Proposed hybrid Model in Online Education

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Abstract

The advancement of technology powering e-learning has brought numerous benefits, including consistency, scalability, cost reduction, and improved usability. However, there are also challenges that need to be addressed. Here are some key considerations for enhancing the technology powering e-learning. Artificial intelligence has revolutionized the field of e-learning and created tremendous opportunities for education Storage, servers, software systems, databases, online management systems, and apps are examples of such resources. This paper aims to forecast students' adaptability to online education using predictive machine learning (ML) models, including Logistic Regression, Decision tree, Random Forest, AdaBoost, ANN. The dataset utilized for this study was sourced from Kaggle and comprised 1205 high school to college students. The research encompasses several stages of data analysis, including data preprocessing, model training, testing, and validation. Multiple performance metrics such as accuracy, specificity, sensitivity, F1 score, and precision were employed to assess the effectiveness of each model. The findings demonstrate that all five models exhibit considerable predictive capabilities. Notably, decision tree and hybrid models outperformed the others, achieving an impressive accuracy rate of 92%. Consequently, it is recommended to utilize these two models, RF and XGB, for predicting students' adaptability levels in online education due to their superior predictive accuracy. Additionally, the Logistic regression, KNN, and AdaBoost, ANN models also yielded respectable performance levels, achieving accuracy rates of 77.48%, 83.77 ,74.17% and 91.06% respectively. In summary, this study underscores the superiority of RF and XGB models in delivering higher prediction accuracy, aligning with similar research endeavours employing ML techniques to forecast adaptability levels.

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1. Introduction

The development and testing of new teaching and learning solutions incorporating intelligent tutoring systems, technological architecture, and AI capabilities are taking place on a global scale. These innovative approaches leverage AI technologies to enhance educational experiences, personalize instruction, and support learners and educators. [1–3]. Overall, different AI technologies (e.g., Machine learning, Deep learning, VR, AR, IOT, Chatbots, Cloud computing for data sharing) have been used in the field of education to improve teaching and learning techniques. E-learning, also known as online learning, has gained significant popularity in the educational field in recent years. It is an approach to learning that utilizes internet-based technologies to deliver educational content and facilitate learning experiences. Online earning includes a wide array of activities, encompasses the development, execution, selection, management, facilitation, and enhancement of learning processes using technology.[4] The fusion of web-based platforms, the internet, and software applications has significantly expanded the accessibility of education. Online educational platforms have made it possible for a broader range of users to connect and engage in educational activities, going beyond just students and educators.

The integration of e-learning systems in educational institutions has spurred research and analysis efforts to predict learner performance and understand the factors influencing the learning process. By leveraging input features and data from online learning platforms, educators and researchers aim to enhance teaching methods, personalize learning experiences, and improve student outcomes in e-learning environments. Universities currently use online learning systems to provide their courses. Analysts and researchers are increasingly utilizing various input features, such as time spent on activities, assessment results, engagement levels, and participation in online discussion forums, to evaluate student performance in e- learning environments. [5] AI in education has the power to significantly boost instructional design and pedagogical development by providing valuable insights into students' performance automatically. [6, 7], monitoring students' learning [8]. Second, AI in education has the power to modify the entire educational system by emphasizing the crucial role of technology. [9, 10], enhancing the mode of knowledge delivery [11]. AI-empowered educational platforms have the capability to revolutionize the traditional teaching model and address the diverse learning needs of students. With the rise of online education platforms, personalized, autonomous, and interactive learning experiences have become essential components of modern education. [12]. Technology has been a game-changer in the field of education, opening novel possibilities for customized learning experiences, dynamic assessments, and enriched interactions in various learning environments [13]. Machine learning is a key component 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 the field of machine learning, algorithms undergo training processes aimed at discerning intricate patterns and correlations within extensive datasets. Their primary objective is to leverage this analysis to make optimal decisions and accurate predictions. [21-25]. Another AI technology is Machine learning. Creating algorithms and models that enable computers to learn and make predictions or judgements without being explicitly programmed is the focus of the subject of study known as machine learning. The usage of machine learning in academic settings can indeed be beneficial. By analyzing student data, such as performance records and learning patterns, machine learning models can help identify potential weaknesses or challenges in the learning process.

This information can enable educators to proactively engage with students and provide personalized interventions or support, leading to a better learning experience and improved student outcomes. [14]. By leveraging machine learning in education, teachers can gain valuable insights into students' learning processes, enabling them to make data-informed decisions and tailor their teaching approaches to meet individual needs. It can also help optimize instructional time and resources by focusing on areas where students require the most attention. Educational researchers have acknowledged the dual significance of data as an asset for uncovering knowledge and the capabilities of computational models and theories in facilitating educational applications and research.[15] The advancements in AI technology, with machine learning as a key component, have opened new possibilities and garnered significant support for its application in education. Machine learning has played a vital role in making AI a feasible and valuable tool in educational settings. By utilizing mathematical algorithms, machine learning can effectively process and analyze complex datasets in an automated and scalable manner. Researchers in the education field have been investigating the incorporation of machine learning into traditional schooling systems. The idea is to use machine learning as teaching aids. to support and enhance the work of human educators [16]. "The latest developments in computational techniques, such as machine learning, have enabled educational researchers to derive data-driven insights concerning the process of learning and its associated outcomes. [17–19]. Educational datasets have often seen the application of machine learning techniques like support vector machines and Naïve Bayes for analysis.'' Indeed,[20] note that, "Two influential trends have bolstered the advancement and heightened adoption of machine learning: the widespread availability of data and the emergence of novel learning algorithms" Deep learning, drawing inspiration from biological neural networks, empowers computational models composed of multiple processing layers to acquire data representations imbued with multiple layers of abstraction." [21]

2. Related Work

The higher education industry has experienced significant transformation due to advancements in ICT over the past decades. These developments have revolutionized the way education is deliver and accessed, leading to the following changes: e learning and online courses, smart classrooms, digital content and open educational resources, virtual laboratories, and simulations by embracing adequate technological implementation, higher education institutions can successfully transition into Education 4.0. This transformation will enable them to meet the evolving needs of learners, deliver high-quality education, and prepare students for the challenges of the digital era [22]. Forecasting the extent of students' adaptability to online education has emerged as a pivotal concern. In this context, researchers and scholars have undertaken endeavours related to machine learning models for the assessment of distance learning and student adaptability. These approaches entail the utilization of algorithms capable of scrutinizing extensive datasets and discerning meaningful patterns. Rolim et al. [23] in their study, employed a Supervised Machine Learning algorithm to identify the presence of effective practices, with a specific

emphasis on feedback gathered from the Learning Management System (LMS) courses. William et al. explored enhancements to the Online Education Model by integrating Machine Learning and Data Analysis into a Learning Management System (LMS) . Researchers of [24] center on the utilization of Machine Learning to assess students' academic performance. It showcases the outcomes and progression of the project, which endeavours to prepare and evaluate the efficacy of various Machine Learning algorithms for the analysis and prediction of students' academic performance within the course. Monica et al. [7] investigated the shift of education towards online platforms and digital course content. In their analysis, they employed Neural Networks, Support Vector Machine (SVM), Decision Tree, and Cluster Analysis as the basis for their study.

Similarly, in the following work [25] introduced an adaptive system designed to predict an individual's educational path. Their methodology encompassed the use of multiple data mining algorithms to extract relevant characteristics and create customized models. The results of their research showcased the notable effectiveness of Machine Learning algorithms in terms of both performance and precision. Similarly, [26] employed Machine Learning (ML) algorithms for the prediction of student performance in the context of online education. Their approach encompassed the utilization of deep neural network algorithms, as well as Support Vector Machine (SVM) and decision tree (DT) classifiers. The outcomes of their study led to the conclusion that the SVM classifier consistently outperformed others in terms of both accuracy and overall performance. Machine learning and data analytics have a wide array of applications within the domain of online education. Harnessing machine learning alongside visualization techniques can enhance the quality of teaching and learning experiences. [27] Machine learning and data analytics have numerous applications in online education, and they can be utilized to improve overall teaching and learning experiences. Learning analytics and educational data mining are fields that focus on extracting valuable insights from educational data using machine learning and visualization techniques Machine learning is a powerful tool for analyzing learner interactions in online learning platforms. It excels at discovering hidden patterns and relationships within complex datasets, even when the relationships are non-linear [27].[28], A study involving 22,437 participants was undertaken to assess students' performance in online education using the deep learning technique known as Long Short-Term Memory (LSTM). The outcomes yielded an accuracy rate of 0.8457, a precision score of 0.8224, and an F1-Score of 0.7943 through the implementation of the LSTM technique.

The authors in [28] investigated the influence of three distinct feature categories—student engagement, demographics, and performance data—on the prediction of student performance. Additionally, the paper examined prediction performance at various time intervals leading up to the final exam. This analysis was conducted on a publicly available dataset from an open university, known as the Open University Learning Analytics Dataset (OULAD). The methodology encompassed the utilization of "Support Vector Machine (SVM), Decision Tree (DT), Artificial Neural Networks (ANNs), Naïve Bayes (NB), K-Nearest Neighbor (K-NN), and Logistic Regression (LR) models for classification tasks, and Support Vector Machine (SVM), Artificial Neural Networks (ANN), Decision Tree (DT), Bayesian Regression (BN), K-NN, and Linear Regression models for regression analysis." There is a need for research to gain a clearer usage of the characteristics and specific requirements of educational establishments, especially higher education institutes, universities, and professional colleges. This understanding is crucial for devising and designing service models that are tailored to their unique needs and can bring maximum benefits [29].

3. Dataset Description

The dataset utilized in our study was sourced from the Kaggle repository. It comprises 1,205 records, derived from a survey conducted between December 10, 2020, and February 5, 2021, involving students enrolled in various educational institutions, including universities, colleges, and schools. This dataset encompasses 14 distinct features, namely: "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." Figure1 shows the correlation between the target variable i.e., student adaptability and other variables. Analysis of the heatmap reveals a strong correlation between class duration, financial condition, and location.
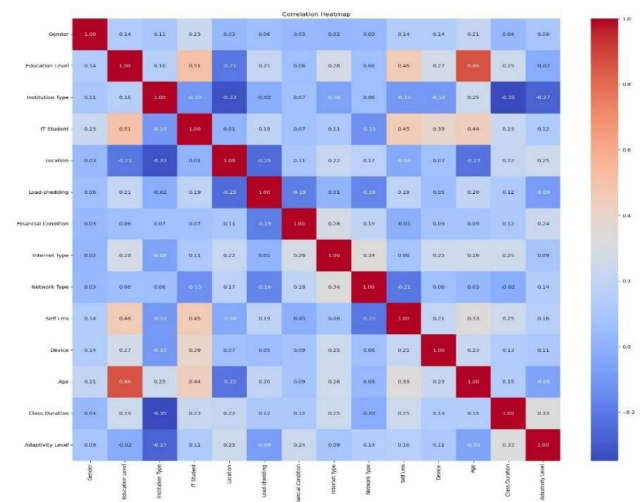

Fig 1: Correlation between the target variable and other variables

4. Research Methodology

In this section, we will outline the methodology employed in our study, encompassing Data Collection, Data Preprocessing, and a Description of the Models used for prediction and analysis. The dataset utilized in our study was sourced from the Kaggle repository. It comprises 1,205 records, derived from a survey conducted between December 10, 2020, and February 5, 2021, involving students enrolled in various educational institutions, including universities, colleges, and schools. The division of data follows a ratio of 75% for the training dataset and 25% for the testing dataset. This partitioning is essential for the subsequent analysis and predictive modeling.
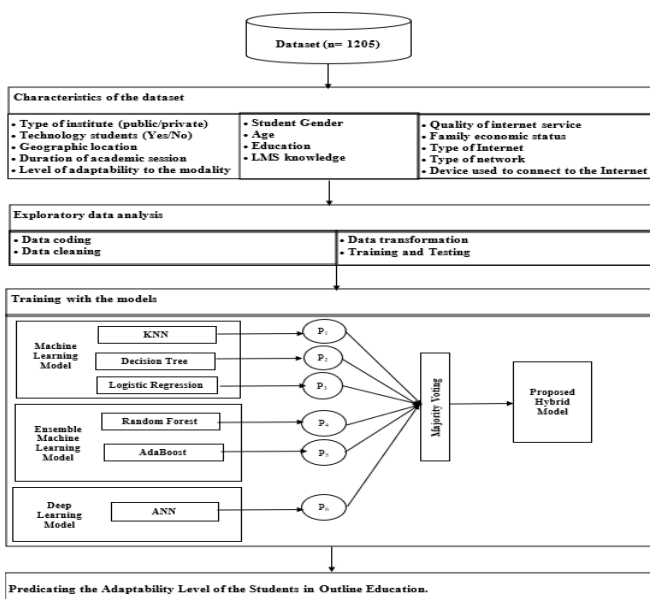

Fig 2: The process shows the attributes of dataset, its analysis, and proposed hybrid model.

4.1 Dataset preprocessing

To this study, the dataset was gathered from the Kaggle repository. It comprises a total of 1,205 records, which were obtained through a survey conducted between December 10, 2020, and February 5, 2021, involving students who are enrolled in universities, colleges, and schools.
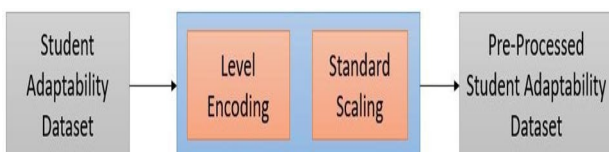

Fig 3: Data Pre-processing

4.1.1. Label Encoding

For ordinal categorical variables (categories with a natural order), Fig 3, label encoding assigns a unique numerical value to each category based on their order. For instance, if you have a "Difficulty Level" variable with categories "Easy," "Moderate," and "Difficult," you can assign values like 1, 2, and 3 to these categories, respectively. Standard scaling, also known as z-score normalization, is a technique used to scale numerical features in a dataset. It transforms the data distribution to have a mean of 0 and a standard deviation of 1. In the context of assessing student adaptability in online education, you might apply process level encoding to convert categorical variables like "student age group," "preferred learning format," or "previous online course experience" into numerical form. Standard scaling, on the other hand, could be applied to numerical features like "time spent on online learning per week" or "number of online assignments completed" to ensure that they are on a consistent scale for machine learning algorithms.

4.2. Models Descriptions Used in the Study

4.2.1. Random Forest

It is a widely used supervised machine learning model particularly well-suited for both classification and regression tasks. It harnesses the power of ensemble learning, where predictions are generated by combining the results of multiple individual models. It achieves this by leveraging ensemble learning models such as boosting and bagging. Bagging creates diverse decision trees that work together to make predictions, while boosting improves prediction accuracy by learning from past mistakes in a sequential manner.

4.2.2. Logistic Regression

It is a powerful analytical tool for predicting binary outcomes. It transforms the relationship between dependent and independent variables into probabilities, facilitating the assessment of event occurrence likelihood. Moreover, it provides a range of performance metrics that aid in evaluating and fine-tuning the model's predictive capabilities. Some of the key results that can be derived from logistic regression include accuracy, ROC curve, precision, F1 score, recall, and the construction of a confusion matrix. These parameters assess a model's performance, its ability to discriminate between the two classes, and its precision in predicting outcomes.

4.2.3. KNN (K-Nearest Neighbour)

It is a straightforward model that relies on the storage of all available data cases to classify new, unseen data points. KNN is often referred to as a "Lazy Learner" because it lacks a discriminative function derived from

the training data. Instead, it retains and memorizes the entire training dataset without undergoing a traditional model learning phase.

4.2.4. Decision Tree

It is a graphical representation resembling a tree that helps in the decision-making process. Tree's each branch represents a potential decision, event, or response. Decision Trees can be employed for both regression and classification tasks. In classification, they are used to categorize data into discrete classes, whereas in regression, they predict numerical or continuous values.

4.2.5. AdaBoost

The AdaBoost algorithm in machine learning serves as a versatile solution for tackling both classification and regression problems. It achieves this by combining multiple weak classifiers to construct a robust classifier.

4.2.6. Artificial Neural Network

ANN is a computer-based model that draws its inspiration from the organization and operation of the human brain. It consists of interconnected nodes, also known as artificial neurons or perceptron's, organized into layers. ANN models are used for various machine learning tasks, including regression, classification, and pattern recognition. ANN models have been applied successfully in a wide range of fields, natural language processing, including image recognition, and financial forecasting. To evaluate the effectiveness of a model the following metrics are examined:

4.2.6.1. Accuracy
The accuracy metric of the model is used to define its performance across all classes. Accuracy helps when all classes are equally important. It can be computed by dividing the total number of predictions by the number of predictions that were correct.

$$Accuracy = \frac{t_p + t_n}{t_p + t_n + f_p + f_n}. \quad (1)$$

4.2.6.2. Recall
The recall measures how well the model can classify Positive samples. It is determined by taking the ratio of correctly classified Positive samples to the total number of Positive samples. The more positive samples that are identified, the recall value is larger.

$$Recall = \frac{t_p}{t_p + f_p}. \quad (2)$$

4.2.6.3. Precision
Precision is calculated as the fraction of correctly classified Positive samples among all samples classified as Positive, regardless of whether they were classified

correctly or incorrectly. Precision measures how well the model categorizes a sample as positive.

$$Precision = \frac{t_p}{t_p + f_n}. \quad (3)$$

4.2.6.4. F1-score

The F1 score is precisely defined as the harmonic mean of both recall and precision.

$$F1\ score = 2 \times \frac{Recall \times Precision}{Recall + Precision}. \quad (4)$$

Where: tp is correctly predicted, fp is incorrectly predicted instances, tn is negatively predicted instances and fn is the negatively predicted instances.

5. Results and Discussion

The dataset underwent training and testing with a diverse set of Machine Learning algorithms for prediction and analysis. These algorithms include K-Nearest Neighbors (KNN), Decision Tree, Random Forest Classifier, Ada Boost Classifier, Logistic Regression, and Artificial Neural Networks (ANN). The objective was to predict the adaptability level of students in the context of E-learning. A hybrid model is introduced with the aim of forecasting students' adaptability levels in online education. In our assessment of model performance, we utilized four evaluation metrics: Precision, Recall, Accuracy, and F1-Score as shown in Table 2. The results demonstrate that the hybrid model proposed in this study exhibited the highest levels of accuracy of 94.04%, recall of 94.04%, precision of 94.03%, and F1-score (94.03%). Subsequently, the Random Forest Classifier yielded similar performance metrics with an accuracy of 94.00%, recall of 94.04%, precision of 94.03%, and F1-score of 94.03%.

Table1: Performance metrics of models

Model Type	Model Name	Accuracy	Recall	F1	Precision
Machine Learning	Logistic Regression	77.48	77.48	77.18	77.44
	Decision Tree	93.38	93.38	93.36	93.38
	KNN	83.77	83.77	83.35	84.63
Ensemble Machine Learning	Random Forest	94.00	94.04	94.03	94.03
	Ada Boost	74.17	74.17	72.41	76.39
ANN		91.06	91.06	91.04	91.05
Proposed Hybrid Model		94.04	94.04	94.03	94.03

The accuracy metric gauges the overall accuracy or correctness of the model's predictions. Among the models, Proposed hybrid model achieved the highest accuracy at 94.04%, closely followed by Random Forest with an

accuracy of 94.00%. Precision indicates the ability of a model to make accurate positive predictions. Proposed hybrid model, Random Forest, Decision tree all exhibit high precision values. This suggests that these models are highly reliable in correctly identifying student adaptability level without generating many false positive predictions. Recall, also known as sensitivity, assesses the model's ability to correctly identify all positive instances. Across all models, there is consistently high recall, with values of 94.04. This signifies that the models are effective in capturing the majority of student adaptability level within the dataset. The F1-Score is a balanced metric that considers both precision and recall. It provides a harmonic mean of these two metrics and is particularly useful when dealing with imbalanced datasets. All models, achieved good F1-Scores of 77.18 or higher, indicating strong overall performance.
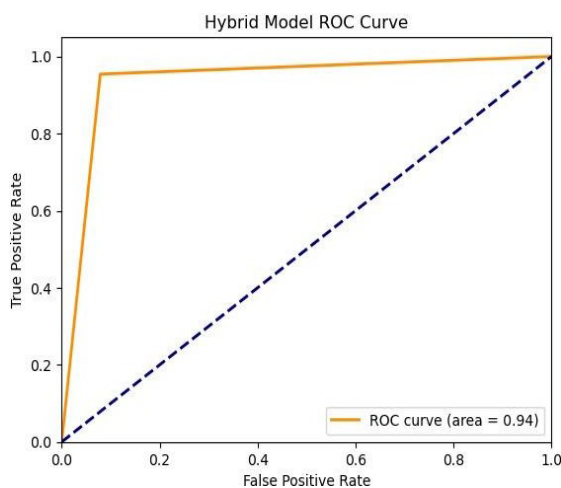

Fig 4: ROC Plot of Proposed Hybrid Model

In Fig 4, the ROC curve is presented, and notably, among all the models, Proposed hybrid model attains the highest AUC (Area Under the Curve) with a score of 94.

6. Conclusion

In conclusion, this research paper has explored the crucial aspect of student adaptability in the context of online education and has proposed a hybrid model as a predictive tool. Our findings have revealed the effectiveness of the hybrid model, as it consistently outperformed the Random Forest Classifier and achieved comparable results to a deep learning algorithm in terms of accuracy, precision, recall, and F1-score. These results underscore the significance of developing specialized models tailored to the unique challenges of online education. Furthermore, they highlight the potential of hybrid models in providing valuable insights into students' adaptability levels, which can inform educators and institutions in designing more effective online learning experiences. As online education continues to play a pivotal role in modern educational

paradigms, understanding and addressing the adaptability of students becomes increasingly pertinent. The hybrid model presented in this paper offers a promising avenue for future research and practical applications in enhancing the quality and efficacy of online education. It is our hope that these findings will contribute to the ongoing dialogue on optimizing online learning environments and ultimately improve the educational outcomes for students in the digital age.

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