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Research Article

A New Approach to Machine Learning Algorithms in Adaptive E-Learning Systems

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ABSTRACT

Introduction: Adaptive e-Learning denotes a collection of methodologies aimed at providing online learn-ers with a personalized and distinctive experience, ultimately intended to enhance their performance. Adaptive e-Learning operates on the premise that each learner possesses distinct characteristics, including varied backgrounds, educational requirements, and learning preferences.

Objectives: The aim of Adaptive e-Learning is to identify individual differences and convert them into pertinent information and training methodologies tailored for each student. This paper explores the used of machine learning (ML) and deep leaning techniques in crafting personalized learning experiences within adaptive e-learning systems, especially estimated the learning style.

Methods: It highlights key algorithms employed for learner modeling, recommendation, assessment, and improved student outcomes by focused on the style of learning for the students. First step, we used an educational dataset that are related to the learning style for 1,210 students. Then, the preprocessing steps were applied on the dataset like checking missing values, and turning object columns type to categorical for easing the transformation process.

Results: The deep learning techniques that were used are deep neural network (DNN), while the ML techniques are Random Forest, XGBoost, AdaBoost, and Logistic Regression. To assess these algorithms, the accuracy, precision, recall, and f1-score. The finding of this paper for all the algorithms are as follows: DNN (91, 89, 90, 90), RF (83, 83, 83, 83), LR (89, 90, 90, 90), XGB (83, 83, 83, 83), and Ada (86, 87, 86, 86). We have shown that the DNN gave the best prediction of learning style compared with the others.

Conclusions: investigating the impact of feature extraction and selection, as highlighted in previous studies, could contribute to refining the accuracy and effectiveness of the system.

Keywords: machine learning, learner modeling, personalization, educational technology, adaptive e-learning

INTRODUCTION

Education constitutes a fundamental human right, a significant catalyst for development, and one of the most effective tools for alleviating poverty and enhancing health, gender equality, peace, and stability. It provides substantial, reliable income returns and is the paramount determinant in ensuring equity and inclusion [1]. Education enhances career opportunities, income, health, and alleviates poverty for individuals. Worldwide, there is a 9% rise in hourly wages for each additional year of education. It promotes sustained economic growth, stimulates innovation, fortifies institutions, and enhances social cohesion within societies. Education serves as a potent catalyst for climate action by promoting widespread behavioral change and equipping individuals with skills for sustainable transitions [1, 2].

E-learning, or electronic learning, denotes the utilization of digital tools and technologies to provide instructional content, enhance engagement, and promote learning [3]. This educational method has experienced swift expansion, becoming as a crucial component of the contemporary educational framework. In another words, E-learning, often known as electronic learning or web-based training, refers to teaching provided over the internet or a corporate intranet, accessible to students and learners via a browser at any time and from any location. Unlike conventional learning methods, e-learning enables students, trainees, and casual learners to engage in a structured educational experience irrespective of their geographical location [4].

During its early development, e-learning platforms largely facilitated the direct transmission of educational content from an instructor to a student. The e-learning experience has progressed to facilitate enhanced multidirectional communication through increasingly engaging tools. Students possess increased autonomy in selecting their methods of engaging with and reacting to e-learning materials, with the potential involvement of numerous peers [5].

E-learning methodologies and technologies are crucial for both student education and employee professional growth in the workforce. The swift advancement of technology has rendered it essential for personnel to possess appropriate skills and training. The anticipated advent of quantum computing capabilities is likely to induce a significant transformation in contemporary company operations, impacting coders, hardware developers, and cybersecurity professionals. E-learning settings will be crucial in the retraining and reskilling of numerous individuals [6].

Moreover, organizations are progressively adopting online learning for continuous training and staff upskilling. Learning management systems (LMS) are very prevalent in corporate environments. Higher education institutions employ online learning methodologies in conjunction with internet-enabled technological devices, both within and beyond conventional classrooms. McKinsey & Company's 2022 poll of 7,000 students across 17 countries reveals that 65% of higher education students desire the continuation of certain online learning elements in the post-pandemic era [5, 6].

Adaptive learning, or adaptive teaching, is an educational approach that employs computer algorithms and artificial intelligence to facilitate learner interaction and provide tailored resources and activities to meet the individual needs of each student. In professional development settings, individuals may "test out" of some training to guarantee their participation in innovative education. Computers modify the delivery of educational content based on students' learning requirements, as evidenced by their responses to inquiries, assignments, and experiences. The technology integrates elements from multiple disciplines, including computer science, artificial intelligence, psychometrics, education, psychology, and neuroscience [7, 8].

Adaptive learning has been partially motivated by the understanding that customized education cannot be effectively implemented on a broad scale by conventional, non-adaptive methods. Adaptive learning systems aim to convert the student from a passive recipient of knowledge to an active participant in the educational process. The principal application of adaptive learning systems is in education; however, they are also widely utilized in business training. They have been developed as desktop apps, web applications, and are now being integrated into comprehensive courses [9].

Adaptive learning systems have conventionally been categorized into distinct components or 'models'. Although various model groups have been introduced, the majority of systems encompass some or all of the following models (often under alternative nomenclature) [10]:

- Expert model - The model containing the information intended for instruction.
- Student model – The framework that monitors and acquires knowledge regarding the student.
- Instructional model - The framework that effectively transmits information.
- Instructional environment - The user interface for system interaction.

Artificial Intelligence and Machine Learning have emerged as disruptive technologies across multiple domains, including education. In the realm of adaptive learning, artificial intelligence and machine learning are essential for facilitating individualized and customized educational experiences. Artificial Intelligence pertains to the creation of intelligent computers capable of emulating human cognition and executing tasks that generally necessitate human intellect, including perception, thinking, and decision-making [11].

The significance of AI and ML in collecting and evaluating learner data is essential for delivering tailored learning experiences. The benefits of AI-enabled learning systems encompass an enhanced learning environment, flexible scheduling, the provision of quick feedback, the capacity to tailor students' learning experiences, and expedited student progress. Artificial intelligence systems may analyze extensive datasets, derive insights from patterns and experiences, and generate forecasts or suggestions. AI facilitates the application of many pedagogical approaches, acknowledging each student's unique talents, abilities, and academic challenges. Artificial Intelligence and Machine Learning algorithms can aggregate learner data from diverse sources, including learning management systems, online platforms, examinations, and digital resources [12].

These algorithms can collect data on student demographics, performance metrics, interaction patterns, learning preferences, and additional pertinent information. Data collection may take place in real time or asynchronously, enabling adaptive learning systems to perpetually update and enhance learner profiles. Artificial Intelligence and Machine Learning methodologies are proficient in the analysis of extensive and intricate datasets. Upon the collection of learner data, these algorithms can analyze the information to reveal patterns, correlations, and trends. Adaptive learning systems may discern individual student attributes, including strengths, limitations, learning preferences, and knowledge deficiencies, through data analysis. This research serves as the basis for developing customized learning experiences. Artificial Intelligence and Machine Learning algorithms can construct learner models derived from the investigated data. Learner modeling entails the development of representations for individual learners, encompassing their cognitive capabilities, knowledge proficiency, learning modalities, and preferences. These models encapsulate the distinct attributes of each student and provide a foundation for customizing the educational experience [12, 13].

Machine Learning is a branch of Artificial Intelligence that concentrates on empowering computers to learn from data and enhance their performance without explicit programming. Machine learning algorithms examine extensive information to discern patterns, correlations, and insights. Machine learning algorithms can generate predictions, classifications, and recommendations by training models on pre-existing data. In adaptive learning, machine learning is employed to analyze student behavior, customize information, and modify instructional tactics. Artificial Intelligence and Machine Learning methodologies provide the examination of extensive learner data, encompassing performance, interactions, and preferences. Through the analysis of this data, adaptive learning systems may generate learner profiles and ascertain individual needs and strengths. AI algorithms can personalize educational content, modify difficulty levels, and provide targeted interventions to enhance learning outcomes. Personalization improves engagement, motivation, and knowledge retention [14].

The objective of this research is to create a proficient system for detecting learning style of the 1,210 students by utilizing a machine learning and deep learning techniques. Fig.1 shows the problem statement formation of this research.

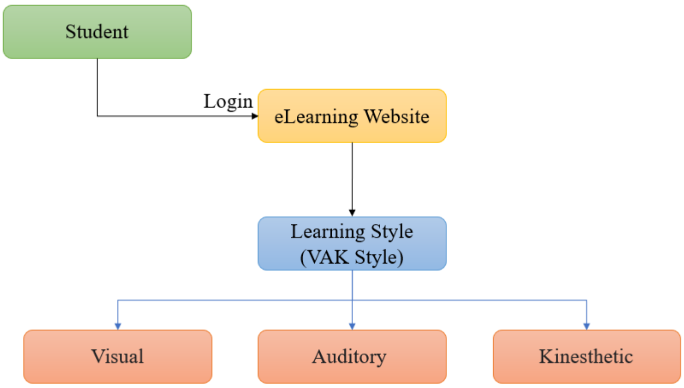

Figure 1: Problem Statement Formation

The reminder for this paper is structured as follows: Section 2 delineates the literature review. Section 3 delineates the approach concerning the dataset, classification methods, and performance indicators employed. Section 4 elucidates and exemplifies the experimental findings. Section 5 delineates the findings. The conclusion of this paper and prospective research endeavors in Section 6.

OBJECTIVES

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LITERATURE REVIEW

This part described the summary of the previous works that are related to this topic in term of the algorithm used, dataset, and the performance results.

EL AISSAOUI et al. [15] suggested a method for the automatic identification of learning styles based on the actions of existing learners, utilizing online usage mining techniques and machine learning algorithms. Web use mining techniques were employed to preprocess the log file obtained from the E-learning environment and to record the sequences of learners. The sequences of captured learners were entered into the K-modes clustering algorithm to categorize them into 16 combinations of learning styles according to the Felder and Silverman model. The naive Bayes classifier was employed to predict a student's learning style in real time. They utilized a genuine dataset derived from the log file of an e-learning system, and to assess the classifier's performance, they employed the confusion matrix method. The findings gathered indicated that their methodology produces exceptional outcomes based on Accuracy, the Recall (Sensitivity), the Specificity, the Precision (PPV) and the NPV as followings: 93.3, 87.5, 99.16, 87.5, and 99.16.

El Aissaoui et al. [16] suggested a method for the automatic detection of learning styles, utilizing the Felder and Silverman Learning Style Model (FSLSM) and machine learning techniques. The suggested methodology consists of two components: The initial phase seeks to extract learners' sequences from the log file, subsequently employing an unsupervised algorithm (K-means) to categorize them into sixteen clusters based on the FSLSM. The subsequent phase involves utilizing a supervised algorithm (Naive Bayes) to forecast the learning style for a new sequence or learner. We utilized a genuine dataset obtained from the log file of an e-learning system to implement our methodology. To assess performance, we employed the confusion matrix method. The findings gathered indicate that our methodology produces exceptional outcomes.

Binh et al. [17] performed an online poll to assess the correlation between learning styles and student performance in specific subjects or full courses, involving students from several disciplines to analyze the impact of diverse learning styles on academic outcomes. This assessment is derived on the Felder-Soloman questionnaire, comprising 44 items categorized into four aspects. They have curated data to identify 316 undergraduate students for the investigation. Based on the questionnaire responses, we employed statistical tools to examine the data and issued several significant observations. In addition to this, they have developed an artificial neural network to forecast academic performance based on students' learning styles. They have demonstrated notable correlations between learning style and testing performance, which bear consequences for course study.

El Aissaoui et al. [18] developed a universal methodology for the automatic detection of learning styles based on a specified learning styles model. Their methodology is not contingent upon a certain LSM. This task has two principal phases. Initially, they extract learning sequences from users' log files utilizing online usage mining techniques. Secondly, we categorize the extracted learners' sequences based on a designated learning style model utilizing clustering methods. They employ the Felder-Silverman Model as the Learning Style Model and Fuzzy C-Means as the clustering algorithm. They have performed an experimental investigation utilizing a real-world dataset. The results indicated that their methodology surpasses conventional approaches and yields encouraging outcomes.

Table 1: Previous Papers Summarization

Ref	Year	Algorithms	Dataset	Evaluation Metrics	Results
EL AISSAOUI et al. [15]	2019	NB K-mode	web log of the E-learning platform	Accuracy Recall Specificity Precision NPV	89.06 87.5 99.16 87.5 99.16
El Aissaoui et al. [16]	2018	NB K-mode	Student dataset from LSM	Accuracy	87.5
Binh et al. [17]	2017	artificial neutral network	316 undergraduate students	-	They have demonstrated notable correlations between learning style and testing performance
El Aissaoui et al. [18]	2021	Felder-Silverman Model Fuzzy C-Means	users' log files	-	These algorithms surpasses conventional approaches and yields encouraging outcomes.

Proposed Methodology

This Section Presents The Proposed Methodology Used In This Work, Which Include Three Steps: The Dataset Used, Preprocessing Steps, Machine And Deep Learning Algorithms, And The Evaluation Metrics To Assess The Performance Of The Algorithms: Accuracy, Recall, F1-Score, And Precision.

Data Collection

In This Paper, We Used The Dataset Related To The Student Performance And The Learning Style For 1,210 Students With 18 Features. Table 2 Shows The Features Names Of This Dataset And Fig.2 Shows A Sample From The Dataset.

TABLE 2: DATASET FEATURES

No.	Feature	Range
1	Gender	(1) Male (0) Female
2	Age	Between 10 And 32
3	I Learn Better By Reading What The Teacher Writes On The Chalkboard.	1 To 5
4	When I Read Instructions, I Remember Them Better.	1 To 5
5	I Understand Better When I Read Instructions.	1 To 5
6	I Learn Better By Reading Than By Listening To Someone.	1 To 5
7	I Learn More By Reading Textbooks Than By Listening To Lectures.	1 To 5
8	When The Teacher Tells Me The Instructions I Understand Better	1 To 5
9	When Someone Tells Me How To Do Something In Class, I Learn It Better.	1 To 5
10	I Remember Things I Have Heard In Class Better Than Things I Have Read.	1 To 5
11	I Learn Better In Class When The Teacher Gives A Lecture.	1 To 5
12	I Learn Better In Class When I Listen To Someone.	1 To 5
13	I Prefer To Learn By Doing Something In Class.	1 To 5
14	When I Do Things In Class, I Learn Better.	1 To 5
15	I Enjoy Learning In Class By Doing Experiments.	1 To 5
16	I Understand Things Better In Class When I Participate In Role-Playing.	1 To 5

17	I Understand Things Better In Class When I Participate In Role-Playing.	1 To 5
18	Learner	(0) A → Auditory (1) K → Kinesthetic (2) V → Visual

Gender	Age	I learn better by reading what the teacher writes on the chalkboard.	When I read instructions, I remember them better.
Male	16	3	3
Male	16	5	4
Male	18	3	4
Male	21	1	3
Female	21	4	4
Male	21	2	3
Female	21	3	3
Male	21	2	3
Female	21	5	5
Male	21	1	3

Figure 2: Dataset Snapshot

Int The Dataset, There Are Three Learning Styles: A, K, And V Distributed In The Fig.3.

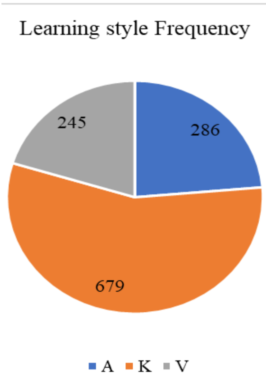

Figure 3: Dataset Frequency

Preprocessing Methods

Data Preparation Is A Critical Phase In Machine Learning And Data Analysis. Data Preparation Include The Processes Of Purifying, Transforming, And Arranging Raw Data Into A Useful Format For Model Training Or Analysis [27]. This Research Employs A Label Encoding Method As A Preprocessing Step To Transform Categorical Data (Age, Gender, Learner) Into Numerical Data. We Utilized A Python Module Known As Labelencoder To Implement This Step. This Technique Counts The Unique Values For Each Column And Replaces Each With A Numeric Value Ranging From 0 To The Number Of Unique Values. For Example, There Are Two Values In The Gender Column: Male, And Female. The Female Is Replaced With 0 And Male Is Replaced With 1. Fig.4 Presents The Dataset After Applied This Method.

Gender	Age	I learn better by reading what the teacher writes on the chalkboard.	When I read instructions, I remember them better.
1	16	3	3
1	16	5	4
1	18	3	4
1	21	1	3
0	21	4	4

Figure 4: Dataset–Applied Labelencoder

Building Models

We Employed Five Classification Methods (Four From Machine Learning And One From Deep Learning) On A Student Dataset To Forecast The Students' Learning Styles.

Deep Neural Network Algorithm

A Deep Neural Network (Dnn) Is A Category Of Artificial Neural Network (Ann) That Employs Multiple Layers Of Processing Units (Neurons) To Discern Hierarchical Patterns From Data. Dnns Are Adept At Modeling Intricate Relationships And Are Extensively Utilized In Diverse Domains, Including Image Recognition, Natural Language Processing, Student Performance Prediction, Adaptive Learning, And Predictive Analytics. The Training Phase Encompasses Forward Propagation, Wherein Inputs Traverse The Network To Produce Predictions, And Backpropagation, During Which Prediction Errors Are Utilized To Modify The Network's Weights Through An Optimization Method Such As Stochastic Gradient Descent (Sgd) Or Adam [28].

There Are Three Types Of Layers Of The Dnn [28]:

Input Layer: This Layer Acquires The Input Data (Features Of This Dataset).

Hidden Layers: These Are Intermediary Layers That Execute Computations On The Inputs. Dnn Possess Several Hidden Layers, Each Responsible For Identifying Increasingly Abstract Features.

Output Layer: This Layer Generates The Prediction Or Classification Result (Style Of The Student Learning: A, K, Or V).

Fig.5 Shows The Dnn Architecture Of The Dnn.

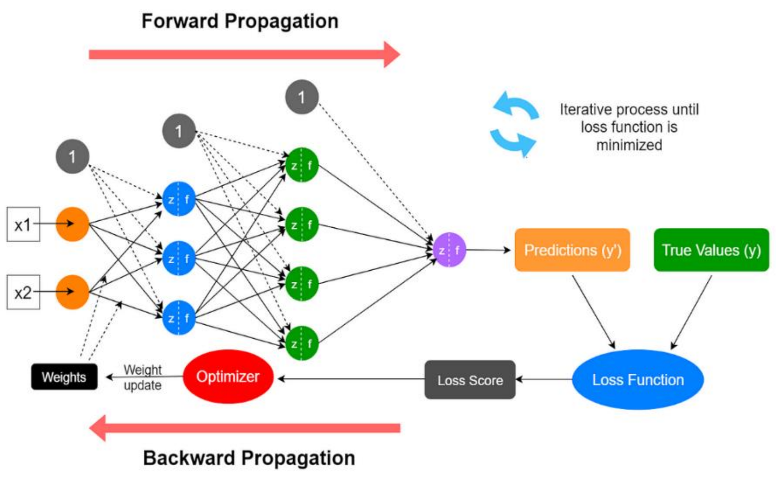

Figure 5: Dnn Architecture

Random Forest (Rf) Algorithm

Random Forest Is An Ensemble Learning Technique Employed For Classification And Regression Applications. It Constructs Numerous Decision Trees During The Training Process And Produces The Majority Vote (For Classification) Or The Average Forecast (For Regression) From All The Trees. Random Forest Is Esteemed For Its Capacity To Enhance Precision And Mitigate Overfitting Relative To Solitary Decision Tree [29]. The Inner Working Of The Rf In Two Stages As Follows [29]:

1) Training Stage:

Data Sampling: A Bootstrap Sample (Random Sample With Replacement) Is Generated From The Training Data For Each Tree.

Tree Construction: A Decision Tree Is Developed On This Sample By Employing A Random Subset Of Features At Each Bifurcation.

This Procedure Is Reiterated For A Specified Quantity Of Trees (E.G., 100 Trees).

2) Prediction Stage:

In Classification, The Random Forest Consolidates The Predictions From All Trees And Identifies The Class With The Highest Number Of Votes.

For Regression, It Calculates The Mean Of All Tree Forecasts.

Random Forests Can Improve Accuracy, Reduce Overfitting, And Adeptly Tackle Complex Issues By Integrating The Predictions Of Several Decision Trees. Random Forests Effectively Capture Many Aspects Of The Data By Employing An Aggregation Of Decision Trees, Leading To More Robust Forecasts. In Equation (1), The Random Forest Computes The Final Prediction Denoted By Y, Where Hi(X) Represents The Forecast For Each Decision Tree, And N Is The Number Of Trees [29].

$$y\ (x) = \frac{1}{N}\sum_{i=0}^{N} h_i(x) \qquad (1)$$

Logistic Regression (Lr) Algorithm

Logistic Regression Is A Statistical Model Utilized Predominantly For Binary Classification Problems, Aiming To Predict One Of Two Or Three Potential Outcomes (E.G., 0 Or 1, True Or False, Yes Or No). Notwithstanding Its Designation, Logistic Regression Is A Classification Algorithm Rather Than A Regression Tool. It Functions By Calculating The Likelihood That A Specific Input Point Is Associated With A Designated Class Through The Logistic (Sigmoid) Function. Logistic Regression Characterizes The Association Between Independent Variables X = {X1, X2, Xn} And The Dependent Variable (Class Label, y) By A Linear Amalgamation Of The Input Features, As Shown In Equation 2 [30]:

Z= B_0+B_1 X_1 +B_2 X_2+⋯+ +B_N X_N (2)

Where:

-Z Is The Linear Combination Of Input Features.

-B0 Is The Intercept (Bias Term).

-B1, B2,…,Bn Are The Coefficients (Weights) Of The Features X1,X2,…,Xn.

Xgboost Algorithm

Xgboost (Extreme Gradient Boosting) Is An Exceptionally Efficient And Scalable Version Of The Gradient Boosting Machine Learning Technique. It Has Emerged As One Of The Most Prevalent And Extensively Utilized Algorithms For Supervised Learning Tasks, Especially In Structured Or Tabular Data. Xgboost Is Recognized For Its Efficiency And Precision, Routinely Achieving Victories In Machine Learning Competitions Owing To Its Capability To Manage Diverse Jobs. The Formula Of This Method Is Shown In Eq. (3) [31]:

$$Objective = \sum_{i=1}^{n} (y_i + \hat{y}_i)\ \sum_{k=1}^{K} \Omega\ (f_k) \qquad (3)$$

Where, N Is The Number Of Training Instances, K Is The Number Of Trees In The Model, Fk Represents The Kth Tree, And Ω(Fk) Is The Regularization Term Which Penalizes Complexity Of The Model To Prevent Overfitting.

Adaboost Algorithm

Adaboost Algorithm, An Abbreviation For Adaptive Boosting, Is A Boosting Approach Employed As An Ensemble Method In Machine Learning. It Is Termed Adaptive Boosting Because Weights Are Reallocated To Each Instance, With More Weights Assigned To Misclassified Cases. Boosting Is Employed To Diminish Both Bias And Variation In Supervised Learning. It Operates On The Premise Of Learners Developing Progressively. With The Exception Of The Initial Student, Each Succeeding Learner Is Derived From Previously Cultivated Learners. Weak Learners Are Transformed Into Strong Learners. The Adaboost Algorithm Operates On The Same Idea As Boosting, With A Minor Distinction. It Generates 'N' Decision Trees Throughout The Data Training Phase. In The Initial Decision Tree/Model, The Improperly Classified Record Is Prioritized. Only These Records Are Provided As Input For The

Second Model. The Process Continues Until We Designate The Desired Quantity Of Basic Learners To Be Generated. The Formula Of This Method Is Shown In Eq. (4) [32].

$$\mathrm{H}\ (\mathrm{X}) = sign\left(\sum_{t=1}^{T} \alpha_t \ .\ h_t(x)\right) \qquad (4)$$

Where, H(X) Is The Strong Learner, H(X) Is The Weak Learner, And Sign (·) Is The Sign Function Which Returns -1 For Negative Values And 1 For Non-Negative Values.

3.4 Performance Metrics

The Experimental Findings For The Specified Machine Learning Model Are Derived From Four Assessment Metrics: Precision, Recall, F1-Score, And Accuracy. The Formulas For Each Measure And A Brief Explanation Are Presented Below, Where Fn Denotes False Negative, Tp Signifies True Positive, Tn Indicates True Negative, And Fp Represents False Positive [33]:

Accuracy Is Computed By Divided The Ratio Of Samples That Are Correctly Predicted To The Total Number Of Samples.

$$\text{Accuracy} = (\text{Tp} + \text{Tn}) \ /\ (\text{Tp} + \text{Tn} + \text{Fp} + \text{Fn}) \qquad (5)$$

Precision Is Calculated By Dividing The Number Of Accurately Predicted Positive Samples By The Total Number Of Anticipated Positive Samples.

$$\text{Precision} = \text{Tp} \ /\ (\text{Tp} + \text{Fp}) \qquad (6)$$

The Ratio Of Genuine Positive Samples In The Dataset To The Total Number Of Anticipated Positive Samples Is Termed Recall.

$$\text{Recall} = \text{Tp} \ /\ (\text{Tp} + \text{Fn}) \qquad (7)$$

F1-Score Is The Weighted Average Of Recall And Precision.

$$\text{F1} - \text{Score} = 2 * ((\text{Precision} * \text{Recall}) \ /\ (\text{Precision} + \text{Recall})) \qquad (8)$$

3.5 Methodology Architecture

Fig.6 Presents The Flow Chart Of The Proposed Methodology Used To Predict The Style Of The Student Learning, Which Contains Four Steps: Dataset Collection, Preprocessing Steps, Building Models, And Evaluation The Performance Of These Models.

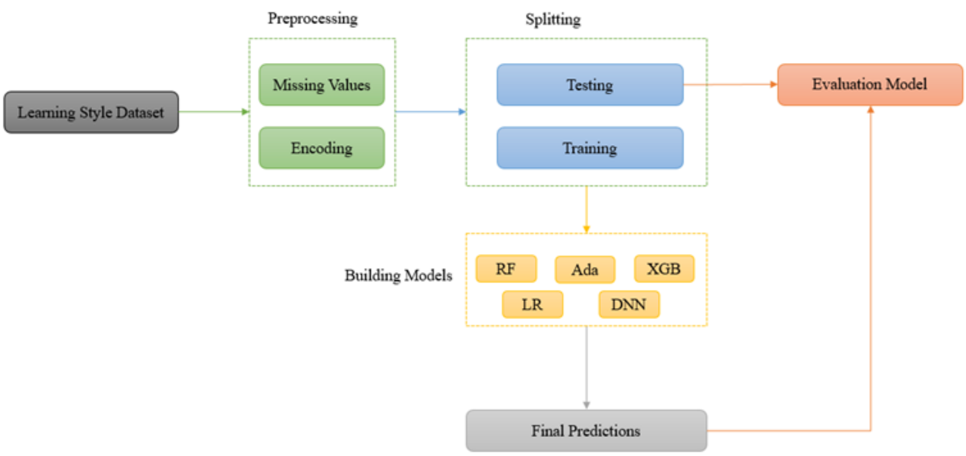

Figure 6: Proposed Methodology

Evaluation And Results

In This Section, We Presented The Experimental Setup And The Results For The Models Used In This Paper To Predict The Learning Style Of The 1,210 Students.

4.1 Experimental Setup

This Part Shows The Parameters Values For The Machine And Deep Learning Algorithms That Are Used, As Shown In Table 3.

Table 3: Classification Algorithms–Experimental Setup

Algorithm	Parameter	Value
Rf	No. Of Estimators	100
	Criterion	Gini
	Max Depth	None
	Random State	42
Xgb	Learning Rate	0.1
	No. Of Estimators	100
	Random State	42
Ada	No. Of Estimators	50
	Learning Rate	0.1
	Algorithm	Sammer.R
	Random State	42
Lr	Penalty	L2
	Tol	0.0001
	C	1.0
Dnn	Input Layer	Dense Layer With 64 Unit, And Input Data
	Hidden Layer	Two Dense Layer With 32, 16 Units Respectively
	Output Layer	Dense Layer With 1 Unit
	Epoch Batch Size Optimization Function	100 32 Adam

Prior To Inputting The Dataset In Classification Algorithms, It Must Be Partitioned Into Two Categories: Testing And Training. The Training Dataset Is Utilized To Construct Models Based On These Algorithms, Whereas The Testing Dataset Is Employed To Evaluate The Performance Of The Constructed Models. This Study Presents The Ratio Of Training To Testing As Follows: 90% Of The Entire Dataset Is Utilized For The Training Phase, While The Remaining 10% Is Allocated For Testing.

4.2 Experimental Results

This Part Delineated Our Findings By Employing Five Machine And Deep Learning Algorithms On The Learning Style Dataset, Utilizing The Specified Assessment Metrics: Recall, Accuracy, F1-Score, And Precision. Subsequently, We Analyze The Experimental Setting For Each Algorithm, Including The Parameters Employed Along With Their Respective Values. We Reached The Following Results For Each Of The Machine-Learning Algorithms As Shown In Table 4 And Fig.7: The Dnn Gave The Best Prediction Of Learning Style Compared With The Others In Terms Of Accuracy, Precision, Recall, And F1-Score As Following: 91, 90, 90, And 89, Respectively. The Numerical Outcomes Provide Insights Into The Effectiveness Of These Machine-Learning Algorithms In Enhancing The Adaptability And Personalization Of E-Learning Platforms.

Table 4: Classification Algorithms Results

Algorithms	Accuracy	Precision	Recall	F1-Score
Dnn	91%	89%	90%	90%
Rf	83%	83%	83%	83%
Lr	89%	90%	90%	90%
Xgb	83%	83%	83%	83%
Ada	86%	87%	86%	86%

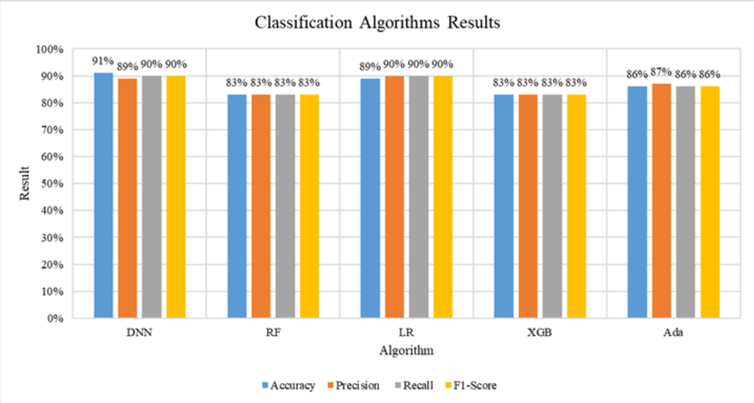

Figure 7. Classification Algorithms Results

4.3 Discussion

This Section Discusses And Explains The Findings Obtained From Our Experiments To Detect Learning Style Of 1,210 Students. These Findings Are Obtained Based On Four Machine Learning Algorithms And One Deep Learning Algorithm: Rf, Lr, Xgb, Adaboost, And Dnn. The Dnn Outperformed The Other Machine Learning Algorithms In This Study And The Previous Studies Based On Evaluation Metrics Used. For Example, El Aissaoui Et Al. [15] And El Aissaoui Et Al. [16] Applied The Same Algorithms For Different Datasets: K-Mode And Nb Algorithms. These Algorithms Gave 89.06, And 87.5, Respectively.

Table 5: Comparison Between Our Work And Previous Works

Ref	Year	Algorithms	Dataset	Evaluation Metrics	Results
El Aissaoui Et Al. [15]	2019	Nb K-Mode	Web Log Of The E-Learning Platform	Accuracy Recall Specificity Precision Npv	89.06 87.5 99.16 87.5 99.16
El Aissaoui Et Al. [16]	2018	Nb K-Mode	Student Dataset From Lsm	Accuracy	87.5
Our Work	2024	Dnn Rf Lr Xgboost Adaboost	1,210 Students	Accuracy Recall Precision F1-Score	Accuracy Of Dnn = 91%

Our Findings Indicate That We Accomplished The Following Objectives:

We Developed A Comprehensive Methodology Utilizing Five Ai Techniques That Achieved Superior Detection Accuracy In Both Datasets Relative To Other Algorithms In This Study And Prior Research.

During The Detection Process, We Required Less Time Than In Prior Studies, Utilizing Identical Computer Configurations.

The False Negative And False Positive Rates Are Reduced By Achieving A Better Accuracy Value With The Robust Methodology Implemented In Both Datasets.

The Contributions Of This Study Are Delineated In The Following Points:

Formulating An Ai Methodology That Employs Robust Machine And Deep Learning Algorithms To Distinguish Among Three Distinct Learning Styles.

Attaining A High Degree Of Precision In Differentiating Among Three Learning Styles.

To Reduce The Incidence Of False Positives In The Detection Of Learning Styles.

Enhanced Detection Accuracy: Machine And Deep Learning Algorithms Can Examine Extensive Datasets To Discern Nuanced Patterns And Traits Indicative Of Phishing Attempts. This Results In Improved Detection Accuracy Relative To Conventional Rule-Based Or Heuristic Approaches.

Conclusion And Future Work

Adaptive E-Learning Refers To A Set Of Strategies Designed To Offer Online Learners A Tailored And Unique Experience, Ultimately Aimed At Improving Their Performance. Adaptive E-Learning Is Based On The Principle That Each Student Has Unique Attributes, Encompassing Diverse Origins, Educational Needs, And Learning Preferences. The Objective Of Adaptive E-Learning Is To Recognize Individual Variances And Transform Them Into Relevant Information And Instructional Strategies Customized For Each Learner. This Study Examines The Application Of Machine Learning (Ml) And Deep Learning Approaches In Developing Individualized Learning Experiences Within Adaptive E-Learning Systems, Particularly In Assessing Learning Styles. It Emphasizes Essential Algorithms Utilized For Learner Modeling, Suggestion, Assessment, And Enhanced Student Results By Concentrating On Students' Learning Styles. Initially, We Utilized An Educational Dataset Pertaining To The Learning Styles Of 1,210 Pupils. Subsequently, Preparation Measures Were Implemented On The Dataset, Including The Examination Of Missing Values And The Conversion Of Object Column Types To Categorical To Facilitate The Transformation Process. The Employed Deep Learning Technique Is The Deep Neural Network (Dnn), Whereas The Machine Learning Techniques Include Random Forest, Xgboost, Adaboost, And Logistic Regression. To Evaluate These Algorithms, The Metrics Of Accuracy, Precision, Recall, And F1-Score Will Be Utilized. The Results Of This Study For All Algorithms Are As Follows: Dnn (91, 89, 90, 90), Rf (83, 83, 83, 83), Lr (89, 90, 90, 90), Xgb (83, 83, 83, 83), And Ada (86, 87, 86, 86). We Have Demonstrated That The Dnn Provided The Most Accurate Prediction Of Learning Style In Comparison To The Alternatives.

As For Future Work, It Would Be Valuable To Explore The Potential Of Incorporating Additional Ai Methods, Such As Ann, Cnn, Bert To Further Enhance The Predictive Capabilities Of The Adaptive E-Learning System. Additionally, Investigating The Impact Of Feature Extraction And Selection, As Highlighted In Previous Studies, Could Contribute To Refining The Accuracy And Effectiveness Of The System. Further Research In These Areas Could Lead To Significant Advancements In The Field Of Adaptive E-Learning Systems.

Refrences

[1] W. Chaimae, K. Mohamed. Machine Learning Approach for an Adaptive E-Learning System Based on Kolb Learning Styles. *International Journal of Emerging Technologies in Learning (ijet)*, 2023.

[2] A. Harish, M. Abdullah, B.T Shobana. Modelling an Adaptive e-Learning System Using LSTM and Random Forest Classification, 2018.

[3] M. Soui, K. Srinivasan, A. Albesher. Intelligent personalized e-learning platform using machine learning algorithms. Machine learning methods for engineering application development. Singapore: Bentham Science Publishers, 110-126, 2022.

[4] S. Alexander. Adaptive machine learning for time-varying systems: low dimensional latent space tuning. *Journal of Instrumentation*, 2021.

[5] H. Slavomír. Adaptive Optimization Algorithms for Machine Learning. arXiv.org, doi: 10.48550/arxiv.2311.10203, 2023.

[6] B., Vijaya, Babu., S., S., Aravinth., K., Gowthami., Petla, Navyasri., Attuluri, Jivitha., Thota, Yasaswini.. Enhancing Personalized Learning Experiences by Leveraging Deep Learning for Content Understanding in E-Learning Recommender Systems, 2024.

[7] R. Setareh., S. Hossein. Advancing Personalized and Adaptive Learning Experience in Education with Artificial Intelligence, 2023.

[8] L. Zhijia. A Review of Personalized Education Based on Machine Learning. doi: 10.61173/mggvmx39, 2024.

[9] C. Waladi, M.S. Lamarti., M. Khaldi. Crafting An AI-Powered Adaptive E-Learning Framework: Based on Kolb's Learning Style. *International journal of religion*, 2024.

[10] A. Ezzaim., A. Dahbi., A. Aqqal, A. Haidin. Novel Machine Learning Approach for an Adaptive Learning System Based on Learner Performance, 2024.

[11] A. Aljuboori., H. Al-lawati. Intelligent Adaptive E-Learning Systems: Current Approaches, Architectures, and Applications. *European Conference on e-Learning*, 2023.

[12] E. Aymane, A. D. Abdelfatteh, Enabling Sustainable Learning: A Machine Learning Approach for an Eco-friendly Multi-factor Adaptive E-Learning System. *Procedia Computer Science*, 2024.

[13] Z., Chen. Integrating Machine Learning Techniques for Real Estate Analysis. *Highlights in Science Engineering and Technology*, 2024.

[14] B. O. Adelakun. D.T. Fatogun, Integrating machine learning algorithms into audit processes: Benefits and challenges. *Finance & accounting research journal*, 2024.

[15] O. El Aissaoui, Y. El Madani. Combining supervised and unsupervised machine learning algorithms to predict the learners' learning styles. *Procedia computer science*, 148, 87-96, 2019.

[16] O. El Aissaoui, Y. El Allioui. A hybrid machine learning approach to predict learning styles in adaptive E-learning system. In *International Conference on Advanced Intelligent Systems for Sustainable Development*, pp. 772-786, 2018.

[17] H. T. Binh, B. T. Duy. Predicting students' performance based on learning style by using artificial neural networks. *In 2017 9th international conference on knowledge and systems engineering (KSE)*, pp. 48-5, 2017.

[18] A. Scheinker. Adaptive machine learning for time-varying systems: low dimensional latent space tuning. Journal of Instrumentation, 2021.

[19] E. Ahmed. Student Performance Prediction Using Machine Learning Algorithms. *Applied Computational Intelligence and Soft Computing*, 2024.

[20] N. Kartik, R. Mahalakshmi. Predicting Students' Performance Using Feature Selection-Based Machine Learning Technique, 2024.

[21] M. R. Alzahrani. Predicting Student Performance Using Ensemble Models and Learning Analytics Techniques, 2024.

[22] K. Roy, H. Nguyen, D. Farid. Impact of dimensionality reduction techniques on student performance prediction using machine learning. *CTU Journal of Innovation and Sustainable Development*, 2023.

[23] G. Kumar. A student performance prediction approach using machine learning, 2024.

[24] F. Gazzawe., M. Mayouf, R. Lock, R. Alturki. The Role of Machine Learning in E-Learning Using the Web and AI-Enabled Mobile Applications. *Mobile Information Systems*, 2022.

[25] D. Patiño. Implementation of machine learning techniques and creation of an artificial neural network for the prediction of the academic performance of students in university environments that use e-learning and streaming. Dyna, 2023.

[26] O. S. Moskalenko, I. Getman. Intelligent search for scientific information in e-learning systems. *Nucleation and Atmospheric Aerosols*, 2022.

[27] S. A. Alasadi, W. S. Bhaya. Review of data preprocessing techniques in data mining. *Journal of Engineering and Applied Sciences*, *12*(16), 4102-4107, 2017.

[28] S. Mittal. A survey on modeling and improving reliability of DNN algorithms and accelerators. *Journal of Systems Architecture*, *104*, 101689, 2020.

[29] S. J. Rigatti. Random forest. *Journal of Insurance Medicine*, *47*(1), 31-39, 2017.

[30] P. Schober, T. R. Tetter.` Logistic regression in medical research. *Anesthesia & Analgesia*, *132*(2), 365-366., 2021.

[31] A. Asselman, M. Khaldi, S. Aammou. Enhancing the prediction of student performance based on the machine learning XGBoost algorithm. *Interactive Learning Environments*, *31*(6), 3360-3379, 2023.

[32] W. Wang, D. Sun. The improved AdaBoost algorithms for imbalanced data classification. *Information Sciences*, *563*, 358-374., 2021.

[33] Ž. Vujović. Classification model evaluation metrics. *International Journal of Advanced Computer Science and Applications*, *12*(6), 599-606, 2021.

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