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Decoding The Attributes Of Learner's Performance In Moocs Using Machine Learning Algorithms

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In the current world of digitization and extensive use of technologies, we see every sphere, be it communication, online shopping, online reservations, web browsing, employment search, advertising, education, etc. untouched by the new algorithms of artificial intelligence and machine learning. This paper emphasizes the application of machine learning algorithms for learner's performance prediction in the aspect of e-learning. The achievement of learner in the massive open online course is of great importance. A methodology for determining the attributes on which the performance of a learner depends is proposed with the application of classification algorithms and the Convolutional Neural Networks algorithm predicts the performance with an accuracy of 99.35%.

Keywords. Machine Learning, e-learning, MOOCs, classification algorithms, performance.

1. Introduction

Machine learning and its related applications in the realm of e-learning have played a significant role in bringing more shrewdness to e-learning resources and methods. For the better part of two decades, the internet has been used to facilitate education through virtual learning, which includes enhancing communication, collaboration, sharing of resources, promotion of active learning, and delivery of education [1]. Many schools throughout the globe now provide online services including application processing and virtual (online) classrooms to better accommodate students' busy schedules and promote lifelong learning. The system employs smart techniques for analyzing, evaluating, and assessing user knowledge and abilities, as well as for controlling, supervising, and optimizing the e-learning process. The education and training imparted over the Internet, has gained high popularity in present scenario. Learners now have access to an abundance of previously inaccessible educational materials and possibilities because of the growing usage of technology and the internet [2]. While there are numerous advantages to online education, many students still have difficulty succeeding in virtual classrooms. In this context, intelligent methods could prove quite useful.

E-learning systems could be adjusted for individual learners using machine learning and other intelligent technologies, improving performance and results. Knowing these aspects, Machine Learning (ML) has become a promising technology. ML and its applications in e-learning have given tools and approaches to intelligence [3]. ML in e-learning helps parents and instructors provide excellent education and training through a computer-based environment, which could improve student performance. ML could lead to e-learning systems that improve decision support systems (DSS) and personalization. The educational system's potential for student-centered, performance-enhancing, system-wide impact would be greatly enhanced by the provision of such an approach. For the better part of two decades, the Internet has been used for the distribution of information, the encouragement of active learning, and the provision of remote education. Teachers are able to utilize the web to collaborate on course objectives, activities, and delivery strategies. Figure 1 describes the relationships between the various components of a smart learning environment.

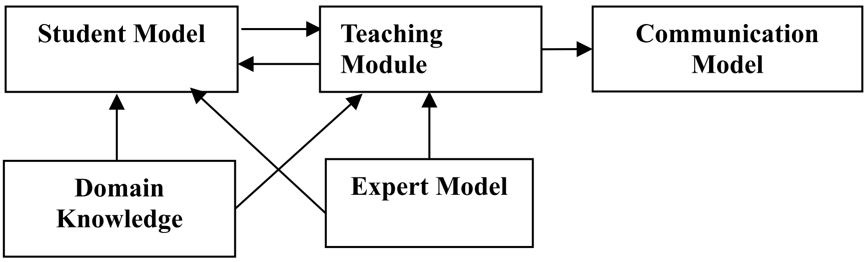

Figure 1. Component interactions in a smart-learning environment [1]

The components are described as under-

- **Student Model:**

Data unique to each student is kept in the "student" model. Such a model, at the very least, monitors how well a pupil is doing with the subject matter at hand.

- **Teaching Module:**

The instructional procedure is modeled in this part. The teaching module determines factors such as when to review, how often to deliver a subject, and what topic to present.

- **Domain Knowledge**:

This section serves as an instructional template. The teaching module determines things like when to review, when to introduce a new subject, and what topic to introduce.

- **Communications Module:**

This section governs the learner's interactions with the screen layouts, such as how can the information be best communicated to the students.

- **Expert Model:**

The expert model, like the domain knowledge, must include the material being conveyed to the student. By comparing the student's work to that of an expert model, a teacher may see exactly where a student went wrong.

1.1 The Effect of E-Learning on Student Performance

The term "e-learning" refers to the practice of using digital tools to gain entry to formal education. It's the process of taking and finishing a course, program, or degree entirely online. Now, e-learning is motivating cultures all over the globe [4]. Getting a formal education is challenging in today's troubled times because of social, economic, and linked challenges.

However, given the opportunity and resources, everyone aspires to further their knowledge. E-learning has revolutionized education by removing limitations of time and space, making learning more flexible and easier. Technology has drastically changed social norms, with both educated and uneducated people using it for enjoyment and benefits. Social media platforms like Facebook, WhatsApp, and Twitter also play an important role in education. Students' interest was piqued by these programs' ability to bring them into contact with people and places all around the globe. Several unfamiliar educational concepts, including "eLearning", are presented to them through these programs. For the sake of their education and networking with others in their industry, e-learners are eager to embrace cutting-edge technological advancements [5]. Figure 2 depicts the relation between E-Learning and student performance.

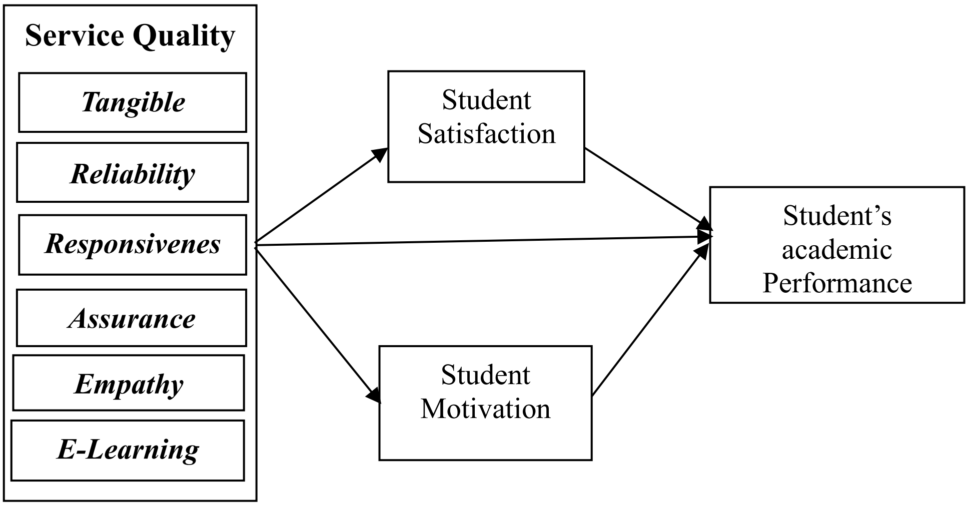

Figure 2. The correlation between E-Learning and student performance [6].

E-learning is becoming increasingly popular worldwide as a means of promoting education. It offers learners flexibility, as there are no limitations regarding time or location. As a result, e-learning is becoming the next era of education. The modes of education have evolved from non-formal to informal, from informal to formal, from formal to distance, and from distance to e-learning, all thanks to the advancements in science and technology [7]. The study examines whether technology can enhance student learning and interest in education. E-learning is being promoted in many countries worldwide, but the study focuses on the positive impacts of technology on student interest. It explores the potential of intelligent techniques to improve performance in e-learning and discusses the challenges of implementing these techniques effectively.

2. Literature review

Many authors have worked in this field aiming to discover the attributes affecting the learner's performance.

Alneyadi et al., (2023) [8] presented a quasi-experimental study with 120 eighth graders in the UAE city of Al Ain to investigate the effectiveness of smart applications in helping students acquire higher proficiency in scientific concepts. The learners were split in two - the experimental group using technology-based aids and the control group using conventional classroom methods. The study found statistically significant differences in the mean scores of scientific concept accomplishment tests, favouring the experimental group. The researchers recommend incorporating smart applications, particularly Alef platform, into the educational process to enhance students' learning of scientific topics.
Bala Kamakshi et al., (2021) [9] explained the influence of online education on college students' ability to acquire new material. The research set out to evaluate how e-learning affected students' motivation and retention. Two hundred and fifty female students from different colleges in Chennai were surveyed using a suitable sampling method. Percentage analysis and a Chi-square test were used to evaluate the data. According to the results, students benefit from having more control over their schedules because of e-learning. According to the findings, students who use e-learning manage the schedules well and are more motivated to study on. Therefore, it's clear that the world is progressing towards IoT at a far quicker rate than anybody had anticipated.
Verma et al., (2021) [10] studied that the COVID-19 pandemic has led to a shift in learning from offline to online. Machine learning is increasingly being used in classrooms to help teachers better gauge their student's progress and tailor their lessons accordingly. This study looks at how Open University (OU) demographic, engagement, and performance data may be used in conjunction with machine learning techniques to make predictions about students' future academic success. The experimental analysis found that the k-nearest neighbours (KNN) approach performed best in some cases, while the artificial neural network (ANN) approach performed best in others, when compared with other algorithms using the OU dataset.
Saleem et al., (2021) [11] explored the application of e-learning management systems to speculate student performance based on extracted features. The researchers selected a dataset from a learning management system and proposed an integrated machine learning model consisting of five traditional algorithms and four ensemble techniques. The suggested model employs four ensemble methods—bagging, boosting, stacking, and voting—to enhance the performance of five machine learning algorithms. The single models achieve the following F1 scores: Decision Tree (0.675), Random Forest (0.777), Gradient Boosting Trees (0.714), Naïve Bayes (0.654) and KNN (0.664). This suggested strategy might help teachers make better choices by providing them with advance notice of their students' expected performance.
Khanal et al., (2020) [12] explained that online learning resources are increasing, making it harder to find data in data pools. Adaptive e-learning and recommendation systems lessen this complexity. Progress has been made in machine learning-based algorithms. Challenges still exist in areas such as data scarcity, cold start, scalability, timeliness, and precision. Four types of e-learning recommendation systems are explored here, including content-based, collaborative filtering, knowledge-based, and hybrid models. Author developed classification scheme for recommender system parts. Important components of machine learning include algorithms, datasets, evaluation, and results. This study offers a welcome summary of recent studies and issues.

Tai et al., (2020) [13] analysed improvement in quality of the e-learning platform with the use of a performance assessment matrix and an analytical model. The study's primary objective was to improve students' learning efficacy, satisfaction, engagement, and effectiveness via the collection and analysis of user feedback using Likert scales. The approach also incorporated a fuzzy membership function and standardized test statistics to address sampling errors, complexity in collecting fuzzy linguistic data, and to increase evaluation efficiency. The study showed that by implementing these changes, the overall quality of the e-learning system improved, as did its users' learning efficacy, satisfaction, and engagement.

Moubayed et al., (2018) [14] intended the rise of technology has led to increased interest in e-learning, which allows people worldwide to access new information. This has generated a large amount of data that needs to be analyzed and processed for useful insights. The goal is to find meaningful patterns in this data, and it is suggested that machine learning (ML) and data analytics (DA) might help. This study explores the interpretation and features of e-learning and talks about difficulties learners face while engaging in it. It provides a quick overview of well-known ML and DA methods, as well as current literature that proposes solutions. Finally, research opportunities using these techniques are proposed for further exploration.

Bouchra et al., (2018) [15] analysed that learning is a complex process influenced by various individual, cognitive, and affective characteristics of the trainee. Working Memory (WM) is a crucial concept that affects learning performance, especially in problem-solving tasks. The capacity and performance of WM are crucial factors in determining academic success, as it involves processing and transforming information within the WM. To improve WM capacity (WMC), educational technologies and strategies that focus on learning content can be used. The study provides an Intelligent Tutorial System (ITS) integrated e-learning platform to support students with poor WMC in mathematics. The goal of the ITS is to boost students' WMC and academic performance by facilitating the consolidation of their mathematical information in long-term memory. e-learning materials created by the projected ITS are designed to improve students' WMC.

Khamparia et al., (2015) [16] introduced that e-learning enables learning from anywhere and at any time. There are different knowledge-based methods (KBM) and intelligent computing methods (ICM) that are used in e-learning, such as rule-based reasoning (RBR), case-based reasoning (CBR), genetic algorithm (GA), particle swarm optimization (PSO), artificial neural network (ANN), multi-agent systems (MAS), ant colony optimization (ACO), and fuzzy logic (FL). These methods are used for generating learning paths, adaptive course sequencing, personalization of recommended learning objects, and other e-learning contexts. From the middle of the 1990s through the end of 2014, a tabular analysis of KBM, ICM, and KBM-ICM approaches to e-learning was provided. The findings indicated that a single KBM is insufficient for solving e-learning challenges and that either a single ICM or an integrated KBM-ICM approach is utilized. The results of this research could be used by new researchers to jumpstart their studies on online education. Table 1 summarises the reviewed literature.

Table 1. Literature Review

Authors	**Techniques**	**Outcomes**	**Research Gaps**

Alneyadi et al., (2023) [8]	Alef platform	The quasi-experimental research reveals that smart apps, notably the Alef platform, could enhance students' scientific conceptions compared to traditional classroom techniques.	This study shows that smart apps improve scientific learning, but further research is required on various subjects and age groups.
Bala Kamakshi et al., (2021) [9]	Chi-square test	Online education increased college students' motivation, learning, and time management, according to the study.	Male students or those from outside of Chennai were not included in the study, but rather solely female students.
Verma et al., (2021) [10]	ANN and KNN	The KNN approach performed best in some cases, while the ANN approach performed best in others, when compared with other algorithms using the Open University dataset.	There is a need for further research on the generalizability of these results to different educational institutions and circumstances, even though the study gives insight into the machine learning approaches in forecasting student success.
Saleem et al., (2021) [11]	DT, RF, GBT, NB, and KNN	The proposed model achieves higher F1 scores in comparison to single machine learning algorithms.	Model's interpretability and critical characteristics that predict student success might be investigated to expand the study's scope.
Khanal et al., (2020) [12]	Collaborative Filtering	Adaptive e-learning and recommendation systems face data shortages, cold start, scalability, time, and accuracy, according to the study.	The study reviews e-learning recommendation system research and issues, however, it does not provide new solutions.
Tai et al., (2020) [13]	Fuzzy Model	The quality of the e-learning system was enhanced because of these changes.	The study did not compare Likert scales to other evaluation techniques. Different feedback-gathering methods may improve e-learning systems.

Moubayed et al., (2018) [14]	Machine learning (ML) and data analytics (DA)	The study addresses the possibility of utilizing ML and DA to find useful patterns in e-learning data.	This study briefly explores common ML and DA strategies for e-learning but does not discuss the problems and limits of applying these techniques to e-learning data.
Bouchra et al., (2018) [15]	Intelligent Tutorial System (ITS)	Proposed ITS generates e-learning matter that focuses on enhancing the learner's WMC.	The research suggests an e-learning platform to improve WMC but does not examine its limits or issues.
Khamparia et al., (2015) [16]	KBM-ICM method	The study presented a comprehensive overview of the different KBM and ICM methods used in e-learning and their applications.	The research covered KBM and ICM approaches in e-learning but did not evaluate their efficacy in addressing challenges.

3. Methodology

The methodology involves selection of the dataset, the exploratory data analysis is done for an understanding of the variation in the values of the dataset. Thereafter, the dataset is preprocessed and the different classification algorithms, namely K- Nearest neighbours, Logistic Regression, Random Forest, Support Vector Machines, Convolutional Neural Networks, Naïve Bayes and Decision Trees, are applied on the dataset.

3.1. Dataset Selection

The dataset which is used in this work is available at [17]. This release contains anonymized data and supporting documentation from HarvardX courses offered during their first year on the edX platform (Academic Year 2013, Fall 2012, Spring 2013, and Summer 2013). These are not raw data but rather recordings of activity in edX course by several different users. Additional details about the earlier studies of this data and the first year of HarvardX courses are available in the HarvardX and MITx working paper, "HarvardX and MITx: The first year of open online courses," by Andrew Ho, Justin Reich, Sergiy Nesterko, Daniel Seaton, Tommy Mullaney, Jim Waldo, and Isaac Chuang (http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2381263). The HarvardX Person-Course Academic Year 2013 De-Identified dataset, version 3.0, was generated on November 12, 2019, and is the first release of this dataset. HXPC13_DI_v3_11-13-2019.csv is the file name. The attributes of the dataset considered are described as under-

Table 2. Description of Attributes

ATTRIBUTES	TYPE	DESCRIPTION
course_id	String	Refers to institution (HarvardX

		or MITx), course and semester, e.g."HarvardX/CB22x/2013_Spring"
userid_DI	String	De-identified, First part refers to Dataset to MITx HarvardX Person---Course AY13),second part is a random ID number. Example ID: "MHxPC130442623".
Registered	Binary	Has value 1 if registered else 0
Viewed	Binary	Has value 1 if accessed courseware tab else 0
Explored	Binary	Has value 1 if accessed >= (1/2) chapters in course
Certified	Binary	Has value 1 if certified else 0
Country	String	Country the learner belongs to
Education	String	Highest level of education
YoB	String	Year of Birth
Grade	Binary	Final grade in the courses, values between 0-1
time_registered	Date	Course registration date
last_event	Date	Date of last activity with course
Nevents	Integer	No. of interactions with course
ndays_act	integer	No. of unique days student interacted with the course
nplay_video	integer	No. of play video events
Nchapters	integer	No. of chapter student interacted with
nforum_posts	Integer	No. of comments in discussion forum
incomplete_flag	Binary	Has value 1 if records are internally inconsistent else 0

3.2. Exploratory Data Analysis

In order to understand the dataset, scatter plots and histograms are plotted to know about the distribution of data.

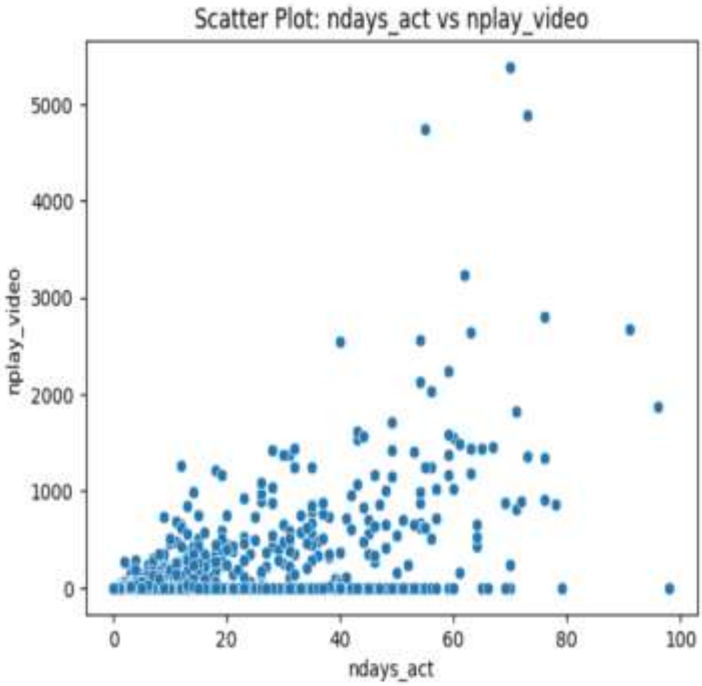

Figure 3. Scatter plot between ndays_act vs nplay_video

From the above scatter plot in Figure 3, it is seen that as the number of days enrolled increases, the students have a tendency to play the videos less often. The histograms in Figure 4 shows the number of learner's on the y-axis and the x-axis shows the range of values.

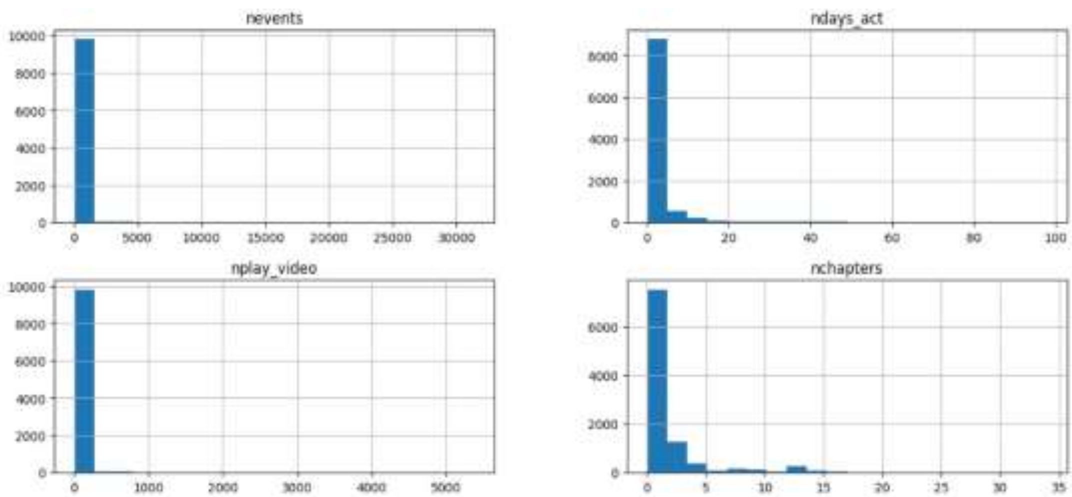

Figure 4. Distribution of values

3.3. Data Preprocessing

The dataset has been preprocessed by removing the records which had a lot of missing values, some record's missing values have been imputed by mean values. Finally the data has been normalized using the min-max scaler which rescales the value of a feature between 0 and 1, as shown in Figure 5.

```
Pre-processed DataFrame:
                  course_id        user_id  viewed  explored  certified  \
0        HarvardX/CS50x/2012  MHxPC130422039     0.0       0.0        0.0
1        HarvardX/CS50x/2012  MHxPC130407931     0.0       0.0        0.0
2  HarvardX/PH207x/2012_Fall  MHxPC130313697     0.0       0.0        0.0
3        HarvardX/CS50x/2012  MHxPC130064950     0.0       0.0        0.0
4  HarvardX/PH207x/2012_Fall  MHxPC130237753     1.0       0.0        0.0

         country   education       YoB gender  grade time_registered  \
0  Unknown/Other   Secondary  0.769231      m    0.0      2012-07-24
1  United States   Secondary  0.476923      f    0.0      2012-07-24
2          India  Bachelor's  0.800000      m    0.0      2012-07-24
3  Unknown/Other    Master's  0.630769      m    0.0      2012-07-24
4  United States   Secondary  0.861538      m    0.0      2012-07-24

   last_event   nevents  ndays_act  nplay_video  nchapters  nforum_posts  \
0  2012-07-24  0.000000   0.000000       0.0000   0.000000           0.0
1  2012-07-24  0.000000   0.000000       0.0000   0.000000           0.0
2  2013-07-27  0.000191   0.030612       0.0000   0.000000           0.0
3  2012-07-24  0.000000   0.000000       0.0000   0.000000           0.0
4  2012-12-24  0.003406   0.081633       0.0013   0.058824           0.0

   incomplete_flag
0              1.0
1              0.0
2              1.0
3              0.0
4              0.0
```

Figure 5. Preprocessed dataframe

4. Experimental Setup

The above the dataset has been uploaded to the Jupyter notebook on Anaconda 3 platform. Finding correlations in the dataset w.r.t "grade" attribute, we find positive correlations with the attributes: "viewed", "explored", "n_events", "ndays_act", "nplay_video" and "nchapters", as shown in Figure 6. Further, the classification algorithms, namely K-Nearest Neighbours, Logistic Regression, Random Forest, Support Vector Machines, Convolutional Neural Networks, Naïve Bayes and Decision Tree are applied on the dataset taking the "grade" variable of the dataset as the target variable.

```
corr['grade']

viewed              0.260817
explored            0.582262
certified           0.966922
YoB                -0.003894
grade               1.000000
nevents             0.575316
ndays_act           0.749897
nplay_video         0.417864
nchapters           0.616084
nforum_posts        0.066240
incomplete_flag     0.008219
Name: grade, dtype: float64
```

Figure 6. Correlation w.r.t "grade" variable

5. Prediction of learner's performance

The features used for the prediction of "grade" are "viewed", "explored", "n_events", "ndays_act", "nplay_video" and "nchapters". The dataset is splitted as 80% training set and 20% test set. The results are obtained when the classification algorithms are applied on the grade field of the dataset i.e the target variable is "grade" of the dataset are summarised in the Table 3, below.

Table 3. Results of Classification Algorithms

```
Test Accuracy: 99.25%
Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      1.00      1953
           1       0.88      0.79      0.83        47

    accuracy                           0.99      2000
   macro avg       0.94      0.89      0.91      2000
weighted avg       0.99      0.99      0.99      2000
```

1. KNN

```
Test Accuracy: 98.90%
Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1953
           1       0.84      0.66      0.74        47

    accuracy                           0.99      2000
   macro avg       0.91      0.83      0.87      2000
weighted avg       0.99      0.99      0.99      2000
```

2. Logistic Regression

```
Test Accuracy: 99.20%
Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      1.00      1953
           1       0.88      0.77      0.82        47

    accuracy                           0.99      2000
   macro avg       0.94      0.88      0.91      2000
weighted avg       0.99      0.99      0.99      2000
```

3. Random Forest

```
Test Accuracy: 99.15%
Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      1.00      1953
           1       0.84      0.79      0.81        47

    accuracy                           0.99      2000
   macro avg       0.92      0.89      0.90      2000
weighted avg       0.99      0.99      0.99      2000
```

4. Support Vector Machine

```
Test Accuracy: 99.35%
63/63 [==============================] - 0s 2ms/step
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1953
           1       0.85      0.87      0.86        47

    accuracy                           0.99      2000
   macro avg       0.93      0.93      0.93      2000
weighted avg       0.99      0.99      0.99      2000
```

5. Convolutional Neural Networks

```
Test Accuracy: 95.65%
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.96      0.98      1953
           1       0.35      0.96      0.51        47

    accuracy                           0.96      2000
   macro avg       0.67      0.96      0.74      2000
weighted avg       0.98      0.96      0.97      2000
```

6. Naïve Bayes

```
Test Accuracy: 99.20%
Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      1.00      1953
           1       0.86      0.79      0.82        47

    accuracy                           0.99      2000
   macro avg       0.93      0.89      0.91      2000
weighted avg       0.99      0.99      0.99      2000
```

7. Decision Tree

6. Performance Comparison

As shown in the bar chart in Figure 7, the classification algorithm, Convolutional Neural Networks (CNN) achieves the highest accuracy of 99.35% among all other classification algorithms. That means CNN can be used to predict the grades of the student with an accuracy of 99.35%. The features on which the classification algorithms have been applied are 'viewed', 'explored', 'nevents', 'ndays_act', 'nplay_video', 'nchapters' and 'nforum_posts'. It can be said from the above observation that more the student has interacted with the enrolled courses, more likely he will obtain greater percentages and hence be certified.

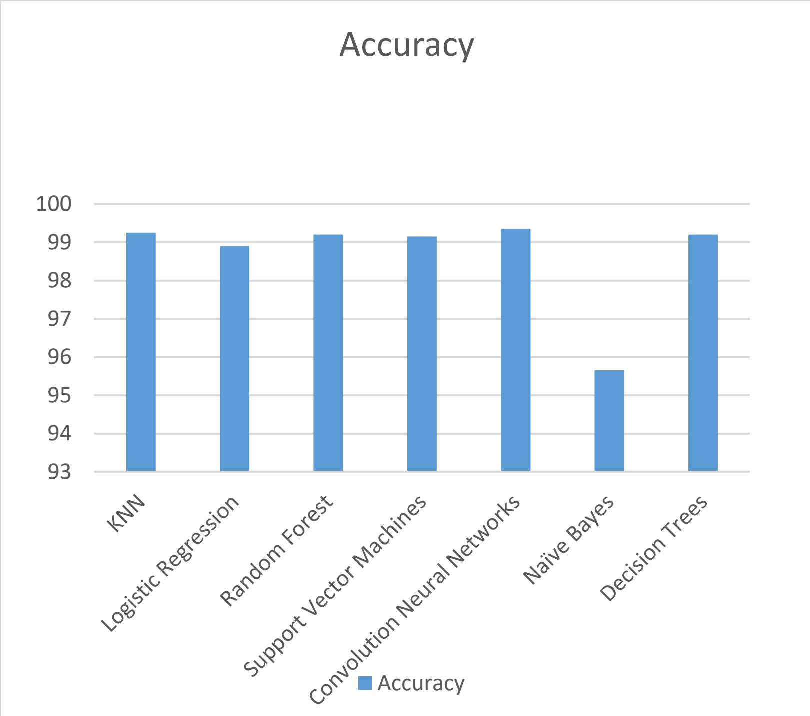

Figure 7. Performance Comparison

7. Conclusion

In today's fast-paced world, traditional learning methods may not be enough to keep up with the ever-changing trends and demands of education. Studies suggest that intelligent e-learning strategies hold great potential in enhancing learner performance. The research delves into the possibilities of using cutting-edge technology to revolutionize e-learning [18]. The focus of these studies is on intelligent e-learning strategies that can propel student performance to new heights while addressing important concerns. Among the most promising of these strategies is the application of classification algorithms. These intelligent algorithms are designed to enhance data processing and trend identification, resulting in more efficient and effective e-learning experiences. Through the results of the study that Convolutional Neural Networks predicts the performance with the highest accuracy, we can determine the performances of the learner at various instants, based on the similar attributes aggregated, so that timely interventions can be made to enhance the performance. The dataset worked upon here has learners' from various age groups, countries, different courses and education levels hence provides a huge dataset, thereby providing reliable results.

The future lies in intelligent strategies that not only enhance learner performance but also cater to individual needs [19]. With the hybrid model's capacity to provide a customized learning experience, the possibilities are truly endless. So, buckle up because the future of education is here, and it's intelligent! By embracing technology and leveraging intelligent algorithms, educators can enhance the effectiveness and efficiency of e-learning and create more personalized and engaging learning experiences for their students.

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References

[1] M. A. Potode and M. P. Manjare, "E-Learning Using Artificial Intelligence," International Journal of Computer Science and Information Technology Research, vol. 3, pp. 78–82, 2015, [Online]. Available: www.researchpublish.com
[2] K. Y. Tang, C. Y. Chang, and G. J. Hwang, "Trends in artificial intelligence-supported e-learning: a systematic review and co-citation network analysis (1998–2019)," Interactive Learning Environments, vol. 31, no. 4, pp. 2134–2152, 2023, doi: 10.1080/10494820.2021.1875001.
[3] Drigas Athanasios and Dourou Athanassia, "A review on ICTs, E-learning and Artificial Intelligence for Dyslexic's Assistance," International Journal of Emerging Technologies in Learning, vol. 8, no. 4, pp. 63–67, 2013.
[4] L. Salamat and D.-I. Latif Saifi, "Effects of E-Learning on Students' Academic learning at university Level," Asian Innovative Journal of Social Sciences and Humanities, vol. 2, no. 2, pp. 1–12, 2018, [Online]. Available: https://www.researchgate.net/publication/347512838
[5] M. Anshari, Y. Alas, and L. S. Guan, "Developing online learning resources: Big data, social networks, and cloud computing to support pervasive knowledge," Educ Inf Technol (Dordr), vol. 21, no. 6, pp. 1663–1677, Nov. 2016, doi: 10.1007/s10639-015-9407-3.
[6] H. M. W. Rasheed, Y. He, J. Khalid, H. M. U. Khizar, and S. Sharif, "The relationship between e-learning and academic performance of students," J Public Aff, vol. 22, no. 3, Aug. 2022, doi: 10.1002/pa.2492.
[7] O. Erstad, B. Eickelmann, and K. Eichhorn, "Preparing teachers for schooling in the digital age: A meta-perspective on existing strategies and future challenges," Educ Inf Technol (Dordr), vol. 20, no. 4, pp. 641–654, Dec. 2015, doi: 10.1007/s10639-015-9431-3.
[8] S. Alneyadi, Y. Wardat, Q. Alshannag, and A. Abu-Al-Aish, "The effect of using smart e-learning app on the academic achievement of eighth-grade students," Eurasia Journal of Mathematics, Science and Technology Education, vol. 19, no. 4, 2023, doi: 10.29333/EJMSTE/13067.
[9] M. Balakamakshi T Y and D. R. Savithri, "EFFECT OF E-LEARNING ON STUDENT'S ACADEMIC PERFORMANCE AT COLLEGE LEVEL PJAEE, 18 (1) (2021) 'EFFECT OF E-LEARNING ON STUDENT'S ACADEMIC PERFORMANCE AT COLLEGE LEVEL,'" PalArch's Journal of Archaeology of Egypt/Egyptology, vol. 18, no. 1, pp. 4690–4694, 2021.
[10] B. Kumar Verma, Dr. N. Srivastava, and H. Kumar Singh, "Prediction of Students' Performance in e-Learning Environment using Data Mining/ Machine Learning Techniques," Journal of University of Shanghai for Science and Technology, vol. 23, no. 05, pp. 596–593, May 2021, doi: 10.51201/JUSST/21/05179.
[11] F. Saleem, Z. Ullah, B. Fakieh, and F. Kateb, "Intelligent decision support system for predicting student's e-learning performance using ensemble machine learning," Mathematics, vol. 9, no. 17, 2021, doi: 10.3390/math9172078.
[12] S. S. Khanal, P. W. C. Prasad, A. Alsadoon, and A. Maag, "A systematic review: machine learning based recommendation systems for e-learning," Educ Inf Technol (Dordr), vol. 25, no. 4, pp. 2635–2664, Jul. 2020, doi: 10.1007/s10639-019-10063-9.

[13] T. S. Lee, C. H. Wang, and C. M. Yu, "Fuzzy evaluation model for enhancing E-Learning systems," Mathematics, vol. 7, no. 10, Oct. 2019, doi: 10.3390/math7100918.
[14] A. Moubayed, M. Injadat, A. B. Nassif, H. Lutfiyya, and A. Shami, "E-Learning: Challenges and Research Opportunities Using Machine Learning Data Analytics," IEEE Access, vol. 6, pp. 39117–39138, Jul. 2018, doi: 10.1109/ACCESS.2018.2851790.
[15] B. El Mamoun, M. Erradi, and A. El Mhouti, "Using an intelligent tutoring system to support learners' WMC in e-learning: Application in mathematics learning," International Journal of Emerging Technologies in Learning, vol. 13, no. 12, pp. 142–156, 2018, doi: 10.3991/ijet.v13i12.8938.
[16] A. Khamparia and B. Pandey, "Knowledge and intelligent computing methods in e-learning," International Journal of Technology Enhanced Learning, vol. 7, no. 3, pp. 221–242, 2015, doi: 10.1504/IJTEL.2015.072810.
[17] HarvardX, "HarvardX Person-Course Academic Year 2013 De-Identified dataset." [Online]. Available: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/26147
[18] A. U. Khan and H. Sadia, "An Effective Mechanism for e-Classroom Using Decision Support System," International Journal of Advanced Research in Engineering and Technology, vol. 11, no. 6, pp. 1039–1045, 2020, doi: 10.34218/IJARET.11.6.2020.93.
[19] Srivastava Shobhit, Haroon Mohd., and Bajaj Abhishek, "Web Document Information Extraction using Class Attribute Approach," 2013 4th International Conference on Computer a.nd Communication Technology (ICCCT), 2013.