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FULL LENGTH ARTICLE

An Intelligent DGGO-Based Machine Learning Framework for Predicting Student Adaptability in Online Education

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ABSTRACT

The recent shift to online education worldwide has highlighted the urgent need to evaluate and improve students' flexibility in the online learning environment. The paper solves that problem by creating a predictive framework that enables measuring students' adaptability using modern techniques for advanced perception of adaptability and advanced machine learning (ML) and metaheuristic optimization methods. The research proposes an improved variant of geese's cooperative flight behavior, called the Dynamic Greylag Goose Optimization (DGGO) algorithm, to optimize the hyperparameters of a base model, a Decision Tree (DT). A comparison of the baseline DT showed an accuracy of 93.81% and a sensitivity (True Positive Rate, TPR) of 93.14%. The DGGO optimization further improved the DT model's performance to 97.15% accuracy and 96.86% sensitivity, with improved convergence and tuning. To be flexible to changes, the optimized model reduces classification errors and improves predictive consistency. The findings demonstrate the effectiveness of metaheuristic-based optimization for educational data mining and provide preliminary evidence that DGGO can serve as a robust, scalable, and intelligent framework to enhance predictive analytics and decision-support capabilities in the modern e-learning environment.

Keywords: Dynamic Greylag Goose Optimization (DGGO) ▪ Machine Learning in Education ▪ Decision Tree Classification ▪ Student Adaptability Prediction ▪ Metaheuristic Optimization

1. INTRODUCTION

Due to the COVID-19 pandemic and other global upheavals, there has been a significant shift in the educational setting, accelerating the shift from face-to-face to online and blended learning. This dramatic change has presented significant problems to students, educators and educational institutions globally [1]. Alterations that would take years to plan, introduce, and test in a traditional educational system were forced to be implemented almost immediately. This consequently forced teachers and learners to quickly adjust to digital platforms, redesigned pedagogies and online forms of communication. Students especially had a lot of challenges as they had to move out of on campus systems, which were marked by physical presence, face-to-face interaction and rigid schedules to learning systems over the internet where they needed to have self-discipline, study and learn on their own and use the new digital tools that were not familiar to them in their systems of learning [2]. This sudden change made adaptability a significant issue, as students had to change their approaches to academic success almost overnight. Additionally, psychological and behavioral responses to the new conditions of online learning were defined by shifts in motivation, stress coping, and patterns of new interaction, and these are not the only ones in the new online learning environment. [3]. The above experiences have shown that adaptability is not a technical skill or knowledge in itself, but a multidimensional factor that involves emotional, cognitive and behavioral flexibility. Socio-economic status, computer literacy, individual learning style, self-regulation, and the availability of the necessary technological tools, including computers and internet access, are all interconnected and have a crucial impact on learners' flexibility in the online learning environment [4]. However, as demonstrated, these factors have complex relationships with one another, which create disparities among students. For example, whereas online learning can perfectly suit some students due to their independence and freedom, others experience loneliness, a lack of motivation or technical problems [5]. All these differences suggest that it is imperative to understand the determinants of adaptability and to provide targeted interventions to support students at the most significant risk of lagging or poor performance. Educational policymakers and institutions, therefore, require predictive and diagnostic tools to identify such learners at an early stage and provide the necessary support mechanisms [6]. In this respect, Artificial Intelligence (AI) and Machine Learning (ML) have become groundbreaking in the educational field, as they can process extensive, complex data and discover unknown patterns, trends, and correlations that enhance students' adaptability [7]. With the help of ML algorithms, one can process large educational datasets and cluster learners based on behavioral and academic predictors. Specifically, classification algorithms offer a good way to learn the differences in adaptability levels based on several student attributes as predictors of these differences [8]. One such method is the use of Decision Tree models, which have gained popularity due to their interpretability and transparency, as well as their very high performance. Decision Trees help teachers understand which factors have the most significant impact on adaptability and provide practical advice on how to intervene and design instruction based on them [9]. In addition, the integration of computing and data analytics has changed how educational data is used. The new variables created in the database are demographics, engagement, attendance, and evaluation performance [10]. Such diversity helps researchers determine the connection between behavioral patterns and students' adaptation to online learning. To illustrate, internet connectivity statistics, the frequency of studies, and previous grades can be reviewed to determine tendencies that predict adaptability [11]. To also optimize machine learning models with advanced analytics, it is possible to improve their accuracy and generalizability. Thus, the mentioned analytical capabilities can enable institutions to personalize the learning experience and develop a specific strategy to promote struggling students [12]. Optimization has also improved the performance and reliability of machine learning models. Natural and biological processes have found many applications in the development of metaheuristic optimization algorithms because of their efficiency in exploring broad solution spaces and avoiding local optima [13]. Algorithms are essential for improving the stability and accuracy of classification predictions in predictive modeling. The optimization of the Decision Tree model in the present study is achieved using the Discrete Greylag Goose Optimization (DGGO) algorithm, which is premised on the migration patterns of a flock of greylag geese. The algorithm has been modeled based on the dynamic adaptations in geese's formation to minimize energy use and maximize group performance. On the same note, in Decision Tree optimization, DGGO would enable the model to balance complexity and accuracy without overfitting or underfitting [14]. What can be attained is a more viable model that can classify students' levels of adaptability more precisely, thereby providing a more precise and comprehensive assessment of diverse students. In summary, the proposed research aims to explore and maximize the type of student malleability in online learning using machine learning and optimization software. The following are the research questions of this project:

1. To classify students' adaptability levels in online education using a Decision Tree model.
2. To integrate and evaluate the Discrete Greylag Goose Optimization (DGGO) algorithm to enhance model performance.
3. To compare the performance of the optimized Decision Tree model with other machine learning models.
4. To analyze the robustness and reliability of the DGGO-optimized model through statistical and visual evaluation metrics.
5. To provide actionable insights for improving adaptability and resilience in online education environments.

The remainder of this paper is organized in the following manner. Section 2 contains a literature review of online education and the state of machine learning in modeling adaptability. Section 3 presents the materials and methods, namely the data set, machine learning models, and optimization methods. Section 4 presents the experimental design and the results, which will be discussed in Section 5. Finally, Section 6 will conclude the paper and provide a recommendation for future research direction. Within the framework provided, one can develop the problem, the methodology, and the implications of the proposed method for improving student adaptability in an online learning environment.

2. LITERATURE REVIEW

MOOCs have transformed the learning experience by introducing a wide array of free learning resources that enable self-directed learning. The research by [15] indicates that big data and artificial intelligence (AI) in MOOCs are beneficial for interpreting and processing raw educational data, thereby enhancing learning for students and educators. Two deep neural network models were created in this paper to predict student performance. A former model identifies the outcomes of student learning when watching videos. The latter, on the contrary, predicts a student's ability to give the correct answers to exam questions based on how the student copes with exercises. The researchers who used performance data from two MOOCs on the National Tsing Hua University platform found that the former model correctly forecasted students' performance based on video-watching behavior. In contrast, the latter model forecasted students' performance based on exercise responses. The authors claim that MOOCs will address current limitations in measuring student performance by leveraging an AI-based system that enables instructors to identify students who need additional support and attention. COVID-19 has drastically changed the education sector, and the world has focused more on the application of online and mobile learning. According to the arguments of [16], the transition to e-learning demanded new approaches to engage students, and a deep learning algorithm that monitors the real-time emotional state of students (e.g., happy, fearful, sad) with the help of a facial recognition system and a survey was created, making virtual classes more interactive. On that note, the article by the author of the present study, namely [17], has also emphasized that the context of the educational communication and management of resources has also been changing, with the Learning Management Systems (LMS) being greatly supplemented with artificial intelligence and data analytics to deliver an adaptive and personalized learning experience. It has the same tendency, and a study by [18] showed that mobile learning platforms emerged as a necessity in higher education in the United Arab Emirates and helped students access materials and assignments. The study, guided by the technology acceptance model, achieved 89.37% predictive accuracy and emphasized that, despite the flexibility these platforms offer, emotional considerations, including fear and stress, can disrupt their effectiveness. Data mining studies in education validate the need to predict student performance to enhance learning outcomes. The article by [19] demonstrated that artificial neural networks (ANNs) as predictors of performance in an online learning environment, which rely on time spent on the content and attendance at a live or a recorded session, have an accuracy of 80.47%. Similarly, the most promising article [20] was devoted to the longstanding issue of online education dropout, constructing a predictive model based on Logistic Regression and Input-Output Hidden Markov Models (IOHMM) with a predictive accuracy of 84 percent and the potential for timely intervention. Besides these techniques, ensemble and deep learning have been applied to 66,000 MOOC reviews by [21]. Nevertheless, the remaining tools provided only 80-95% predictive accuracy and little insight into how learners interact in online learning. There is an increased use of AI performance prediction models in education sector to address students at-risk and simplify the learning process. Another study, published by [22] also asserts that the existing models focus more on the accuracy of the algorithms than on the feedback to be given in real-time to enhance the quality of learning. In response, AI performance prediction and learning analytics were integrated into the study to enhance student learning in a collaborative environment. In a quasi-experimental study of an online engineering course, the integrated approach improved customer satisfaction, collaborative learning performance, and student engagement. This study will inform the development of AI-based learning analytics, providing insights into what is in store in this area. Learning style plays a critical role in assisting students to memorize and learn concepts in the long run. According to the analysis by [23], determining learning styles in offline and online study is typically conducted through questionnaires. However, new trends are to determine learning styles automatically based on attributes without interfering with the learner. As a continuation of the authors' work, the paper introduces new features beyond those already stated and further develops the identified ones to define learning styles even more accurately. The authors used different classification algorithms, compared their accuracies on the data, and identified interesting patterns in learners' behavior across different concepts. Language acquisition without grammatical competence cannot result in communicative competence, as was observed by [24]. The article explains how virtual reality (VR) technology can be used in college English instruction by applying artificial intelligence and machine learning to improve students' English proficiency. In one study comparing two samples of freshmen, the experimental group, which implemented VR-based and immersion-based constructionist teaching, received an average score 2.8 points higher than the control group, which used usual teaching methods. The findings suggest that combining constructivism with VR technology can enhance students' English fluency. Studies on online learning during the COVID-19 pandemic and its aftermath reveal the significance of self-regulation and metacognition in university studies. Although the study by [25] was conducted among technologically competent students, it shows that competence in metacognition for effective learning in the online setting has not yet been mastered. The researchers, who studied 770 IT students at universities, concluded that students who used metacognitive strategies were better positioned to become more self-conscious and to maintain control over the learning process, thereby excelling academically. Likewise, a study by [26] examined the experience of first-year students during the emergency online learning process and concluded that internet connectivity, the overlap of the learning space, and poorer social connectedness influenced students' learning satisfaction and outcomes. Since other students enjoyed greater freedom, some students became a nuisance, lacking interaction and motivation. The results highlight that self-regulation and metacognition play a vital role in increasing flexibility and effectiveness in online learning, particularly in the context of disruptions. As a measure to improve teaching quality and student performance, schools are seeking to understand what influences student learning so that they can make necessary adjustments to the curriculum. The findings of the research by [27] allow us to conclude that Virtual Learning Environments (VLEs) facilitate the implementation of a greater number of students, as geographical limitations are eliminated, not to mention the possibility of accessing resources more and monitoring interactions more. The article experimented with automatic learning algorithms, including tree-based methods and Artificial Neural Networks (ANNs), on a publicly accessible dataset, showing that the frequency of resource access on VLE sites should be an important factor in student achievement. This was corroborated by a case study of 120 master's students in Computer Engineering at the University of Salamanca. The most recent studies show that e-learning systems are increasingly interactive and flexible, thereby improving online education. According to the case described in [28], the problem of student performance prediction remains among the primary ones, and their research used the Moodle interaction data to various models, such as exploratory factor analysis, regression, and cluster analysis, to identify the predictors, i.e., Access, Questionnaire, Task, and Age. Results showed that platform interaction had a strong correlation with students' performance, and the Age variable negatively affected performance. In a bid to tackle the issue of technology equity, [29] made comparisons between FAQ chatbots and webpages in MOOCs and revealed that traditional webpages are more preferable due to fewer barriers and the ability to accommodate regional and native-language differences, which points to the need for digital tools to be more inclusive. In adaptive learning, the paper by [30] offered a more advanced system that used multi-layer topic modeling and the Felder-Silverman model to automatically identify the learning styles, which ultimately improves the precision of personalized content presentation. Further, based on this, the research article by [31] employed explainable artificial intelligence (XAI) to identify the most critical parameters influencing student adaptability across all levels of education during the pandemic, offering additional insights into learning behaviors. In addition, the article by [32] also discussed students' use of next-generation learning management systems and found that students mostly use administrative capabilities but desire more advanced features, such as content curation, collaboration within personal groups, and mobile features. When combined, these studies suggest that e-learning technologies are increasingly inclusive, adaptive as well and learner-centered. The rise of science and technology has dramatically transformed traditional teaching methodologies in higher education institutions, enabling blended learning. Based on [33], this paper analyzes the learning outcomes of blended learning through machine learning algorithms and regression models, particularly Rain Classroom Learning Management Service. The paper will gauge the interdependence among a set of variables on the Rain Classroom blended learning platform and scores on the College English Test Band 4 in English proficiency. The findings identify the most essential factors for improving student scores and for classifying students by learning outcomes using decision trees. The regression model will then identify the impact of Rain Classroom on students with varying degrees of proficiency, so that high- and low-proficiency students receive a practical learning experience through individualized teaching resources and methods. One factor that makes learning style crucial in any learning environment is the fact that learners perceive, receive, and comprehend information differently. As reported by [34], the significance of e-learning systems capable of determining the learning style of a student without any human intervention has increased. This paper proposes an algorithm based on a Convolutional Neural Network and the Levy Flight Distribution that learns style using a prediction-based approach. The adaptive e-learning system has two components: automatic prediction of learning style and classification based on the quantity of learning styles. After the student has been logged in, the student's information, questionnaire scores, session IDs, login time, and the sequence of user activity are accessed. An algorithm based on a CNN is then used to predict the learning styles Active/Reflective, Sensing/Intuitive, Visual/Verbal, and Sequential/Global based on these features. The model was written in Java, and the data were collected in a Massive Open Online Course (MOOC). The experimental results show that the proposed algorithm achieves 97.09% precision, surpassing other algorithms in specificity, sensitivity, and overall precision. Table 1 summarizes the reviewed papers in the field of the implementation of artificial intelligence and machine learning in the education domain, along with the objective of each, their methodology, and key findings.

3. MATERIALS AND METHODS

To provide a detailed overview of the experiment's workflow, Figure 1 depicts the methodological framework followed in the current experimental study. The seven phases include the Data Preprocessing stage, which involves gathering the dataset, data cleaning and normalization, and preliminary data analysis to identify key patterns and distributions. The clean data is further split into training and test sets (80% and 20%, respectively) to facilitate model development. The next stage, referred to as Model Optimization and Evaluation, involves training and fine-tuning a variety of machine learning models using the Dynamic Greylag Goose Optimization (DGGO) algorithm to improve their predictive performance. Lastly, various performance indicators are calculated to assess the model's efficiency, and the findings are also discussed through graphical analysis and comparison. This provides methodological rigor and reproducibility through the workflow's systematic nature across all experimental stages.

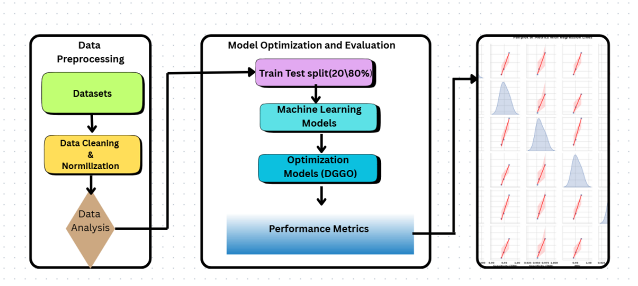

Figure 1. Overall methodological framework illustrating the workflow from data preprocessing and model optimization to performance evaluation and analysis.

3.1 Dataset Description

This paper presents an excellent experiment that an inexperienced machine-learning researcher can use to train and test a wide range of methods for predicting students' online flexibility. The data would be used to construct and test predictive models to determine how different variables influence a student's adaptation to virtual learning environments. The level of adaptivity within the online learning environment—the students' ability to adapt to it—is the dependent variable in the dataset presented. The data include several independent variables that characterize each student's demographic, academic, and environmental characteristics. These features are summarized in Table 2. All in all, the dataset represents various socio-economic, technological, and individual factors that are essential to defining students' adaptability in online learning settings. The attributes can deeply model and analyze the contribution of various factors to adaptability, which can be very useful to educational institutions and policymakers. To establish patterns and trends in student data, it is necessary to understand how numerical variables relate to each other. The given pairplot Figure 2 shows how the numerical characteristics, namely, Age and Class Duration, interact among the various gender groups. This visualization helps identify any possible gender-based differences in the data. The diagonal density plots show the distributions of age and class duration for boys and girls, and the off-diagonal scatter plots show potential relationships between the variables. These

Table 1. Summary of Reviewed Studies on Artificial Intelligence and Machine Learning in Education

Reference	Objective	Methodology	Key Findings
[15]	Predict student performance in MOOCs using learning behaviors.	Two deep neural networks trained on students' video-watching and exercise performance data.	Both models achieved high accuracy; behavioral metrics effectively predict performance and support instructor intervention.
[16]	Monitor real-time engagement in online learning environments.	Deep learning framework combining facial emotion recognition and Mean Engagement Score (MES) computation.	Automated emotion-based engagement tracking enhances online class interactivity and monitoring.
[17]	Integrate AI and analytics into LMS-based online education.	Conceptual model linking machine learning and data analysis with learning management systems.	AI-driven LMS fosters adaptive learning and personalized educational experiences.
[18]	Analyze intention to use mobile learning platforms during COVID-19.	Extended TAM and TPB models combined with J48 decision tree classifier on UAE university dataset.	Classifier achieved 89.37% accuracy; emotional factors (stress, anxiety) reduce technology adoption.
[19]	Predict academic performance in e-learning environments.	Artificial neural network using demographics, scores, and time spent on content.	Achieved 80.47% accuracy; attendance and time-on-task most influential on performance.
[20]	Early detection of student dropout in online learning.	Logistic regression with regularization and IOHMM models trained on interaction logs.	Models achieved 84% accuracy; early intervention can significantly reduce dropout rates.
[21]	Sentiment analysis on MOOC reviews for quality assessment.	Ensemble and deep learning models (LSTM + GloVe embeddings) on 66,000 reviews.	LSTM-GloVe achieved 95.8% accuracy, outperforming traditional ML and ensemble methods.
[22]	Integrate AI performance prediction with learning analytics.	Quasi-experimental study in an online engineering course using analytics-based interventions.	Integration improved collaboration, engagement, and satisfaction compared to traditional feedback.
[23]	Detect students' learning styles automatically in e-learning.	Multiple ML classifiers on learner behavioral attributes; compared with survey-based methods.	Automatic detection improved accuracy and revealed behavioral learning patterns.
[24]	Enhance English language learning using AI and VR.	Constructivist immersive VR-based teaching vs. traditional methods.	VR class achieved 2.8-point higher average; AI–VR combination effectively enhances learning outcomes.
[25]	Examine impact of metacognitive strategies on online learning success.	Survey of 770 IT students analyzed via structural equation modeling (SEM).	Metacognitive awareness and regulation strongly correlated with improved learning outcomes.
[26]	Explore first-year students' autonomy in emergency remote teaching.	Qualitative case study guided by the C-flat model; interviews with 15 chemistry students.	Autonomy increased, but social connectedness declined; self-regulation essential for success.
[27]	Analyze academic performance using virtual learning environment (VLE) data.	Tree-based ML models and artificial neural networks on student activity logs.	Resource access frequency emerged as the strongest predictor of academic achievement.

Table 2. Description of Dataset Features

Feature	Description
Gender	Indicates the gender type of the student.
Age	Specifies the age range of the student.
Education Level	Represents the level of education or the institution level at which the student is currently enrolled.
Institution Type	Denotes the category of the educational institution (e.g., public or private).
IT Student	Specifies whether the student is pursuing a program related to Information Technology.
Location	Indicates whether the student resides in an urban (town) or rural area.
Load-shedding	Refers to the frequency or level of power outages experienced in the student's area.
Financial Condition	Describes the economic condition of the student's family, reflecting their financial stability.
Internet Type	Represents the type of internet connection primarily used by the student's device (e.g., broadband, mobile data).
Network Type	Specifies the type of network connectivity used by the student, indicating the overall quality of their internet connection.

visual insights can help interpret features before developing a model.

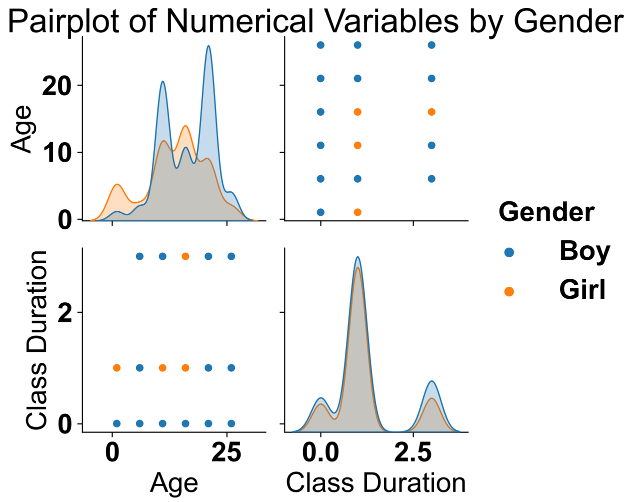

Figure 2. Pairplot of numerical variables (*Age* and *Class Duration*) by gender, showing distributions and relationships across male and female students.

The distribution of the target variable must be analyzed before training the model to identify any class imbalance issues that may affect predictive performance. Figure 3 gives the visualization of the distribution of classes in the original dataset, taking into consideration the three levels of student adaptivity: Low, Moderate and High. The bar chart on the left shows the number of students at each adaptivity level, and the pie chart on the right shows the percentage distribution of students. As shown in the figure, the dataset is very skewed; most of them (approximately 52%) are in the first class (Moderate), the second class (Low) is the Second-Largest (approximately 8%)), and the last class (High) is the smallest (approximately 8%)). This skew implies the need to train the models fairly by using resampling or other balancing techniques.

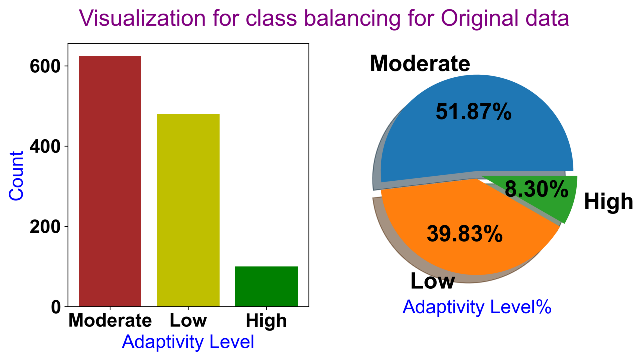

Figure 3. Visualization of the original dataset's class distribution across different adaptivity levels (*Low*, *Moderate*, and *High*). The bar chart and pie chart collectively reveal the imbalance among the target categories.

3.2 Data Preprocessing

Breaking down raw data into usable machine learning models constitutes the initial phase of processing. It assures uniformity, soundness and appropriateness of analytical modelling of data. Preprocessing is the step that converts dirty inputs into clean, well-formatted inputs, thereby improving model performance and generalization. Some preprocessing methods were used in the work, including normalization, handling missing and null values, and feature encoding. Normalization is a scaling technique that scales all numerical attributes so that extreme values do not dominate the learning process. It enhances the model's convergence and stability during training. The most frequently used normalization is Min-Max normalization, and it is as follows:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}, \tag{1}$$

And where X is the original value, Xmin and Xmax are the minimum and maximum values of the feature, respectively, and X is the normalized value in the range [0, 1]. The procedure has the advantage of making all features equally contributeimportant for training a model. Data loss can introduce bias and reduce the accuracy of the predictive model. Therefore, they should be addressed sequentially. The problem of missing values in this analysis had been solved with the help of imputation means that involve: mean, median or mode replacement, depending on the character of the feature:

$$X_{\text{imputed}} = \begin{cases} \text{mean}(X), & \text{for continuous variables,} \\ \text{mode}(X), & \text{for categorical variables.} \end{cases} \tag{2}$$

The method ensures data integrity and reduces data loss while maintaining statistical representativeness. Non-numeric or missing entries may skew statistical calculations and model training. The dataset was filtered to remove rows or columns with many null values (an established threshold). When the number of null values was few, imputation techniques were used instead of deletion to preserve important data. The principle by which it was done was:

$$\text{If } \frac{\text{null entries}}{\text{total entries}} > \tau, \text{ then remove the record,}$$

where τ represents the acceptable threshold (typically 30% in this study). Machine learning models require numerical values; hence, nominal variables need to be converted to numerical values. Two primary encoding methods were used:

- **Label Encoding:** Converts categorical classes into integer values. For a categorical feature with values $\{C_1, C_2, \ldots, C_k\}$, label encoding maps each category to a unique integer:

$$f(C_i) = i, \quad i = 1, 2, \ldots, k.$$

- **One-Hot Encoding:** Creates binary (0/1) variables for each category to avoid introducing ordinal relationships among non-ordered variables. For example, a feature with three categories $\{A, B, C\}$ is transformed as:

$$A = (1,0,0), \quad B = (0,1,0), \quad C = (0,0,1).$$

Encoding features can ensure that learning algorithms use categorical attributes appropriately without imposing natural numeric hierarchies. Overall, preprocessing tasks such as normalization, handling missing and null values, and feature encoding improved the quality and consistency of the data and, therefore, enabled machine learning models to be more accurate and resilient in predicting students' adaptability levels.

3.3 Machine Learning Models

The following section describes the machine learning models that will be applied to predict students' adaptability to online learning. The chosen ones are Decision Tree (DT), Multilayer Perceptron (MLP), Random Forest (RF) and Support Vector Machine (SVM). These two algorithms are based on various classification and pattern recognition methods, each with distinct advantages for working with the dataset.

Decision Tree (DT)

A decision tree (DT) model is a nonparametric supervised learning model used for classification and regression. It operates by recursively subdividing the space of features according to attribute values into a tree of decision nodes (internal nodes) and leaf nodes (corresponding to the final output class). The algorithm chooses the attribute with the highest information gain (or Gini impurity) at a given node. Information gain of an attribute A:

$$IG(D,A) = Entropy(D) - \sum_{v \in Values(A)} \frac{|D_v|}{|D|} \times Entropy(D_v), \tag{3}$$

where $Entropy(D)$ is defined as:

$$Entropy(D) = -\sum_{i=1}^{n} p_i \log_2(p_i), \tag{4}$$

and p_i represents the probability of class i in dataset D. DTs are highly interpretable and allow visualization of decision paths, making them suitable for educational data analysis.

Multilayer Perceptron (MLP)

A multi-layer perceptron (MLP) is a feedforward artificial neural network that computes target outputs as a function of input features, with successive layers of neuron-linked connections. Each neuron computes a weighted average of its inputs and applies a nonlinear activation function. For an input vector $\mathbf{x}$, the neuron's output is defined as:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right), \tag{5}$$

where w_i are the weights, b is the bias term, and $f(\cdot)$ is an activation function such as sigmoid, ReLU, or tanh. The learning process involves adjusting weights via backpropagation to minimize the loss function $L(y,\hat{y})$, often defined as:

$$L(y,\hat{y}) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2. \tag{6}$$

MLPs are useful for nonlinear data analysis and for predicting adaptability when many variables interact in complex ways.

Random Forest (RF)

A Random Forest (RF) model is an ensemble learning method that uses a collection of Decision Trees to improve predictive performance and robustness. Individual trees are trained on random subsets of the data and features, and the majority vote of the trees makes the final prediction.

Mathematically, for a set of trees $T_1, T_2, \ldots, T_k$, the final classification output $\hat{y}$ is given by:

$$\hat{y} = mode\{T_1(\mathbf{x}), T_2(\mathbf{x}), \ldots, T_k(\mathbf{x})\}, \tag{7}$$

where $mode\{\cdot\}$ denotes the most frequent class label predicted by the ensemble. RFs are highly resistant to overfitting and perform well with heterogeneous and noisy data.

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised algorithm of learning algorithm applied to classification to identify the best hyperplane to maximize the difference between classes. This aims to identify a decision boundary that maximizes the distance between data points from different classes. The optimization problem has been formulated as:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2, \tag{8}$$

subject to the constraint:

$$y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1, \quad \forall i = 1,2,\ldots,N, \tag{9}$$

where $\mathbf{w}$ is the weight vector, b is the bias term, and $y_i \in \{-1,+1\}$ are the class labels. For nonlinear separations, kernel functions such as Radial Basis Function (RBF) are employed:

$$K(\mathbf{x}_i,\mathbf{x}_j) = \exp(-\gamma\|\mathbf{x}_i - \mathbf{x}_j\|^2), \tag{10}$$

where γ controls the spread of the kernel. SVMs are applicable in high-dimensional spaces and when one has fewer samples than features. This study uses and compares these models to determine whether they are effective at gauging students' adaptability in online learning. The hyperparameters of each model are tuned to maximize predictive accuracy.

3.4 Role in Hyperparameter Optimization

Machine learning model optimization is a crucial procedure in designing and optimizing machine learning models. It directly impacts the model's performance, including learning behavior, model complexity, and generalization. Classical approaches to hyperparameter optimization, such as grid search and random search, can be computationally infeasible and rely on trial-and-error. Metaheuristic algorithms offer an adaptive and efficient alternative to hyperparameter optimization. These algorithms automatically tune and optimize the best parameter combinations within stochastic and evolutionary plans, thereby improving the accuracy and robustness of models. By balancing exploration and exploitation, metaheuristics avoid the need for manual intervention and generalize better to unknown data. They are therefore crucial for automating the optimization process and accelerating the training of machine learning models towards optimal configurations.

3.5 Proposed Greylag Goose Optimization (GGO) algorithm

Geese are socially and dynamically adaptive and cooperative. They establish long-lasting relationships with their mates, which is fidelity in the form of vigilance during times of illness or wounds. Interestingly, a goose can lounge alone after losing one of its partners and remain unmarried thereafter, an indication of a high degree of loyalty that is uncommon among many other animals. When the birds breed, the male guards the nests, while the females tend to them. There is nest-site fidelity in some geese that continually revisit the same nesting site under favorable conditions, and this represents their commitment to the protection of the next generation. Geese flock together in larger groups (gaggles). In these groups, people serve as sentry guards, protecting the group from predators while others take a meal. Such mutually supportive conduct resembles teamwork, in which people support each other to ensure no one is injured. Well-being geese have been seen guarding injured persons and acting as a brood, in general. Migration is also a marvel: they travel thousands of kilometers in massive flocks, fly in V formation to reduce air resistance, and use less energy on long journeys. Geese are furnished with shared memory and direction and make use of known reference points and celestial markers. These dynamic behaviors inspire the Greylag Goose Optimization (GGO) algorithm, as described in [10]. It starts randomly generating individuals, each of whom is a potential solution. The population is split into two groups — exploration and exploitation — whose sizes are dynamically adjusted based on the performance of the best solution. This facilitates good exploration of the solution space and minimizes the likelihood of getting trapped in local optima, as shown in Figure 4.

Figure 4. Exploration and exploitation in Greylag Goose Optimization. The exploration group searches broadly (left inset), while the exploitation group refines around the best solution (right inset).

Exploration operation

The exploration phase focuses on locating promising areas of the search space and avoiding premature convergence by guiding agents relative to the current best solution. One key position-update equation is

$$X(t+1) = X^*(t) - A \cdot \left| C \cdot X^*(t) - X(t) \right|. \tag{11}$$

Another update uses three random search agents X_{Paddle1}, X_{Paddle2}, and X_{Paddle3}:

$$\begin{aligned} X(t+1) = {} & w_1 X_{\text{Paddle1}} + z w_2 \left(X_{\text{Paddle2}} - X_{\text{Paddle3}}\right) \\ & + (1-z) w_3 \left(X - X_{\text{Paddle1}}\right), \end{aligned} \tag{12}$$

where $w_1, w_2, w_3 \in [0,2]$ are updated during iterations and z is computed exponentially based on the iteration number.

Additionally, an update involving oscillatory search and attraction to the best solution is

$$\begin{aligned} X(t+1) = {} & w_4 \left|X^*(t) - X(t)\right| e^{bl} \cos(2\pi l) \\ & + \left[2w_1(r_4 + r_5)\right] X^*(t), \end{aligned} \tag{13}$$

where b is a constant, $l \in [-1,1]$ is random, $w_4 \in [0,2]$, and $r_4, r_5 \in [0,1]$.

Exploitation operation

The exploitation phase improves high-quality solutions based on fitness. At each cycle's end, the best solutions are identified and refined via two strategies. Three sentries estimate the local best direction. For each sentry (X_1, X_2, X_3),

$$X_1 = X_{\text{Sentry1}} - A_1 \cdot \left| C_1 \cdot X_{\text{Sentry1}} - X \right|, \tag{14}$$
$$X_2 = X_{\text{Sentry2}} - A_2 \cdot \left| C_2 \cdot X_{\text{Sentry2}} - X \right|, \tag{15}$$
$$X_3 = X_{\text{Sentry3}} - A_3 \cdot \left| C_3 \cdot X_{\text{Sentry3}} - X \right|, \tag{16}$$

with $A = 2ar_1 - a$ and $C = 2r_2$ (applied per sentry via A_1, A_2, A_3 and C_1, C_2, C_3). The population is then updated as the mean of the three estimates:

$$X(t+1) = \frac{1}{3}\left(X_1 + X_2 + X_3\right). \tag{17}$$

Individuals explore the neighborhood of the current best (leader) to seek improvements:

$$X(t+1) = X(t) + D(1+z)\, w \left(X - X_{\text{Flock}}\right), \tag{18}$$

where X_{Flock} denotes the leader/ideal response, D is a constant, z depends on the iteration number, and w is a weighting parameter. When the agent is initialized, each solution is evaluated for fitness, and the best agent is chosen. The algorithm is then adaptive, segregating the population into two categories: an exploration group that searches widely to identify leaders, and an exploitation group that focuses its search in high-quality areas. There is always an exchange of information among groups. The population usually begins at half exploration and half exploitation, and the sizes are dynamically changed through iterations to balance exploration and refinement, thereby increasing the likelihood of arriving at a near-optimal (or optimal) solution.

3.6 Benchmark Optimizers for Comparison

To test the performance of the proposed Dynamic Greylag Goose Optimization (DGGO) algorithm, its efficiency was compared with that of several well-established metaheuristic optimization algorithms, namely the Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO). The chosen benchmark algorithms have been proven helpful in solving complex optimization problems and are often used for hyperparameter tuning in machine learning. All algorithms were

Algorithm 1 GGO Algorithm

Initialize population X_i $(i = 1, \ldots, n)$, n, $t_{\max}$, objective $F(\cdot)$
Initialize $a, A, C, b, l, c, r_1, \ldots, r_5$
  and $w, w_1, \ldots, w_4, A_1, A_2, A_3, C_1, C_2, C_3$
Set $t \leftarrow 1$
Evaluate $F(X_i)$ for all i; set $P \leftarrow \arg\min / \arg\max F$ (best)
Split population into exploration (n_1) and exploitation (n_2)
while $t \leq t_{\max}$ **do**
  for $i = 1$ to n_1 **do** ▷ Exploration group
    if t mod $2 = 0$ **then**
      if $r_3 < 0.5$ **then**
        if $|A| < 1$ **then**
          Update via (11)
        else
          Select $X_{\text{Paddle1}}, X_{\text{Paddle2}}, X_{\text{Paddle3}}$
          $z \leftarrow 1 - (t/t_{\max})^2$
          Update via (12)
        end if
      else
        Update via (13)
      end if
    else
      Update via neighborhood search (18)
    end if
  end for
  for $i = 1$ to n_2 **do** ▷ Exploitation group
    if t mod $2 = 0$ **then**
      Compute X_1, X_2, X_3 via (14)–(16)
      Update $X(t+1)$ via mean (17)
    else
      Update via neighborhood search (18)
    end if
  end for
  Re-evaluate $F(X_i)$; update parameters
  $t \leftarrow t + 1$; project infeasible X_i back into bounds
  if best F unchanged for two iterations **then**
    Increase n_1 (exploration), decrease n_2 (exploitation)
  end if
end while
return best agent P

implemented during hyperparameter optimization to improve the predictive performance of the chosen models. The comparative analysis provided an objective metric for evaluating the efficiency, convergence rate, and robustness of the proposed DGGO algorithm. The findings of such a comparison indicate the potential of DGGO to achieve high optimization performance and better model generalization than traditional metaheuristic algorithms.

4. EVALUATION METRICS

To assess the accuracy of predictions, sensitivity, and reliability, several classification measures were used to evaluate the models' performance. A combination of these metrics may indicate the ability of all the models to categorize students' levels of adaptability correctly. These assessment measures are Accuracy, Sensitivity (True Positive Rate), Specificity (True Negative Rate), Positive Predictive Value (PPV), Negative Predictive Value (NPV) and the F-Score. Each metric is defined and shown in the equations in Table 3.

The overall impact of these measures is to provide a complete picture of the classification models' efficiency, so that both correct and incorrect classifications are displayed equally. This is made clear by the application of both sensitivity and specificity, which emphasize the model's capacity to discriminate between adaptive and non-adaptive learners.

5. EMPIRICAL RESULTS

In this section, the findings of the proposed framework experiment are presented, including the baseline model comparison, optimization results, and overall performance studies based on various evaluation metrics.

5.1 Baseline Model Comparison

The data was trained with baseline machine learning models to get a point of comparison with the performance of different models. The comparative results provide a synoptic view of each model's predictive performance (as measured by key performance indicators) for Accuracy, Sensitivity (True Positive Rate, TPR), Specificity (True Negative Rate, TNR), Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F-Score. Table 4 shows the raw performance of four models, i.e., the DT, MLP, RF and SVM.

Based on the findings, the optimal overall accuracy of 93.81% and the same performance were achieved using the Decision Tree (DT) model, which had the highest sensitivity and specificity compared to other models. The Multilayer Perceptron (MLP) was also observed to be effective and the second-best in terms of accuracy and generalization, after DT. The RF model was otherwise more consistent, with lower accuracy, yet showed an ensemble averaging effect. However, the Support Vector Machine (SVM) was ideal but not particularly effective, because it was sensitive to hyperparameter choices and the kernel used. The preliminary findings are then used to compare the effects of the streamlined models and the metaheuristic fine-tuning processes addressed in the next section. To perform a comprehensive analysis of the Decision Tree (DT) model, several essential assessment indicators were considered: Accuracy, Sensitivity (TPR), Specificity (TNR), Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F-Score. These scores are then displayed as a radar chart in Figure 5, providing a multidimensional perspective on the model's categorization. This graphic presentation will allow defining the benefits and weaknesses of the DT model across various performance areas to provide a clear picture of its predictive balance and reliability. The almost homogeneous form of the radar chart shows that all the measures are regularly performed and, therefore, the model will be predictable with the same predictive power.

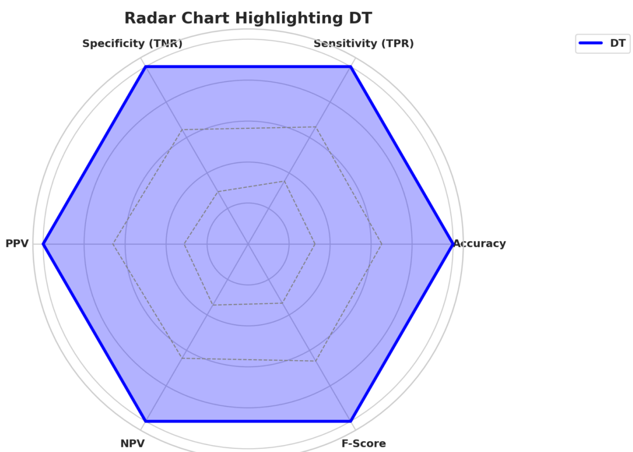

Figure 5. Radar chart showing the performance of the Decision Tree(DT) model using various evaluation metrics, such as Accuracy, Sensitivity, Specificity, PPV, NPV, and F-Score.

Table 3. Classification Evaluation Metrics and Their Mathematical Formulations

Metric	Mathematical Expression	Description
Accuracy	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$	Represents the overall proportion of correctly classified instances among all samples.
Sensitivity (TPR)	$TPR = \frac{TP}{TP+FN}$	Measures the model's ability to correctly identify positive (adaptive) instances.
Specificity (TNR)	$TNR = \frac{TN}{TN+FP}$	Indicates the model's ability to correctly identify negative (non-adaptive) instances.
Positive Predictive Value (PPV)	$PPV = \frac{TP}{TP+FP}$	Represents the probability that a predicted positive instance is truly positive.
Negative Predictive Value (NPV)	$NPV = \frac{TN}{TN+FN}$	Represents the probability that a predicted negative instance is truly negative.
F-Score	$F\text{-Score} = \frac{2 \times Precision \times Recall}{Precision+Recall} = \frac{2TP}{2TP+FP+FN}$	Harmonic mean of Precision and Recall; provides a balanced measure of accuracy between false positives and false negatives.

Table 4. Baseline Model Performance Comparison

Model	Acc.	TPR	TNR	PPV	NPV	F-Score
DT	0.9381	0.9314	0.9443	0.9399	0.9364	0.9357
MLP	0.9293	0.9216	0.9364	0.9301	0.9286	0.9258
RF	0.9211	0.9127	0.9286	0.9200	0.9220	0.9163
SVM	0.9128	0.9024	0.9220	0.9109	0.9144	0.9066

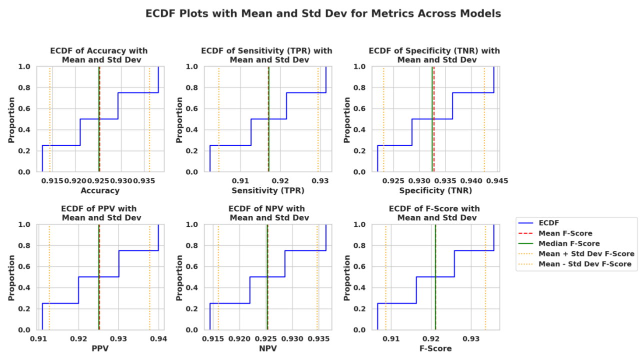

Figure 6. ECDF plots of key performance metrics (*Accuracy*, *Sensitivity*, *Specificity*, *PPV*, *NPV*, and *F-Score*) showing the mean, median, and standard deviation across evaluated models.

To obtain more data on the consistency and variability of model performance, the Empirical Cumulative Distribution Function (ECDF) was used to evaluate the distributions of assessment measures for both tested models. Figure 6 illustrates the ECDF of six key measures, which are the Accuracy, Sensitivity (TPR), Specificity (TNR), Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F-Score. Both subplots present the cumulative percentage of metric values, as well as the average and standard deviation, which give an idea of the distribution of the results. The sharp ECDF curve slope indicates less variation and greater model stability, whereas a gradual slope indicates greater dispersion. The predictive performance of the models can be evaluated using such a visualization, and the degree to which a model has correctly classified behavior can be determined.

The models were summarized in terms of their mean, median, and standard deviation to provide a brief overview of overall consistency in performance across all evaluation measures. The following overview is displayed in the heatmap format as illustrated in Figure 7 that graphically shows the summary scores of each performance measure, i.e., Accuracy, Sensitivity (TPR), Specificity (TNR), Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F-Score. The fact that the mean and median were close to each other, and that the standard deviation across all measures was low, indicates that the models were close and exhibited only slight differences. It is this uniformity that contributes to the framework's predictability in revealing patterns of student adaptability across various evaluation parameters. The average performance and variation of different machine learning models were plotted as bar plots with error bars to compare their predictive performance. These comparisons are made with reference to six key evaluation metrics, as shown in Figure 8, namely: Accuracy, Sensitivity (TPR), Specificity (TNR), Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F-Score. The figure presents the performance of the four models in each subplot: Decision Tree (DT), Multi-Layer Perceptron (MLP), Random Forest (RF), and Support Vector Machine (SVM), along with the standard deviation for each model. This is what is easily understood intuitively from the

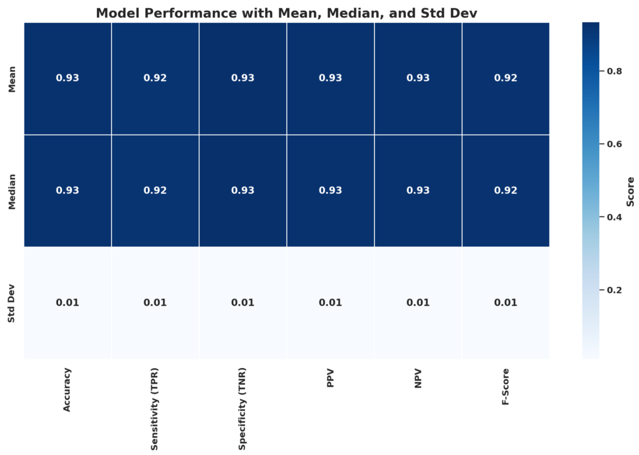

Figure 7. A heatmap visualizing the model's performance across various evaluation metrics, including the mean, median, and standard deviation for each metric.

illustration: the key performance trends and the uncertainty of each model. The shorter the error bars, the more predictable and steady the predictions are; the greater the deviations, the more different the predictions are across runs or folds.

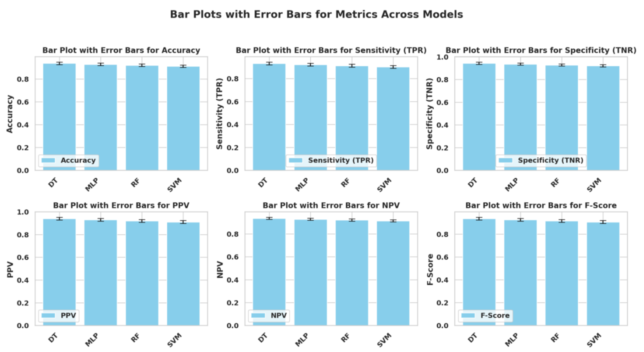

Figure 8. Bar plots with error bars representing the mean and standard deviation of key performance metrics (*Accuracy*, *Sensitivity*, *Specificity*, *PPV*, *NPV*, and *F-Score*) for Decision Tree (DT), Multi-Layer Perceptron (MLP), Random Forest (RF), and Support Vector Machine (SVM).

5.2 DT Optimization Results

Three metaheuristic algorithms, namely, Dynamic Greylag Goose Optimization (DGGO), Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO), were used to optimize the Decision Tree (DT) model. All optimization techniques were used to tune the model hyperparameters to improve forecasting and generalization. The optimized performance metrics for each metaheuristic technique are provided in Table 5.

Table 5. Optimized Decision Tree (DT) Performance using Different Metaheuristics

Model	Acc.	TPR	TNR	PPV	NPV	F-Score
DGGO-DT	0.9715	0.9686	0.9742	0.9721	0.9710	0.9704
PSO-DT	0.9525	0.9478	0.9567	0.9513	0.9535	0.9495
GWO-DT	0.9462	0.9384	0.9527	0.9431	0.9487	0.9408

The result indicates that the highest accuracy (97.15%) and the best results across all evaluation measures were achieved by the Decision Tree using the dynamic Greylag Goose Optimization (DGGO) algorithm. The sensitivity, specificity, and aggregate F-score were better than those of the PSO-DT and GWO-DT models, indicating that it possessed a more robust, well-generalized learning ability. Such improvements indicate that DGGO was a good balancing tool between exploration and exploitation. During the optimization process, the number of classification errors decreased, and the correlation between the predicted and actual levels of adaptability increased. A performance evaluation of presentations was conducted to test further the efficacy of the advanced Dynamic Greylag Goose Optimization (DGGO) against other benchmark metaheuristic optimizers. Accuracy, Sensitivity, Specificity, PPV, NPV and F-Score were the significant statistical measures used in the comparative analysis. As Table 5 shows, the DGGO-optimized DT was the most successful in all measures. Specifically, the lowest error rates and the highest predictive consistency were obtained with DGGO. This was followed by the PSO-DT model, which was good but slightly less successful, and GWO-DT was determined to be stable, less sensitive and less precise. Overall, DGGO was more efficient in convergence, more stable, and more adaptive, confirming that it can be regarded as an advanced algorithm for hyperparameter optimization in educational modelling. It has a higher ratio of exploration to exploitation, which allows it to be more accurate in its classification and, therefore, a highly efficient optimizer for a complex prediction task, such as analyzing the importance of adaptability in students. To compare the performance of all Decision Tree (DT) models optimized by different metaheuristic algorithms, a stacked bar chart was created to show their combined scores for each metric. Figure 9 depicts the cumulative performance of three distinct optimization algorithms, viz, DGGO-DT, PSO-DT and GWO-DT on six significant evaluation measures, that is, starting with Accuracy and then Sensitivity (TPR), then Specificity (TNR), then Positive Predictive Value (PPV), then Negative Predictive Value (NPV) and then F-Score. The different metrics representing each optimized model's contribution to the overall predictive quality are the bar segments. This hierarchical presentation offers a comprehensive comparative evaluation, with emphasis on the harmony and overall effectiveness of each optimization approach for enhancing the DT model's classification performance.

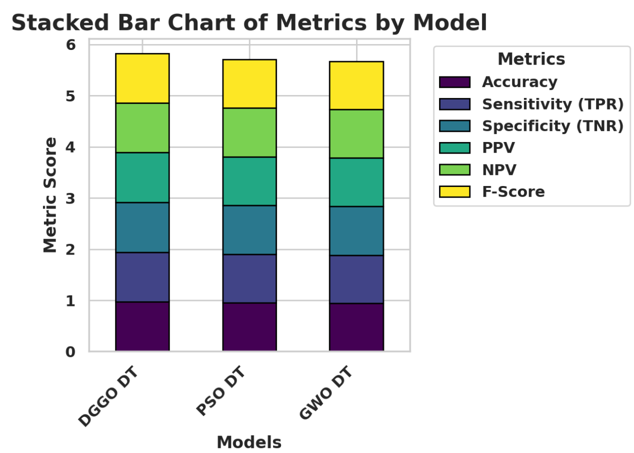

Figure 9. Stacked bar chart comparing the cumulative performance of DGGO-DT, PSO-DT, and GWO-DT models across multiple evaluation metrics.

Hierarchical clustering analysis of the correlation matrix of model evaluation scores was performed to gain better insight into the interrelationships among the performance measures and to identify similarity patterns. The resulting heatmap with dendrograms, as shown in Figure 10, visually depicts the level of correlation between metrics (e.g., Accuracy, Sensitivity (TPR), Spec, Genetic, Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F-Score). The hierarchical clustering metrics together groups variables whose statistical behavior is closely related, showing that some indicators, such as the ones associated with the variables, such as, but not limited to, the Accuracy and F-Score, tend to show a very similar pattern, indicating the similarity in model performance as determined by a particular evaluation criterion. This analysis will be of great value in identifying redundancy between metrics and may help interpret the model more efficiently, identifying critical dependencies between key performance indicators.

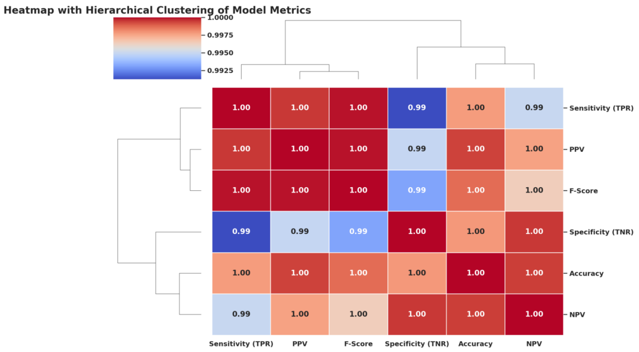

Figure 10. Heatmap with hierarchical clustering showing the correlation structure among model evaluation metrics. Closely related metrics are grouped together based on their correlation coefficients.

Histograms of each evaluation measure were plotted, from which the variability and distribution of performance scores across the different models were established. Figure 11 demonstrates the histogram of six main metrics, i.e., Accuracy, Sensitivity (TPR), Specificity (TNR), Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F-Score. Each subplot's frequency distribution is also accompanied by the signs of the mean (red dotted line) and the standard deviation (green dotted lines). It is a simple and intuitive interpretation of the stability and central tendency of trial model performance. Minor variations around the mean indicate high uniformity across the models, and significant variations indicate high variability or sensitivity to data conditions.

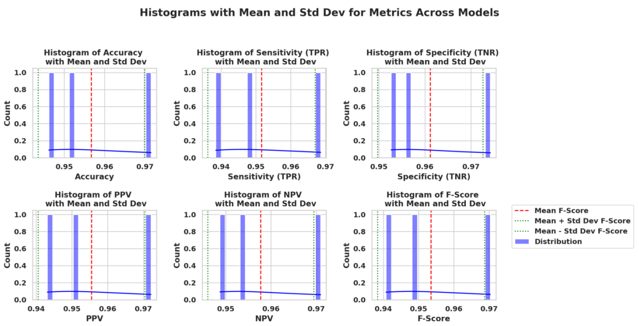

Figure 11. Histograms illustrating the distribution of performance metrics (*Accuracy*, *Sensitivity*, *Specificity*, *PPV*, *NPV*, and *F-Score*) with mean and standard deviation markers across evaluated models.

To gain better insight into the distributional characteristics of the model evaluation metrics, Kernel Density Estimation (KDE) was applied to plot the probability density of the performance scores for all models. Figure 12 presents the KDE of six significant measures, such as Accuracy, Sensitivity (TPR), Specificity (TNR), Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F-Score. The subplots show the smoothed distribution curves, thereby enabling the central tendency, dispersion, and shape of each metric performance profile to be better understood. The bell-shaped curves imply that most models had high scores and low skew, indicating very high and stable predictive performance across the evaluation dimensions.

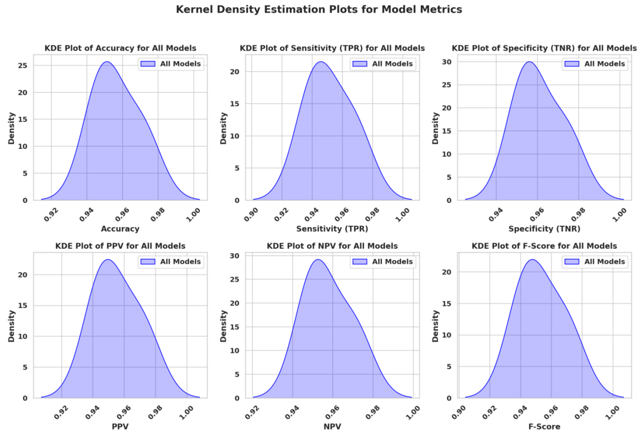

Figure 12. Kernel Density Estimation (KDE) plots illustrating the distribution of model performance metrics (*Accuracy*, *Sensitivity*, *Specificity*, *PPV*, *NPV*, and *F-Score*) across all evaluated models.

6. DISCUSSION

As demonstrated in this paper, a predictable baseline Decision Tree (DT) model can successfully predict students' online learning adaptability by incorporating key socio-economic, technological, and subjective features. The baseline DT was very high, with an Accuracy of 0.9381, Sensitivity/TPR of 0.9314, and Specificity/TNR of 0.9443, indicating that even a simple, comprehensible model could be highly predictive. After optimizing hyperparameters with the Dynamic Greylag Goose Optimization (DGGO) algorithm, the DT model performs much better, with an Accuracy of 0.9715 and a Sensitivity/TPR of 0.9686. The results obtained were superior to those of Particle Swarm Optimization (PSO) and the Grey Wolf Optimizer (GWO), yielding values of 0.9525 and 0.9462, respectively. Across all performance indicators, such as PPV, NPV, and F-Score, the DGGO-DT model consistently achieved the highest ranking, lower classification errors, and a balance of sensitivity and specificity. DGGO is superior to the other due to its dynamic balance between exploration and exploitation; it does not get trapped in local minima but rather searches promising areas of the search space. It incorporated adaptive population reallocation, mixed movement methods, directed search, neighborhood search, and paddle-based recombination, resulting in greater convergence stability and accuracy. The mechanisms have been discovered to act mainly in the discrete, non-convex hyperparameter area of the DT, such as tree depth and split criteria. The optimized DT with DGGO could be interpreted, which is a very essential criterion in the implementation of education, where clarity and explanation are paramount. The model states that the educator and the administrator can determine which variables are most essential for adaptability — namely, internet connectivity, load-shedding rate, and financial status — and develop specific interventions. This interpretability enables the educational stakeholders to make transparent, data-driven, and fair decisions and to predict as accurately as more complicated black-box models. The findings showed that all evaluation metrics —Accuracy, TPR, TNR, PPV, NPV, and F-score —show gradual increases across all cases, indicating that the DGGO algorithm improves the sensitivity and specificity of the prediction. However, the skewed dataset, particularly in the small High adaptability category, suggests that more robustness tests are needed using stratified cross-validation, per-class F1-values, probability calibration, and decision-curve analysis to assess the model's reliability across different data conditions. The preprocessing methods that yielded more stable models and more uniform error distributions included normalization, imputation, and feature encoding. Further experiments may be conducted with additional encoding schemes and cross-validation steps in preprocessing pipelines to reduce the risk of data leakage. Even though the overall outcomes suggest that DGGO is the superior option, statistical significance tests (paired t-tests, Friedman comparisons, Wilcoxon signed-rank tests, etc.) should be accompanied by confidence interval reporting in the future to support superiority claims. In addition, the cost-performance trade-offs might have been described by a sensitivity analysis of DGGO hyperparameters, such as population size and update coefficients. Certain limitations remain, particularly within the dataset's scope, which might limit the extent to which it can be generalized to other educational contexts, regional relationships, and institutional typologies. The model results may be biased by self-reported information (e.g., financial status or place) and unobserved confounders (e.g., home study setting or psychological factors). Moreover, DT models are interpretable, but can be sensitive to small data perturbations, so an ensemble approach, e.g., bagged DTs trained by DGGO, can be used to overcome this problem. In practice, the DGGO-DT model has a strong foundation for developing early-warning systems within learning institutions. It can also continuously process learning management system (LMS) and administrative data to identify students at risk of poor adaptability, enabling prompt implementation of interventions such as individualized coaching, adaptive testing, and technology assistance. It is made explicable to allow advisors to justify predictions and develop effective support strategies with students. Future research must expand the model to incorporate gradient-boosting models, such as XGBoost, LightGBM, and CatBoost, as well as deep learning models, and audit fairness and calibration by demographic lines. The long-term applicability of the models and their ethical appropriateness would also be improved by explainability approaches, such as SHAP and LIME, cost-sensitive learning methods, and longitudinal studies to track adaptability. Lastly, the DGGO algorithm has maximally improved Decision Tree results without compromising interpretability, yielding gains as large and significant as those of standard optimizers. The suggested DGGO-DT framework is a feasible, realistic, and scalable method for facilitating adaptive learning analytics in contemporary online education models, paving the way for intelligent, transparent, and equitable data-driven decision-making in the depths of the digital learning realm.

7. CONCLUSION AND FUTURE WORK

The study demonstrated an ingenious approach to predicting students' adaptability to distance learning using interpretable machine learning and advanced metaheuristic optimization. It was founded on the Decision Tree model because it is easy to understand and explain, and its initial performance is good: Accuracy of 0.9381, Sensitivity (TPR) of 0.9314, and Specificity (TNR) of 0.9443. The DGGO hyperparameter-tuning algorithm was another optimization that improved the model's generalization and predictive capabilities. The DT with DGGO achieved the highest level of accuracy (0.9715) and Sensitivity/TPR (0.9686), surpassing those of benchmark optimizers such as PSO and the GWO. The results substantiate the argument that DGGO offers a highly efficient trade-off between exploration and exploitation, as the population equilibrium is automatically maintained to avoid local optima and find the global one. The research also covers the significance of optimization and interpretability in data mining, as well as performance measures. Compared to the more predictive DGGO-tuned DT, the DGGO-tuned DT was transparent. As such, it allowed educational institutions and policymakers to view the critical adaptability factors as including network reliability, financial stability, and the type of institution. This justifies the pragmatic consequences of the early-warning intercessions, intercessory acts, and integrative learning models of courses. The findings, overall, support the utility and effectiveness of DGGO as an optimizer that can not only improve model performance but also be interpreted, scaled, and valuable in practice in a real educational context. Although the suggested DGGO-DT framework showed promising results, several avenues remain for future studies. Firstly, it would be possible to introduce the model by extending the ensemble and deep learning frameworks using Gradient Boosting Machines (XGBoost, LightGBM, CatBoost) and Neural Networks to evaluate the flexibility of DGGO across various learning paradigms. Second, the strength of the observed improvements will have to be assessed using statistical validation, cross-validation, confidence intervals, and nonparametric tests of significance. Third, a future study should address class imbalance using advanced resampling techniques or cost-sensitive learning to achieve equal performance across all adaptability levels. Moreover, explainable AI tools such as SHAP (Shapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) can provide more information about features and improve transparency in decision-making. It is also essential to conduct fairness audits based on gender, age, and socio-economic background to ensure the ethical use of predictive models in education. In addition, longitudinal and real-time adaptability prediction should be considered in the future by leveraging streaming data from learning management system (LMS) models to detect evolving behavioral patterns. Lastly, it is suggested that the DGGO-DT model be applied to real educational institutions and user-centrically evaluated for its operational efficiency and effectiveness in terms of student success. These empirical implementation studies will bridge the gap between optimal model behaviour in theory and practical improvements in education, opening the way to adaptive, equitable, and data-driven online learning systems that facilitate inclusiveness and resilience.

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