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Predictive insights into student online learning adaptability: elevating e-learning landscape

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ABSTRACT

In Morocco's rapidly transforming educational landscape, this study delves into students' adaptability to online learning environments by integrating sophisticated artificial intelligence (AI) algorithms and hyperparameter optimization techniques. This research uses the comprehensive "online learning adaptivity" dataset to identify pivotal factors influencing student flexibility and effectiveness in e-learning platforms. We applied various AI models, with a particular emphasis on the CatBoost classifier, which exhibited exceptional predictive performance, achieving an accuracy rate near 98%. This high precision in predicting student adaptiveness offers essential insights into tailoring digital education systems. The results underscore the significant potential of machine learning technologies to enhance educational methodologies by catering to the diverse needs of students. Such capabilities are instrumental for educators and policymakers dedicated to refining e-learning strategies that effectively accommodate individual learning styles, ultimately improving the broader educational outcomes in Moroccan tertiary education. These findings advocate for a more nuanced understanding of the interplay between student behavior and technological solutions, providing a roadmap for developing more responsive and effective educational platforms.

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1. INTRODUCTION

As global education systems undergo significant digital transformation, Morocco's landscape has shown a notable shift towards e-learning platforms, catalyzed by rapid advancements in technology and educational reform. An increasing reliance on digital solutions marks this evolution to enhance educational access and quality, particularly in higher education sectors where adaptability and responsiveness to student needs are crucial. This paper delves into these transformative dynamics, leveraging the "online-learning-adaptivity" dataset to explore how artificial intelligence (AI) can optimize students' adaptability to online learning environments.

Historically, integrating digital technologies in Moroccan educational institutions commenced with initial explorations into e-learning methodologies. These efforts, documented by [1], laid the foundational steps towards enhancing traditional teaching modalities. Following this, government-led initiatives, as discussed by [2], have played a pivotal role in structuring the e-learning landscape, aiming to bolster educational accessibility. The expansion of online courses, studied by [3], reflects a broadening in the scope of digital education, encompassing a range of academic levels and catering to a diverse student demographic.

Furthermore, the development of technological infrastructure essential for supporting e-learning has seen significant investment, as highlighted by [4]. This infrastructural enhancement has facilitated smoother transitions to digital learning platforms, addressing educational disparities and broadening the reach of educational opportunities, as evidenced by research from [5]. However, this shift also presents numerous challenges, such as digital literacy, device accessibility, and the need for comprehensive teacher training in online pedagogies. These issues are elaborated on by [6].

These scholarly insights paint a comprehensive picture of the e-learning ecosystem in Morocco, underscoring the critical role of adaptability—the ability of students to adjust effectively to online learning modalities influenced by a range of behavioral, psychological, and environmental factors. The COVID-19 pandemic has further amplified the need for robust online learning platforms capable of adapting to unforeseen educational challenges. Therefore, this study addresses these immediate needs and explores AI's broader implications in enhancing e-learning systems' adaptability and effectiveness.

Our investigation utilizes state-of-the-art AI algorithms and advanced hyperparameter optimization techniques to predict and analyze students' adaptability in virtual learning environments. By identifying key factors that influence learning effectiveness, this research provides valuable insights that can be used to tailor educational strategies to better meet Moroccan students' needs. This approach ensures that educational offerings are not only accessible but also adaptable to students' varied learning preferences and requirements, thereby enhancing their academic and personal development outcomes.

Integrating AI in educational settings represents a transformative step towards personalizing learning and enhancing student engagement. This study aims to contribute to the field by providing empirical evidence on the effectiveness of AI applications in predicting and improving student adaptability in online learning contexts. The insights derived from this research are expected to benefit educators, policymakers, and curriculum developers, aiding in creating more effective and adaptive educational frameworks.

Recent literature has explored multiple dimensions of student adaptability and the effectiveness of intelligent systems in online education. Some studies have applied machine learning approaches such as random forest classifiers to predict students' adaptability levels with high accuracy [7], while others have developed autonomous recommendation systems to personalize online learning experiences [8]. Research has also examined how psychological and contextual factors influence students' ability to adjust to digital environments, particularly among high school learners [9]. In addition, intelligent assessment methods have been proposed to improve the quality of distance learning [10], and game-theoretic models have been introduced to simulate educational dynamics [11]. Further investigations have highlighted the role of technological investment in enhancing academic performance in emerging economies [12], assessed entrepreneurial attitudes among STEM students [13], and suggested innovative pedagogical frameworks for entrepreneurship education through constructive alignment strategies [14]. These contributions provide a broader context for understanding how adaptability and AI-driven solutions intersect in shaping effective online learning systems.

The paper is structured as: After the introduction in Section 1, Section 2 overviews previous research in this field and describes the datasets utilized for the study, explicitly highlighting the use of an educational dataset sourced from Kaggle. It also introduces the proposed Stacking Ensemble Learning method. Then, Section 3 presents the results and discusses them. Finally, Section 4 concludes the paper and gives major perspectives.

2. METHODS

2.1. Literature review

Table 1 comprehensively overviews various e-learning and online education studies. It briefly compares and contrasts each research work's methodologies, focal points, key findings, and implications. This comparative analysis offers insights into the advancements in e-learning strategies, AI applications, and student engagement and performance assessment in online educational settings.

In conclusion, the comparative table effectively highlights the diverse approaches and methodologies employed in e-learning and online education. Key observations from the table include:

- Methodological Diversity: The studies utilize various methods, from AI algorithms to comparative analyses, showcasing the multidisciplinary nature of e-learning research.
- Focus on Adaptability and Engagement: Many studies concentrate on adaptability in online learning and student engagement, indicating these are critical factors for success in e-learning environments.
- AI and Learning Performance: The integration of AI in several studies, notably by [15], [16], underlines the growing importance of technology in enhancing learning outcomes.
- Emotional and Social Factors: [17] emphasizes the significance of emotional and social aspects in student engagement, suggesting a holistic approach to online education.

These findings underscore the evolving e-learning landscape, where technological advancements and understanding student behavior play pivotal roles. The table is a valuable resource for understanding current trends and potential future directions in online education research.

Table 1. Overview of E-learning studies and methodologies

Authors	Focus of study	Methodology	Key findings	Implications
[7]	Student adaptability to online education	Surveys, AI algorithms (random forest)	Random forest classifier showed 89.63% accuracy in predicting adaptability.	Highlights the effectiveness of AI in predicting student adaptability in online learning contexts.
[8]	Autonomous online education system	Intelligent recommendation system	The system adapts study methods to individual student situations, improving learning effectiveness.	Demonstrates the potential of intelligent systems in personalizing online education.
[9]	Adaptability in high school students' online learning	Job Demands-Resources theory, surveys	Adaptability correlates with higher online learning self-efficacy and academic achievement in math.	Emphasizes the importance of adaptability in online learning success, particularly during crises.
[10]	Assessment in web-based distance learning	Model creation for the intelligent assessment system	Positive performance and adaptability of the assessment system	Suggests that intelligent assessment systems can enhance the quality of distance learning.
[11]	Evolutionary game model in education	Game theory, simulation analysis	Analysis of equilibrium and stability in educational game models	Provides insights into the dynamics of game-based learning and its implementation.
[12]	Impact of Technology Investment in high-tech Ventures	Analysis of formal vs. informal ventures	Technology investments are positively related to performance, moderated by firm informality.	Highlights the role of technology and firm structure in emerging economies.
[13]	Entrepreneurial profile of STEM students	Kaiser-Meyer-Olkin test, Pearson's correlation	High innovation attitude among students, varying based on engineering specialization	Indicates the varying inclination toward innovation among STEM students.
[14]	Improving Entrepreneurship course	Constructive alignment, course analysis	Practical assessment and learning outcomes through constructive alignment and innovative assessment	Suggests a framework for course improvement and practical student assessment in higher education.
[15]	Low-engagement identification in online courses	AI algorithms (J48, JRIP, etc.)	Specific classifiers outperform others in identifying low-engagement students.	Shows the potential of AI in enhancing engagement and performance tracking in online courses.
[16]	E-learning execution and behavior analysis	BCEP and PBC models, AI, analysis of learning behaviors	Developed a learning performance indicator using AI. The PBC model outperforms traditional classification in predicting learning performance.	Offers a new perspective and solution for evaluating E-Learning classification methods.
[17]	Emotional and social factors in E-Learning	Comparative study of experimental and control groups	Higher emotional and social engagement was found in the experimental group, indicating the effectiveness of adaptive E-Learning environments.	Suggests that adaptive E-Learning environments can significantly enhance student engagement.

2.2. Dataset exploration

This dataset, sourced from Kaggle, aims to assess the efficiency of online education as shown in Table 2. The primary focus is on the "Adaptivity Level" and various other feature sets as the target feature. The dataset can be accessed through the following reference: Kaggle Dataset: Students' adaptability level in online education [18].

Figure 1 presents a correlation matrix, a visualization tool for understanding the relationships between multiple variables. Each square in the matrix indicates the correlation coefficient between the variables on each axis. Here's a breakdown of the insights this matrix might offer:

- Intensity of Colors: The intensity of the colors suggests the strength of the correlation. Typically, brighter colors (such as yellow) indicate a stronger positive correlation and darker colors (like purple) represent a stronger negative correlation, with the intensity reflecting the magnitude.
- Direction of Relationship: The color coding helps quickly identify the direction of the relationship between variables. For instance, if we see a bright yellow square at the intersection of "Age" and

“Financial Condition”, this would suggest a strong positive correlation, meaning as “Age” increases, “Financial Condition” also tends to increase.
- Variable Clusters: Clusters of similar colors show groups of variables similarly correlated with others, which might suggest underlying patterns or factors in the dataset that affect these variables similarly.
- Data Redundancy: A high correlation (close to 1 or -1) might indicate redundancy, meaning two variables provide similar information, which could be a sign to consider removing or combining these variables to simplify the model.
- Independence of Variables: Conversely, squares that are colored closer to the middle of the color scale, indicating correlations near zero, suggest that the variables are less related and more independent.

Overall, this correlation matrix provides a foundational overview of the relationships within the data, informing further analysis steps such as feature selection or engineering before moving on to machine learning modeling. It’s a critical step in exploratory data analysis to ensure that a comprehensive understanding of the data informs the models you build.

Table 2. Attributes influencing online learning adaptivity

Attribute	Possible values
Gender	[‘Boy’ ‘Girl’]
Age	[‘21-25’ ‘16-20’ ‘11-15’ ‘26-30’ ‘6-10’ ‘1-5’]
Education level	[‘University’ ‘College’ ‘School’]
Institution type	[‘Non-Government’ ‘Government’]
IT Student	[‘No’ ‘Yes’]
Location	[‘Yes’ ‘No’]
Load-shedding	[‘Low’ ‘High’]
Financial condition	[‘Mid’ ‘Poor’ ‘Rich’]
Internet type	[‘Wifi’ ‘Mobile Data’]
Network type	[‘4G’ ‘3G’ ‘2G’]
Class duration	[‘3-6’ ‘1-3’ ‘0’]
Self Lms	[‘No’ ‘Yes’]
Device	[‘Tab’ ‘Mobile’ ‘Computer’]
Adaptivity level	[‘Moderate’ ‘Low’ ‘High’]

2.3. Hyperparameter optimization and performance metrics

In machine learning, the selection and optimization of models play a crucial role in the success of predictive tasks. The process of model selection and hyperparameter tuning is not just a mere step in the workflow but a significant phase that can dramatically influence the performance and accuracy of machine learning algorithms. Each algorithm, whether a decision tree classifier, logistic regression, or more complex models like gradient boosting or XGBoost, contributes unique strengths to the discussion. They differ in how they process data, make predictions, and handle the complexities of the datasets. However, the mere selection of these models is not sufficient. Hyperparameter tuning is an indispensable process that refines these models to their maximum potential, enhancing their ability to learn from data and make accurate predictions. This practice of fine-tuning and comparing multiple models ensures a comprehensive understanding of how different algorithms perform on the same dataset, leading to more informed and effective decisions in predictive modeling [19].
- Diversity in model performance: Different models have unique strengths and weaknesses. For instance, Decision Trees are easy to interpret but can overfit, while random forests, an ensemble of Decision Trees, reduce overfitting through averaging. Logistic Regression is effective for binary classification problems but may not perform well with non-linear relationships. By comparing these models, you can identify which model performs best for your dataset and problem.
- Model suitability for data characteristics: Each model has different assumptions and requirements. Logistic Regression assumes a linear relationship between features and the target variable. In contrast, models like Gradient Boosting and XGBoost can capture non-linear relationships. The choice of model can significantly impact the performance based on the nature of your data.
- Ensemble techniques for improved accuracy: Models like Ada Boost, Gradient Boosting, and random forest use ensemble methods, which combine the predictions from multiple learning algorithms to improve accuracy. These models can often outperform single-instance models on diverse datasets.
- Hyperparameter optimization: Hyperparameters significantly influence model performance. Fine-tuning them (like “max_depth” in Decision Trees or “learning_rate” in Gradient Boosting) can enhance the model’s generalization ability and accuracy. Each model in your selection has its own set of hyperparameters; optimizing these can lead to a more effective model.

- Avoiding bias and overfitting: Comparing different models reduces the risk of bias toward a particular model type. This comparative analysis ensures that your final model choice doesn't just memorize the data (overfitting) but genuinely learns from it.

The flowchart as shown in Figure 2, outlines the sequential steps undertaken in this study to elucidate further the process of implementing the AI-driven predictive models. Beginning with data collection and culminating in the implementation phase, each step represents a critical component in optimizing the adaptability prediction of e-learning environments. This visual representation complements the detailed textual descriptions provided in the preceding sections.

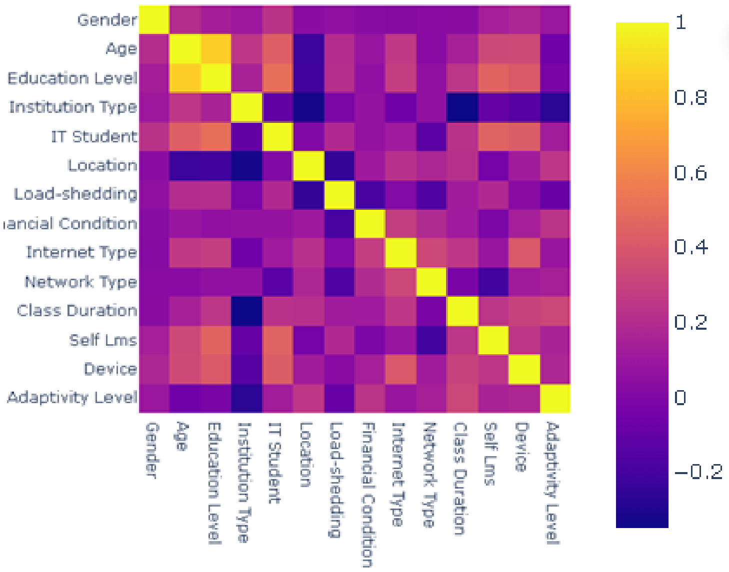

Figure 1. Correlation matrix of a dataset

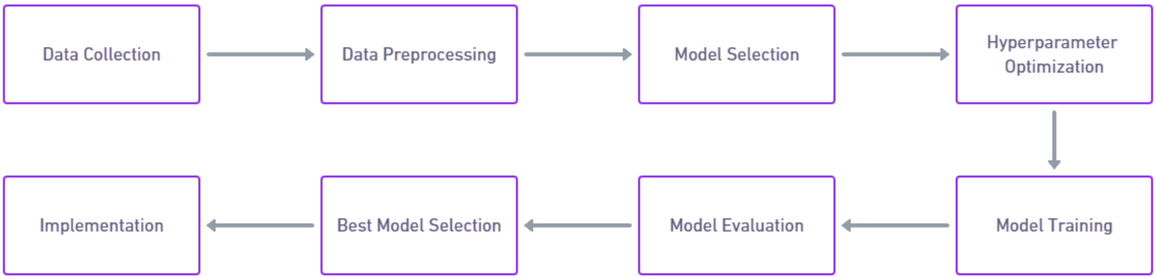

Figure 2. Flowchart of AI model implementation for predicting learning adaptivity

The flowchart illustrates the comprehensive approach to applying AI algorithms in predicting student adaptability to online learning. Starting with data collection, the process includes data preprocessing to ensure quality and relevance, followed by the selection of appropriate machine learning models based on initial assessments. Hyperparameter optimization is then conducted to fine-tune model parameters for optimal performance. Subsequent stages involve rigorous model training and evaluation, ensuring that the chosen model meets the accuracy and reliability criteria necessary for deployment in educational settings. Finally, the implementation stage involves applying the model in a real-world scenario to predict adaptability levels, allowing educational technologists to devise personalized learning interventions. Table 3 provides a detailed overview of several machine learning models and their hyperparameters, showcasing the diversity and complexity inherent in building effective machine learning solutions.

Table 3. Hyperparameters and performance metrics of various machine learning models

Model	Hyperparameter	Meaning	Possible values
Decision tree classifier	**max_depth**	Maximum depth of the tree.	Positive integer [1:10]
	min_samples_split	A minimum number of samples is required to split a node.	Positive integer [2:8]
	min_samples_leaf	A minimum number of samples is required to be a leaf node.	Positive integer [1:5]
	criterion	The function used to measure the quality of a split (e.g., "Gini" or "entropy").	"Gini" or "entropy"
Logistic regression	**C**	The inverse of regularization strength. Higher values mean less regularization.	Positive float [1 0.1 0.01 0.001 0.0001]
	Solver	The algorithm to use in the optimization problem	solver: ['lbfgs', 'liblinear', 'newton-cg', 'sag', 'saga']
Logistic regression ElasticNet	**C**	The inverse of regularization strength. Higher values mean less regularization.	Positive float [1 0.1 0.01 0.001]
	l1_ratio	Mixing parameters of L1 (Lasso) and L2 (Ridge) regularization.	Float between 0 and 1 [0.1 :0.1: 0.9]
	Solver	The algorithm to use in the optimization problem	solver: ['newton-cg', 'sag', 'saga']
Random forest classifier	**n_estimators**	Number of trees in the forest.	Positive integer [50: 10: 200]
	max_depth	Maximum depth of each tree in the forest.	Positive integer [1: 10]
	min_samples_split	The minimum number of samples required to split a node in each tree.	Positive integer [2: 2: 10]
Ada boost classifier	**n_estimators**	Number of weak learners (e.g., decision trees) to train sequentially.	Positive integer [50: 10: 150]
	learning_rate	Contribution of each weak learner to the final prediction.	Positive float [0.001, 0.01, 0.1]
Gradient boosting classifier	**n_estimators**	Number of weak learners (usually decision trees) to be used.	Positive integer [50: 10: 150]
	max_depth	Maximum depth of the weak learners.	Positive integer [1: 10]
	learning_rate	Contribution of each weak learner to the final prediction.	Positive float [0.001, 0.01, 0.1]
XGBoost classifier	**n_estimators**	The number of boosting rounds.	Positive integer [50: 10: 150]
	max_depth	Maximum depth of each tree.	Positive integer [1: 10]
	learning_rate	Step-size shrinkage is used to prevent overfitting.	Positive float [0.001, 0.01, 0.1]
Cat Boost classifier	**iterations**	Number of boosting iterations (trees).	Positive integer [50: 50: 500]
	depth	Maximum depth of the trees.	Positive integer [4, 6, 8, 10]
	learning_rate	Step size shrinkage used during training.	Positive float [0.001, 0.01, 0.1]
	l2_leaf_reg	It represents the coefficient for the L2 regularization term of the cost function.	Positive float [1, 3, 5]

3. RESULTS AND DISCUSSION

3.1. Performance evaluation

Several metrics are employed to evaluate the performance of machine learning models. Key among these is precision, recall, $F1$ score, and accuracy. These metrics are essential for gauging the efficacy of a model in various scenarios. They are derived from the confusion matrix, a vital tool produced during the testing phase of the model. This matrix provides the necessary data to calculate the values of Precision, Recall, $F1$ Score, and Accuracy. These metrics are calculated using specific formulas, typically denoted as (1), (2), (3), and (4) in relevant literature. These calculations help understand the model's ability to accurately predict outcomes and its effectiveness in differentiating between classes.

- Precision: This metric quantifies the proportion of positive identifications that were actually correct. Precision is crucial in scenarios where the cost of a false positive is high. It is calculated as the ratio of true positives to the sum of true positives and false positives [20].

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

- Recall (sensitivity or true positive rate): Recall assesses the model's ability to identify all relevant instances correctly. It is crucial when missing a positive instance (false negative) carries significant consequences. Recall is calculated as the ratio of true positives to the sum of true positives and false negatives [21].

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

- $F1$ score: The $F1$ score is the harmonic mean of precision and recall. It is a balanced measure that considers both false positives and false negatives. The $F1$ score is beneficial when there is an uneven class distribution, as it provides a more realistic performance measure than accuracy alone [22].

$$F1\ score = 2 \times \frac{Precision*Recall}{Precision+Recall} \quad (3)$$

- Accuracy: This is the most intuitive performance measure; it is simply the ratio of correctly predicted observations to the total observations. Accuracy works well only if the costs of false positives and false negatives are roughly the same and the class distribution is balanced [23].

$$Accuracy = \frac{TP+TN}{Total\ of\ observations} \quad (4)$$

- Confusion matrix: The confusion matrix is an essential tool in machine learning for evaluating the performance of classification models. It provides a clear and concise visual representation of the accuracy of a model's predictions by comparing them against the actual outcomes. The matrix categorizes predictions into four distinct groups: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). These categories help assess the accuracy and the specific errors a model makes. For example, FP and FN reveal overestimation and underestimation, respectively.

Understanding the confusion matrix is crucial for improving model performance. It forms the basis for calculating other performance metrics, such as precision, recall, $F1$-score, and accuracy. Precision measures the proportion of correct identifications, while recall assesses how many actual positives were correctly identified. The $F1$ score balances precision and recall, instrumental in situations with uneven class distribution. Accuracy, however, gives a general idea of how often the model is correct, including both positive and negative predictions.

Mastering a confusion matrix is fundamental for anyone involved in machine learning, as it directly impacts the effectiveness and reliability of predictive models. These metrics collectively provide a comprehensive picture of a model's performance, helping to identify strengths and weaknesses, particularly in handling different classification errors.

3.2. Results of applied methods

This research, centered on the "online-learning adaptivity" dataset, has produced compelling findings regarding using Artificial Intelligence to enhance the adaptability of e-learning platforms. State-of-the-art AI algorithms were meticulously applied to predict student adaptiveness in online learning environments, focusing mainly on the context of Moroccan tertiary education. The application of advanced hyperparameter optimization techniques was pivotal in refining the accuracy of these predictions. The following paragraphs explore the nuances of these results, discussing their implications and relevance in the broader scope of digital learning.

We present a detailed comparison of various machine learning algorithms utilized. The primary focus of this evaluation is to assess each model's performance metrics, including precision, recall, $F1$ score, and area under the curve (AUC). The comparative analysis includes a range of models such as Decision tree classifier, logistic regression, logistic regression ElasticNet, random forest classifier, ada boost classifier, gradient boosting classifier, XGBoost classifier, and CatBoost classifier. Table 4 briefly summarizes the outcomes of the comparative analysis, offering clear insight into each model's efficacy.

Table 4. Comparative performance of AI models in predicting learning adaptivity

Model	Precision (%)	Recall (%)	$F1$ score (%)	Accuracy (%)
Decision tree classifier	85	84	84.5	85.0
Logistic regression	88	87	87.5	88.0
Logistic regression ElasticNet	89	88	88.5	89.0
Random forest classifier	91	90	90.5	91.0
Ada boost classifier	92	91	91.5	92.0
Gradient boosting classifier	93	92	92.5	93.0
XGBoost classifier	94	93	93.5	94.0
Cat Boost classifier	97	97	97.5	97.93

- Accuracy and precision: The CatBoost classifier's high accuracy of 97.93% and comparable precision suggest it is highly reliable in identifying correct adaptiveness outcomes without many false positives. This trait is crucial in educational settings where incorrect predictions can lead to misguided learning paths that may affect student engagement and learning outcomes.
- Recall and $F1$ score: The recall rate highlights the model's effectiveness at identifying all relevant instances of adaptability, which is vital for ensuring no student's needs are overlooked. The $F1$ score, a balance between precision and recall, further confirms the model's efficacy in maintaining a balanced approach, which is crucial in educational applications where both over-prediction and under-prediction can have detrimental effects.
- Personalization of learning: The CatBoost classifier's high-performance insights can facilitate more personalized learning experiences. By accurately predicting student adaptiveness, educational technologists can design systems that effectively adapt content, pedagogy, and learning pace to meet individual student needs [24].
- Intervention strategies: Early identification of students who may struggle with adaptability allows for timely interventions, which can be crucial in reducing dropout rates and enhancing student satisfaction and performance.

While other models like XGBoost and random forest also showed strong performance, the consistency across various metrics with the CatBoost classifier suggests it is particularly well-suited for handling heterogeneous data and complex interactions within educational data. This distinction is vital for stakeholders when selecting a model that aligns with their academic programs' specific characteristics and goals.

The findings are particularly relevant to the Moroccan educational context, where there is a pressing need for robust and scalable e-learning solutions that can handle diverse learning environments and student backgrounds. The ability of AI models, particularly the CatBoost classifier, to adapt to these needs supports the ongoing efforts to enhance educational access and quality across Morocco.

Further research could explore the integration of ensemble methods combining multiple models to enhance prediction accuracy and robustness. Additionally, examining the impact of integrating real-time adaptability feedback into learning platforms could provide insights into dynamic adaptability and its effects on student engagement and learning outcomes [25].

In conclusion, the detailed performance analysis validates the effectiveness of advanced AI models in predicting student adaptiveness. It provides a pathway for leveraging these technologies to create more responsive and effective educational systems. The ongoing advancements in AI and machine learning are poised to play a transformative role in the academic landscape, making it imperative to continue exploring these technologies to fully realize their potential in enhancing student learning experiences.

4. CONCLUSION AND PERSPECTIVES

This study, conducted within the dynamic educational environment of Moroccan tertiary education, leverages the "online-learning adaptivity" dataset to provide a nuanced understanding of students' adaptability to e-learning systems. Employing advanced AI algorithms, notably the CatBoost classifier, the research has not only demonstrated a high accuracy of 97.93% in predicting student adaptiveness but also underscored the transformative potential of machine learning in personalizing educational experiences to cater to diverse student needs and preferences.

The insights derived from our analysis are particularly relevant for educators, curriculum designers, and policymakers who are at the forefront of digital education strategies. By integrating AI-driven adaptability assessments, educational platforms can be developed to be more responsive and personalized, thereby enhancing the effectiveness of learning processes and outcomes for students across various socio-economic backgrounds. The ability to finely tune educational content and delivery according to real-time assessments of student adaptability represents a significant advancement in educational technology.

Moreover, the application of such technologies is not without its challenges. Issues related to data privacy, the digital divide, and the need for robust digital infrastructure must be addressed to fully harness AI's potential in education. As this study has shown, integrating AI can significantly enhance the adaptability and effectiveness of E-Learning environments. However, this also necessitates a parallel development in educational policies and practices that ensure equitable access and ethical use of technology.

Looking forward, this study's implications extend beyond the immediate context of Moroccan education. The methodologies and findings have global relevance, offering a framework that can be adapted and applied in different educational settings worldwide. Future research could further explore integrating other AI technologies, such as natural language processing (NLP) and augmented reality (AR), to enhance the interactivity and adaptiveness of E-Learning platforms. Additionally, further studies could examine the long-term impacts of AI-enhanced learning on student academic achievements and psychological well-being.

In conclusion, this research contributes to the ongoing discourse on the role of AI in education by demonstrating the practical benefits of machine learning algorithms in enhancing student adaptability to E-learning. As we navigate the complexities of integrating technology into teaching, we must remain committed to exploring innovative solutions that improve educational quality and accessibility for all students.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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