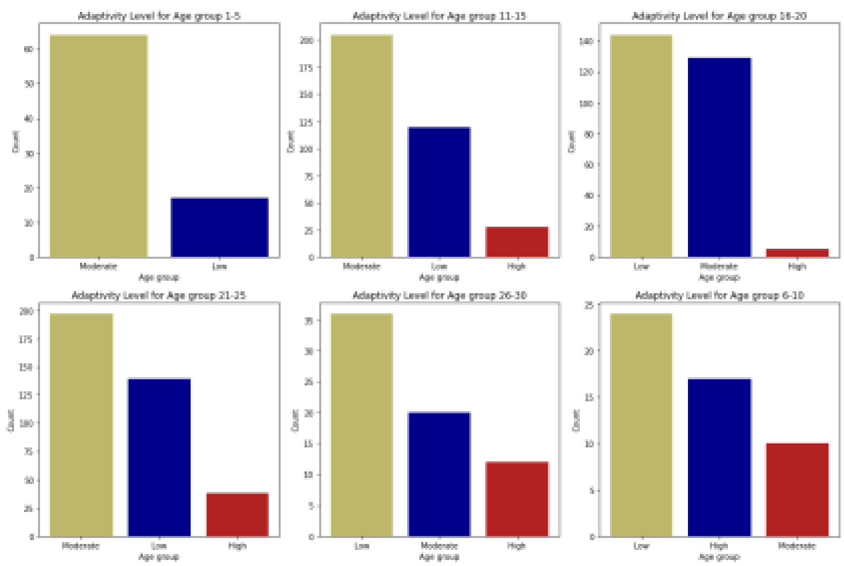

Figure 2: Age Group impacts on adaptability level to e-learning education

3. How Education Level impacts e-learning education?

From Figure 3, **Colleges** and **Universities** showed larger population with **Low** adaptability in comparison with Schools.

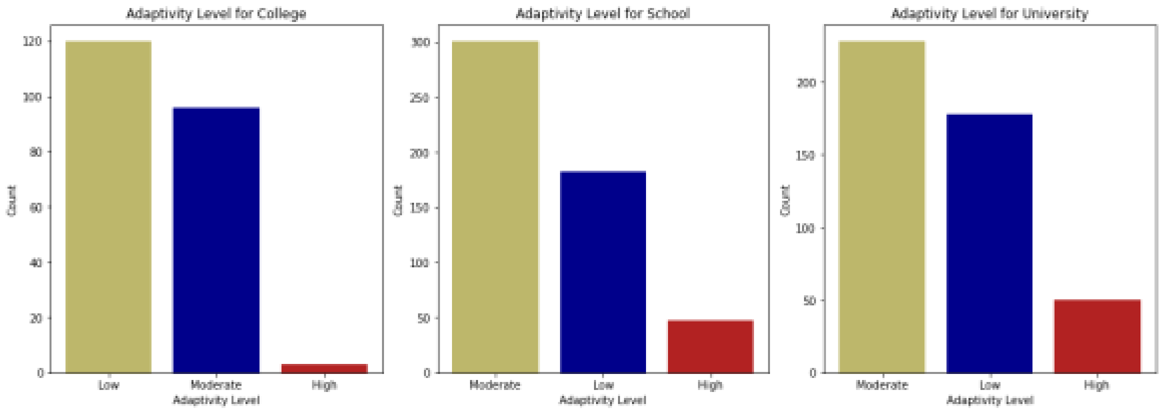

Figure 3: Education Level impacts on adaptability level to e-learning education

4. How Institution Type impacts e-learning education?

Government institutions showed a **Lower** adaptability in comparison with **Non-Government** institutions as in Figure 4.

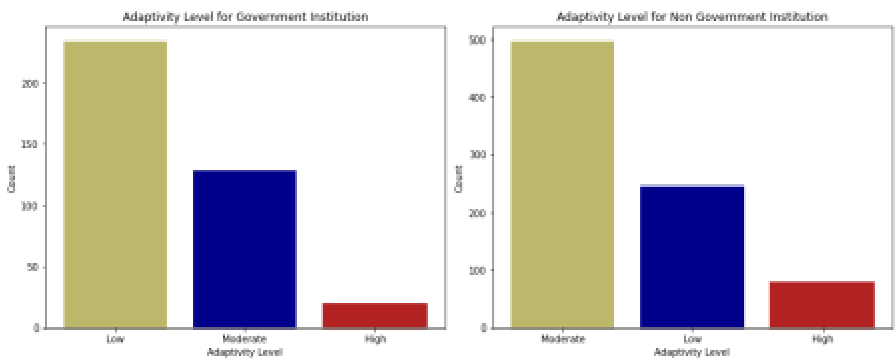

Figure 4: Institution Type impacts on adaptability level to e-learning education

5. Are IT Students more suited to e-learning education?

IT Students are more suited to e-learning education in comparison to Non-IT Students as shown in Figure 5.

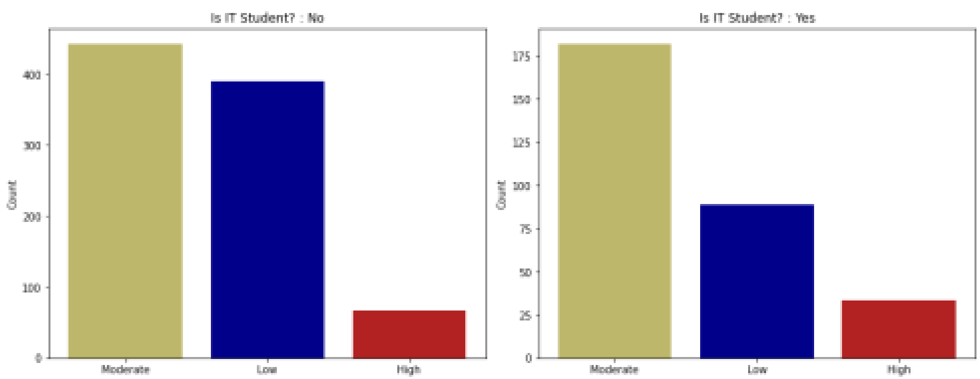

Figure 5: IT Students adaptability level to e-learning education

6. How location impacts e-learning education?

Students in **Town** have a better adaptability to e-learning education in comparison to students out of town as in Figure 6.

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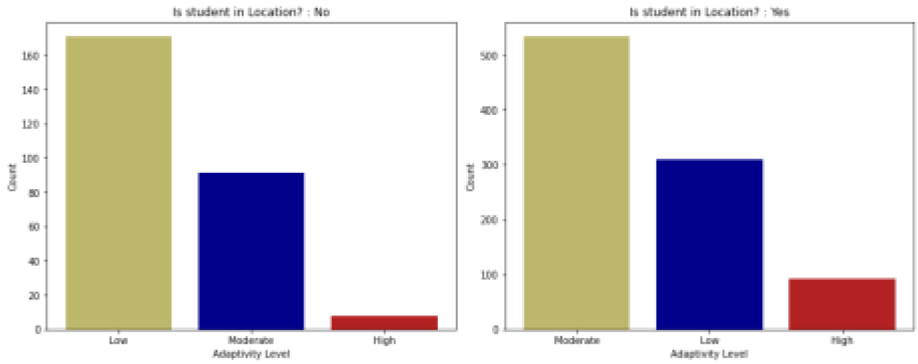

Figure 6: location adaptability level to e-learning education

7. How power outage impacts Online Education?

Students located in places with large frequency of load-shedding or power outage tends to have low adaptability due to lack of power and internet as shown in Figure 7.

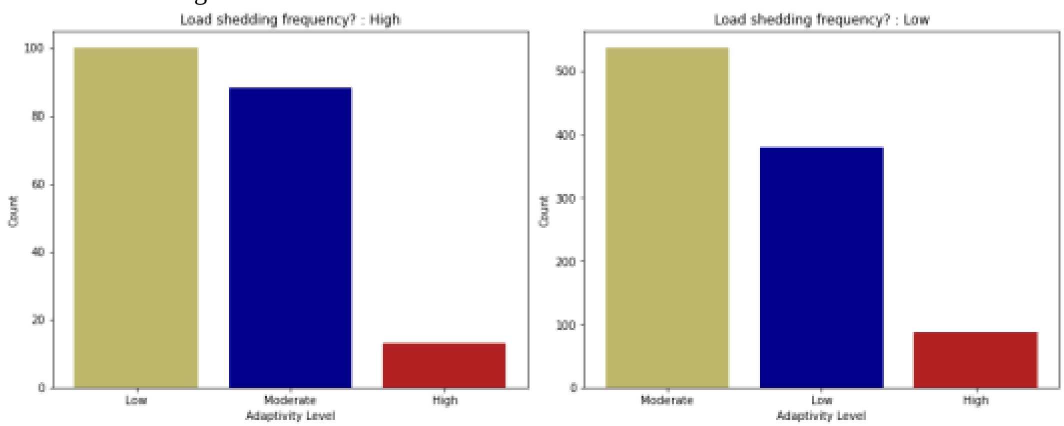

Figure 7: power outage impacts on adaptability level to e-learning education

8. How Family Background impacts Online Education?
   People belonging to Middle and Upper section of the financial band tends to have better adaptability due to the monetary ease of affording digital devices and internet services as can be seen in Figure 8.

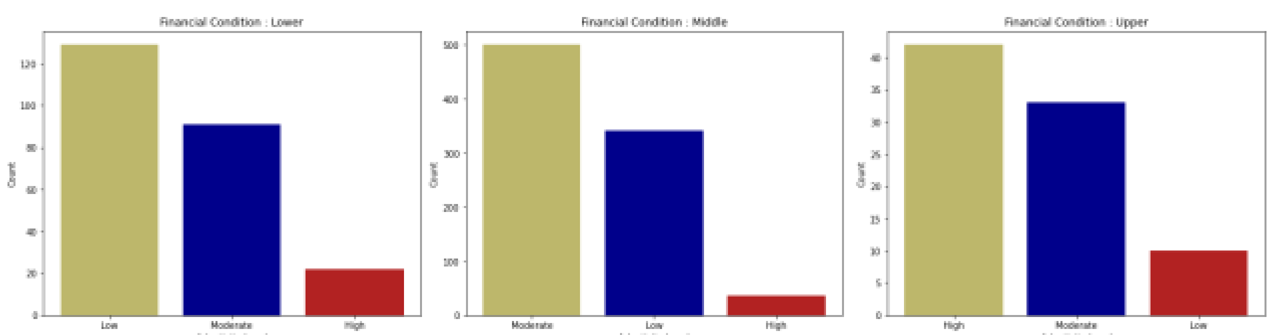

Figure 8: Family Background impacts on adaptability level to e-learning education

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9. How Internet impacts Online Education?

Relatively, **Wifi** proves to be a better option compared to **Mobile Data** as in Figure 9.

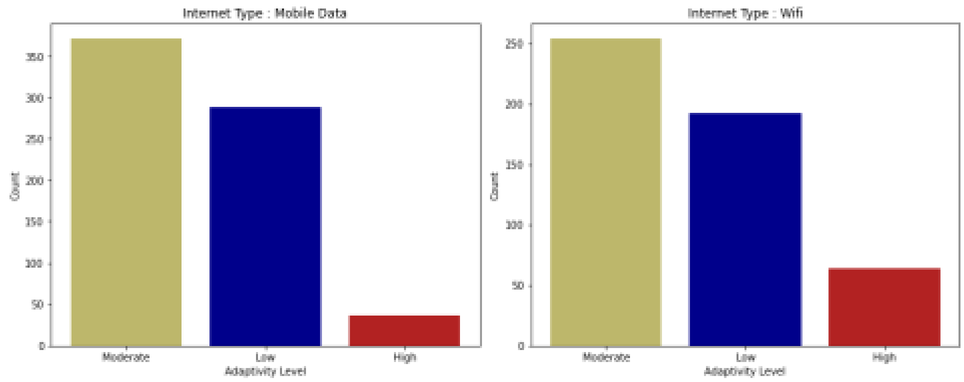

Figure 9: Internet impacts on adaptability level to e-learning education

10. How Network Type impacts Online Education?

3G and **4G** proves to be a better option in comparison with **2G** as in Figure 10.

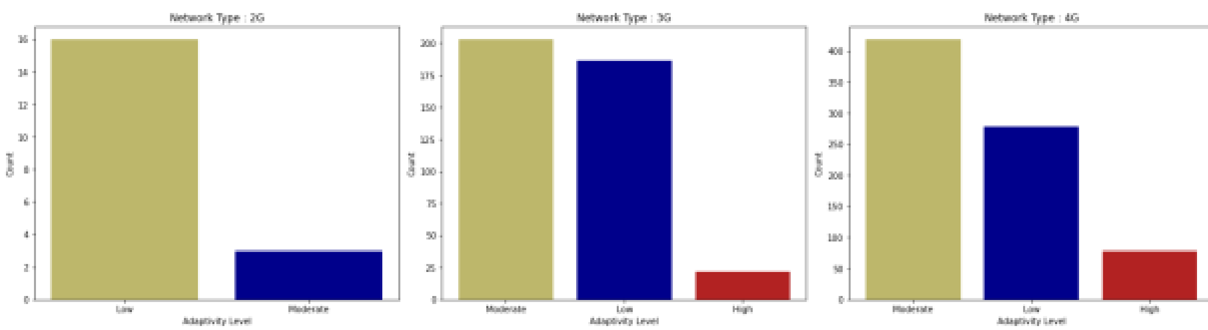

Figure 10: Network Type impacts on adaptability level to e-learning education

11. How Class Duration impacts Online Education?

From 0-1 hours has least impact on adaptability level e-learning education; however, class duration from 1-3 hours has the highest impact on adaptability level e-learning education as can be seen in Figure 11.

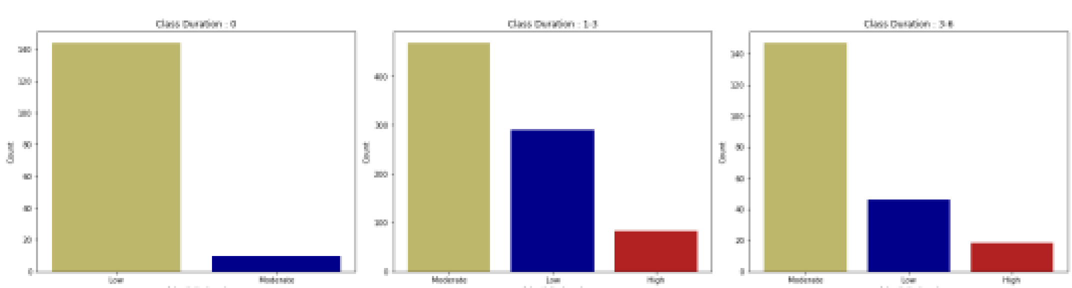

Figure 11: Class Duration impacts on adaptability level to e-learning education

12. How Self Learning Management (SLM) Platforms impact e-learning Education?

A LMS Platform tends to **drive up** the adaptability level to e-learning education as shown in Figure 12.

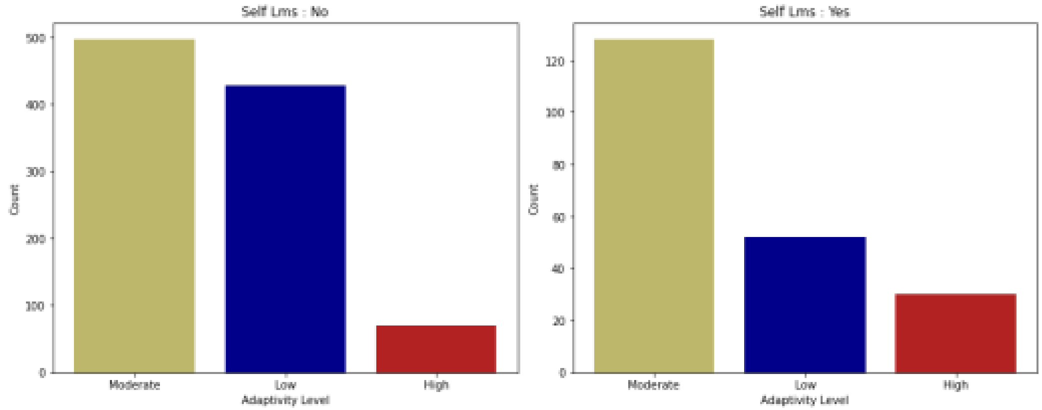

Figure 12: Self SLM Platforms impact on adaptability level to e-learning education

13. How device type impacts e-learning education?
    Computer and **Tab** is more preferred over a **Mobile** as can be seen in Figure 13.

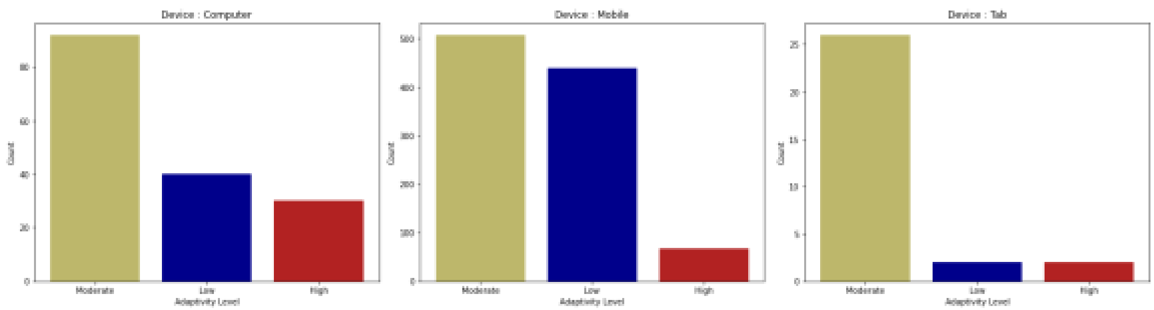

Figure 13: Device Type impact on adaptability level to e-learning education

Data Preparation

All of the 14 features of the dataset are of categorical type: Gender, Education Level, Institution Type, IT Student, Location, Load-shedding, Financial Condition, Internet Type, Network Type, Class Duration, Self LMS, Device, Adaptability Level, and Age. Therefore, we labeled encoded categorical values.

We checked the class (Adaptability Level) balancing and found that the class is not balanced as in Figure 14. So, we used Smote function to balance the class.

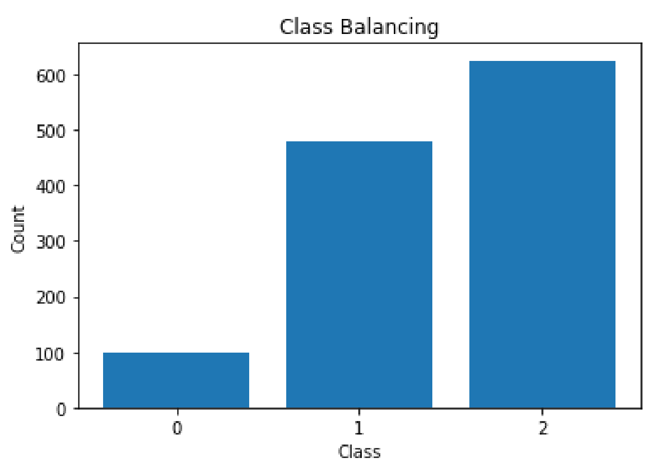

Figure 14. Class (Adaptability Level) Balancing

Dataset splitting

We have split the dataset into three datasets: Training validating, and testing datasets. The ratio of splitting is (60%, 20%, 20%).

C. Description of Models Used in the Study

There are many algorithms of ML that can be used in the prediction of student adaptability levels to e-learning education. We have trained and tested our dataset with 26 various ML algorithms. The algorithms that were used for prediction and analysis are : Gaussian Mixture, Perceptron, Nu SVC, Nearest Centroid, Multinomial NB, Logistic Regression CV, Linear SVC, Linear Discriminant Analysis, Label Propagation, Extra Tree Classifier, SGD Classifier, Calibrated Classifier CV, Quadratic Discriminant Analysis, SVC, Gaussian NB, Random Forest Classifier, Complement NB, MLP Classifier, Bernoulli NB, Bagging Classifier, LGBM Classifier, Ada Boost Classifier, KNeighbors Classifier, Logistic Regression, Gradient Boosting Classifier, Decision Tree Classifier to predict the student's adaptability level in e-learning.

Furthermore, a deep learning model was proposed to predict the student's adaptability level in e-learning. The DL proposed model consists of 7 Dense layers: one input layer (13 features), 5 hidden layers (256,128, 64, 32, and 16 neurons), and one output layer with 3 classes and softmax function as can be seen in Figure 16.

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 13)]              0

 dense (Dense)               (None, 256)               3584

 dense_1 (Dense)             (None, 128)               32896

 dense_2 (Dense)             (None, 64)                8256

 dense_3 (Dense)             (None, 32)                2080

 dense_4 (Dense)             (None, 16)                528

 dense_5 (Dense)             (None, 3)                 51

=================================================================
Total params: 47,395
Trainable params: 47,395
Non-trainable params: 0
_________________________________________________________________
```

Figure 16: Structure of the proposed deep learning model

The steps of the methodology used in the study for predicting the adaptability level in the e-learning are summarized in Figure 17.

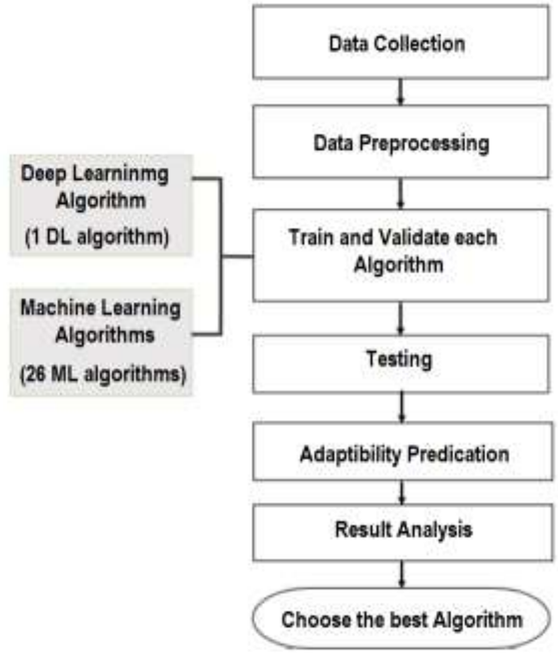

Figure 17: Methodology for predicting the adaptability level in the e-learning education

IV. RESULT AND ANALYSIS

In this section, the obtained outcome of each classifier is described. This part has been divided into two sub-parts namely Performance Evaluation and Performance Analysis of the Applied Models. The in-detailed descriptions and analysis are given below.

A. Performance Evaluation

A number of measures can be used to assess the performance of ML models. Precision, Recall, F1 score, and Accuracy are the most important characteristics used to assess a model's performance. The value of the confusion matrix which is generated during the testing of the model is considered to calculate the score of the precision, recall, F1-Score, and accuracy. The formulas [19] that are used in these computations are given in equations 1, 2, 3, 4.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (3)$$

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

Where TP represents True positives, TN: true negatives, FP: false positive, and FN: false negatives.

B. Performance Analysis of Applied Models

In this study, we used twenty six machine learning algorithms including Gaussian Mixture, Perceptron, Nu SVC, Nearest Centroid, Multinomial NB, Logistic Regression CV, Linear SVC, Linear Discriminant Analysis, Label Propagation, Extra Tree Classifier, SGD Classifier, Calibrated Classifier CV, Quadratic Discriminant Analysis, SVC, Gaussian NB, Random Forest Classifier, Complement NB, MLP Classifier, Bernoulli NB, Bagging Classifier, LGBM Classifier, Ada Boost Classifier, KNeighbors Classifier, Logistic Regression, Gradient Boosting Classifier, Decision Tree Classifier to predict the student's adaptability level in e-learning. Furthermore, a deep learning model was proposed to predict the student's adaptability level in e-learning.

The objective was to get a more reliable predictive model by comparing the performance of these models. We used 60% of the dataset as a training, 20% as validating dataset and the remaining 20% as a testing dataset.

To assess the model's performance, we employed four sorts of evaluation measures: Precision, Recall, Accuracy, and F1-Score and time required for each model to run is shown in Table 2. It is observed that the Decision Tree Classifier achieved Accuracy (92.00%), Precision (92.00%), Recall (92.00%), F1-score (92.00%); however, the proposed deep learning algorithm achieved Accuracy (94.67%), Precision (94.80%), Recall (94.70%), F1-score (94.61%).

Table 2: Performance of the Machine and Deep Learning Algorithms

Model Type	Model Name	Accuracy	Precision	Recall	F1_score	Time in Sec
Machine Learning	**DecisionTreeClassifier**	**92.00%**	**92.00%**	**92.00%**	**92.00%**	**0.01**
	RandomForestClassifier	91.73%	91.73%	91.73%	91.73%	0.23
	ExtraTreeClassifier	91.20%	91.20%	91.20%	91.20%	0.01
	LabelPropagation	90.93%	90.93%	90.93%	90.93%	0.15
	BaggingClassifier	90.67%	90.67%	90.67%	90.67%	0.06
	LGBMClassifier	89.87%	89.87%	89.87%	89.87%	0.22
	GradientBoostingClassifier	84.27%	84.27%	84.27%	84.27%	0.55
	NuSVC	80.00%	80.00%	80.00%	80.00%	0.14
	KNeighborsClassifier	79.47%	79.47%	79.47%	79.47%	0.02
	MLPClassifier	79.20%	79.20%	79.20%	79.20%	1.24
	QuadraticDiscriminantAnalysis	76.00%	76.00%	76.00%	76.00%	0.01
	AdaBoostClassifier	67.47%	67.47%	67.47%	67.47%	0.12
	LogisticRegressionCV	63.47%	63.47%	63.47%	63.47%	0.77
	LinearSVC	61.87%	61.87%	61.87%	61.87%	0.06
	LogisticRegression	61.87%	61.87%	61.87%	61.87%	0.05
	SGDClassifier	61.60%	61.60%	61.60%	61.60%	0.01
	CalibratedClassifierCV	61.60%	61.60%	61.60%	61.60%	0.29
	LinearDiscriminantAnalysis	61.33%	61.33%	61.33%	61.33%	0.01
	BernoulliNB	60.53%	60.53%	60.53%	60.53%	0.01
	GaussianNB	59.73%	59.73%	59.73%	59.73%	0.01
	SVC	56.00%	56.00%	56.00%	56.00%	0.07
	MultinomialNB	52.80%	52.80%	52.80%	52.80%	0.00
	NearestCentroid	51.20%	51.20%	51.20%	51.20%	0.00
	ComplementNB	50.40%	50.40%	50.40%	50.40%	0.01
	Perceptron	48.00%	48.00%	48.00%	48.00%	0.01
	GaussianMixture	33.07%	33.07%	33.07%	33.07%	0.03
Deep Learning	Proposed Deep Learning Model	**94.67%**	**94.80%**	**94.70%**	**94.61%**	**0.83**

CONCLUSIONS

In this study, we used 26 Machine Learning algorithms and a deep learning algorithm predicting the level of adaptation among students to e-learning during the COVID-19 epidemic era.

The dataset was collected from Kaggle Depository [92]. We applied the machine and deep learning models for the prediction.

The machine learning models used are Gaussian Mixture, Perceptron, Nu SVC, Nearest Centroid, Multinomial NB, Logistic Regression CV, Linear SVC, Linear Discriminant Analysis, Label Propagation, Extra Tree Classifier, SGD Classifier, Calibrated Classifier CV, Quadratic Discriminant Analysis, SVC, Gaussian NB, Random Forest Classifier, Complement NB, MLP Classifier, Bernoulli NB, Bagging Classifier, LGBM Classifier, Ada Boost Classifier, KNeighbors Classifier, Logistic Regression, Gradient Boosting Classifier, Decision Tree Classifier and we proposed one deep learning model to predict the student's adaptability level in e-learning.

Among all the machine learning models used, Decision Tree Classifier with Accuracy (92.00%), Precision (92.00%), Recall (92.00%), F1-score (92.00%); however, the proposed deep learning algorithm achieved Accuracy (94.67%), Precision (94.80%), Recall (94.70%), F1-score (94.61%).

This work may benefit decision-makers of the education sector to get a proper idea about the current e-learning system and the level of adaptability of the students to e-learning.

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