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Leveraging Metaheuristic Optimized Classifier Exploitability to Detect and Understand Student Dropout

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Abstract

Education is crucial for social progress, fostering knowledge, skills, and cognitive development, and is closely linked to long-term economic growth. By enhancing the general knowledge and skills of the population, education fuels innovation and the adoption of new ideas, making human capital a key driver of economic development. A well-educated workforce significantly contributes to research and development, integrating innovations into production and promoting economic growth. Despite extensive research, maintaining high enrolment and low dropout rates remains challenging. The potential of artificial intelligence (AI) in addressing this issue is underexplored. This work aims to fill this gap by leveraging metaheuristic optimized deep neural networks to detect students at risk of dropping out. A modified version of the firefly algorithm (FA) is introduced specifically to meet the demands of this optimization. Additionally, explainable AI (XAI) techniques are employed to better understand the factors influencing student decisions, thereby aiding in the formulation of effective retention policies. The introduced methodology is evaluated on a real-world dataset, with the best models achieving an accuracy exceeding 82% for dropout detection.

Key words: *Academia; Deep Neural Networks; Explainable Artificial Intelligence; Firefly Algorithm; Legal regulation and Ethical Principles*

Introduction

Education is the foundation and measure of progress for every social community. It involves acquiring knowledge, developing practical skills and habits, and serves as the basis for the development of cognitive strengths and abilities (Lajšić, Janjetović & Janjetović, 2014). The connection between education and long-term economic growth and development can be observed through the enhancement of general knowledge and skills of the population, ensuring the capacity for innovation and the transfer of new knowledge and ideas. Economic growth is driven by new ideas and discoveries that result in better products and more efficient production technologies, indicating that human capital is a key driving force. A well-educated workforce increases contributions to research and development, enabling greater absorption of innovations into the production structure, ultimately leading to the country's economic growth.

Globally, school dropout has become a significant challenge for most universities. According to a recent UNESCO (UNESCO, 2020) study, the COVID-19 pandemic has put 24 million students worldwide at risk of not continuing their education. The study highlights that higher education is likely to experience the highest dropout rate, with a predicted decrease of 3.5% in enrolment rates, potentially resulting in 7.9 million fewer students.

Preventing dropout brings numerous benefits, including increasing graduation rates, which improves students' professional and personal prospects and contributes to economic development through a more educated workforce. Students who complete their studies have better opportunities, develop a better skill set, and thus significantly contribute to the overall development of society. Many students face various challenges during their school life, which can eventually lead them to decide to drop out of their studies (Larsen, Kornbeck, Kristensen, Larsen & Sommersel, 2013). By collecting and analysing data on the reasons for dropping out, higher education institutions can anticipate and prevent student dropout through their activities. Researchers have shown the potential of artificial intelligence (AI) in mitigating this challenge.

AI models can analyse large amounts of student data, including academic performance, class attendance, social interactions, and other relevant factors. Based on these data, AI can identify students at risk of dropping out and enable universities to take preventive measures in time. Ethical guidelines for the development, implementation, and use of reliable and responsible artificial intelligence (AI) aim to ensure that AI is developed in a way that does not endanger human beings, animals, and the environment. To make AI reliable, safe, and compliant with laws and ethical principles, three key components - technical reliability, legal compliance, and ethical values - must be in harmony. Only then can AI be evaluated as reliable and responsible.

In the context of student safety, these guidelines ensure that AI tools used in education are aimed at improving their experience, identifying risks, and providing support to those at risk of dropping out. Thus, AI helps create a safe and fair educational environment that respects the rights and well-being of all students. This paper aims to explore the potential of AI in addressing challenges related to student dropout. However, algorithm performance is closely related to the choice of hyperparameters, and metaheuristic algorithms are applied to improve the performance of the algorithm for the given task. Leveraging explainable AI (XAI) techniques helps understand the factors that influence and drive model decisions, providing a better understanding of the problem as well as the model.

Beyond technical performance, the successful application of such models in educational settings requires careful integration into existing student support frameworks. The model should be used as a tool to assist educators and policymakers rather than as an automated decision-maker, ensuring that human expertise guides interventions. Additionally, ethical considerations, data privacy, and adaptability to different educational contexts must be prioritized to ensure responsible and effective implementation.

Educational institutions in the higher education sector collect and store a large amount of data related to participants in the educational process, primarily students, but also the educational process itself (Šidlauskas, & Limba, 2019). According to the provisions of the Personal Data Protection Act, higher education institutions take all necessary steps for the proper collection, storage, and processing of personal data of candidates for enrolment at all levels of study. It is necessary to understand the basic data about the data controller. The legal entity responsible for this process is the higher education institution and its legal representative where the candidate enrolls. This basic data allows students to be aware of who is responsible for processing their data and where they can turn for additional information or complaints.

The purpose of data collection and processing is multifaceted. The higher education institution maintains records with the aim of monitoring and improving the quality, efficiency, and effectiveness of its work. Additionally, data processing serves to enhance the educational level of students, enable students the right to enroll in the academic year, conduct competitive and examination periods, perform statistical data processing, and issue public documents. (Stepanović Ilić, Tošković, & Krstić, 2020).

Students mainly drop out for four main reasons: internal reasons, external reasons, student characteristics, and their skills. These reasons encompass sub-factors such as academic and social integration, financial status, and personal reasons (Lau, 2003). University staff, including lecturers and support staff, are often unaware of these reasons. The main challenge for higher education institutions is to create and improve policies that increase student retention, especially in the early years of study. Preventing school dropout is a critical issue. A growing number of scientific papers address this challenge, and many countries have established educational policies aimed at preventing and reducing dropout rates. Preventive measures that can be taken depend on the reasons why students drop out of university. They differ when considering students who completely stop studying or those who switch to another study program. The purpose of data processing is not only administrative but also has a direct impact on the quality of education and operational processes within the faculty.

While extensive research has been conducted across multiple fields to better understand students and the factors influencing their decisions, maintaining high enrolment rates and reducing dropout rates remains a challenge. The potential of AI for tackling this challenge remains unexplored in literature. Furthermore, the application of XAI holds substantial potential for gaining deeper insight and a better understanding of the factors that influence student decisions. Understanding these factors is the foundation on which policies that help improve student retention can be built. This paper seeks to address this literature gap, exploring the potential of metaheuristic optimized deep neural networks for the detection of students at risk of leaving education. A further contribution is the exploration of XAI techniques to provide a deeper understanding of the factors that influence student decisions on a global as well as local level.

Methodology

An artificial neural network (ANN) (Yegnanarayana, 2009) is a form of AI algorithm that draws inspiration from mechanisms observed in real biological brains. By mathematically modelling information transport between neurons using weights and biases, aggregating inputs and using activation functions to process the aggregated data, neural networks can address complex tasks. The basic building block of an ANN is the neuron. Neurons are interconnected with other neurons in the network with weighted connections. These weighted connections are aggregated by the neuron as per Eq. (1):

$$\sum_{n=0}^{n} w_i x_i \tag{1}$$

where w denotes the weights, and x the input value n denotes the number of inputs to a given neuron.

The activation function is applied to the results from the aggregation and is used to determine a neurons output. There are several activation functions popular among researchers. Some notable examples being the sigmoid Eq (2) and rectified linear unit (relu) functions Eq. (3):

$$\sigma(x)= \frac{1}{1 + e^{-x}} \tag{2}$$

$$f(x)= \frac{1+|x|}{1 + e^{-x}} \tag{3}$$

here the input value (output of the aggregation function) is denoted as x, the || symbols denote an absolute value. The structure of a typical simulated neuron can be seen in Figure 1.

The training process for an ANN relies on several techniques such as stochastic gradient descent and backpropagation to adapt a network to a given problem. A notable trait of ANN is that networks can take on diverse architectures depending on the complexity of the task being tackled. Simple tasks often require simpler networks, while more complex non-linear problems require more complex networks. Neurons

W1

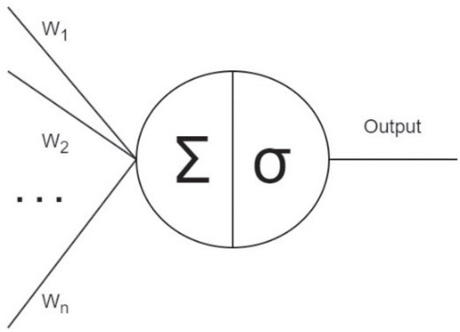

Figure 1. Simulated neuron structure.

within networks are often organized into individual layers. The first layer is typically considered the input layer, while the last layer is considered the output layer. Layers between the input and output are considered hidden layers. The structure of a simple ANN is provided in Figure 2.

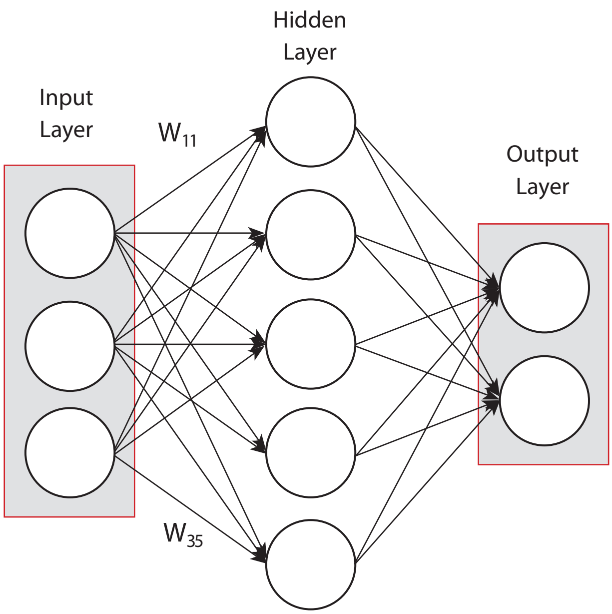

Figure 2. Simple neural network architecture.

By stacking multiple hidden layers, a deep neural network (DNN) (Cichy & Kaiser, 2019) can be created. This architecture can address more complex tasks but requires more training data and has higher computational demands. The use of DNN allows more complex problems to be addressed. This type of network can address more complex and highly abstract data.

The application and use of AI techniques has become increasingly popular to address many challenging problems in the real world. However, as algorithms are developed, researchers design and tune models to retain a certain level of flexibility. Models in their default state demonstrate good general performance on a vast number of applications. However, to attain desired performance form algorithms, hyperparameter adjustments are needed. This selection process is often considered NP-hard (Dréo, 2006) due to the vast range of possible values and is traditionally handled through trial and error. Adopting an empirically driven experimental approach is often found to be ineffective and tedious. Techniques capable of handling NP-hard optimization have been adopted for hyperparameter tuning.

Metaheuristic algorithms take an inherently randomized and iterative approach towards tackling optimization. While the attained results cannot be mathematically confirmed to be the best, an acceptably suitable solution can be located within reasonable time frames and on realistic hardware. Each subsequent iteration improves the chances that a suitable solution is located. Various source of inspiration and forms of optimizers have been proposed by researchers with well-established examples such as the particle swarm optimizer (PSO) (Kennedy & Eberhart, 1995) variable neighborhood search (VNS) (Hansen, Mladenović, & Moreno Perez, 2010) being a very popular choice among researchers for handling optimization. More recent examples of optimizers that have shown decent performance applied to challenging optimization tasks include the Sinh Cosh Optimizer (SCHO) (Bai, Li, Zheng, Khatir, Benaissa, Abualigah & Wahab, 2023) as well as the COLSHADE (Gurrola-Ramos, Hernàndez-Aguirre & Dalmau-Cedeño, 2020) optimizers.

Optimizers have been effectively applied to hyperparameter tunning in several fields. Some notable examples include medicine (Jovanovic, et al., 2023; Savanović, et al., 2023) as well as cybersecurity (Salb, et al., 2023). Hybrid optimizers have been shown to overcome limitations of base algorithms and demonstrate an overall improvement on the base algorithm performance. Hybrid optimizers have also shown excellent performance applied to hyperparameter tunning tasks (Damaševičius, et al., 2024; Stankovic, et al., 2022; Pilcevic et al., 2023).

As AI algorithms grow more complex, transparent understanding has become of critical importance. In most cases, trained models are considered black boxes taking inputs and providing outputs based on training data. However, hidden biases within the models as well as biases in training data can go unnoticed in models. It is vital to develop a body of tools and techniques that can be leveraged to interpret black box models and understand the driving forces behind model decisions.

Complexity associated with DNN makes it difficult to interpret using simple trial and error techniques. Biases and anomalous classifications can be more difficult to detect and understand in comparison to those in simpler models. Several techniques have been proposed in literature for tackling complex model explainability. There is no accepted standard for model, and several interpretations should be considered when assessing models.

A notable approach for model explainability is the use of Shapley additive explanations (SHAP) (Lundberg & Lee, 2017) that is based on game theory. Inputs are conceptualized as players participating in a game with outcomes conceptualized as the payouts. Adopting this game-theory based approach allows researchers to determine the contributions of each player (input) towards the game outcome (model output). Explainer estimators are used to approximate the initial predictive model as per Eq. (4):

$$h(z') = \emptyset_0 + \sum_{i=1}^{N} \emptyset_i Z'_i \tag{4}$$

here h denotes the explainer model, z' symbolized the features, the number of inputs is denoted as N and Ø denotes a feature's attribution. The value of Ø is computed as per Eq. (5):

$$\emptyset_i = \sum_{K \subseteq M i} \frac{|K|!\,(N - |K| - 1)!}{N!} [g_x(K \cup i) - g_x(K)] \tag{5}$$

where denotes expected values for a subset of inputs denoted as K, M is a set of all available inputs.

While SHAP tells us how much each feature contributes to individual predictions, further analysis is beneficial to determine how much a model depends on each feature for overall predictions. This can be discerned by leveraging Shapley additive global importance (SAGE) (Covert, Lundberg & Lee, 2020) techniques. While a full computation of all samples is inherently exponentially complex, approximations can be used to compute SAGE values. A random subset of features $S \subseteq D$ is selected and a marginal distribution sample $X_{\bar{S}}$. In practice, sampling is conducted in a limited iterative process while monitoring several estimator uncertainties and detect convergence. Importances can be established once the convergence criterion of the algorithm in Eq. (6) is fulfilled:

$$\max_i \frac{\sigma_i}{\sqrt{n}} < t \left(\max_i \widehat{\phi_i}(v_f) - \min_i \widehat{\phi_i}(v_f) \right) \tag{6}$$

where denotes the computed SHAP values, σ defines a constant that that following n interactions meets the requirement of Var $\left(\widehat{\phi_i}(v_f)\right) \approx \sigma_i^2 / i$. The interpretation algorithm can be considered converged once the largest standard deviation is a sufficiently low proportion t (e.g., t = 0.01).

By considering both SAGE and SHAP analysis outcomes, a deeper understanding of both the forecasting model can be attained. Furthermore, hidden biases in the data and predictions can be discerned. Finally, considering analysis outcomes can help improve data collection for future research.

The need for optimization of deep learning networks is necessary. This section discusses the firefly algorithm (FA) (Yang & Slowik,2020). Some of the limitations of the original FA are discussed, along with potential modifications that can help the optimizer overcome them, leading to the introduction of a modified version of the algorithm.

The FA draws inspiration from the reproductive behaviors observed in light producing insects that rely on bioluminescence to find suitable mates. Some simplifications are applied to make the algorithm suitable for mathematical modelling. Such as that all fireflies are attracted to brighter agents. The firefly's attractiveness is directly proportional to it's brightness. The brightness is defined by the objective function. Should two agents have the same brightness both move randomly.

Attractiveness is governed by perceived brightness (I) which is roughly mathematically modelled as per Eq. (7):

$$I(r) = \frac{I_s}{r^2} \tag{7}$$

where I_s is the brightness of an agent at the source and r the distance between two fireflies. Distance effectively decreases attractiveness between agents. Brightness at the source is determined by the objective function as per Eq. (8):

$$I_s = f(x_i). \tag{8}$$

The exact function is problem dependent and can be selected accordingly. Attractiveness β can be modelled as per Eq. (9):

$$\beta(r) = \beta_0 e^{\gamma r^2} \tag{9}$$

where attractiveness as r=0 is denoted as β_0 and γ is a factor used to simulate light absorption as it propagates though a medium. Attractiveness is used to motivate agent movement. Positions are updated as per Eq. (10):

$$x_i(t+1) = x_i(t)\beta_0 e^{-\gamma r2}(x_i = x_j) + \alpha\epsilon_i \tag{10}$$

here movement between agents x_i and x_j is simulated with representing mutual attraction and denoting a parameter used to introduce a randomization factor. The brightest firefly in the population moves in a random direction as per Eq. (11):

$$x_i(t+1) = x_i(t) + \alpha\epsilon_i \tag{11}$$

The original FA (Yang & Slowik, 2020) is well established as an effective optimizer and well known for possessing a powerful explanation mechanism. The exploitation mechanism has often been effectively integrated into other algorithms as well through hybridization to boost convergence in cases where such a modification is deemed desirable. Nevertheless, this mechanism can lead to premature convergence of the original algorithm. This can result in overall decreased performance when tackling optimization. This paper seeks to propose a modified version of the FA algorithm that overcomes some of the observed shortcomings, boosting diversification. The proposed algorithm draws inspiration from the genetic algorithm (GA) (Mirjalili& Mirjalili, 2019) and is named the diversity guided genetic GA (DGGFA).

To promote diversification the L! norm is introduced that accounts for diversity within the agent population. Norm parameters are defined as per Eq. (12), Eq. (13) and Eq. (14):

$$\overline{x_j} = \frac{1}{m}\sum_{i=1}^{m} x_{ij} \tag{12}$$

$$D_j^p = \frac{1}{m}\sum_{i=1}^{m\backslash} vline\ x_{ij} - \overline{x}_j \backslash vline \tag{13}$$

$$D^p = \frac{1}{n}\sum_{i=1}^{n} D_j^p\ , \tag{14}$$

here *m* denotes the current solution and *n* the specific diversity of the L1 norm. Parameter represents the array of mean agent positions across dimensions. The parameter denotes an individual's location as the L1 norm and is the diversity scaler. Higher diversity is desirable in earlier optimization stages. To manage diversity the L1 norm is leveraged through a dynamic threshold parameter .

Parameter *nrs* is also introduced and used to define the number of agents that are replaced in each iteration of the optimization. This value has been empirically selected as 2 for the optimization need of this study. At the onset of algorithm execution, initial value is computed as per Eq. (15).

$$D_{t0} = \sum_{j=1}^{NP} \frac{\left(ub_j - lb_j\right)}{2 \cdot NP}, \tag{15}$$

In each subsequent iteration is recomputed as per Eq. (16):

$$D_{t+1} = D_t - D_t \cdot \frac{t}{T} \tag{16}$$

Additionally following every iteration, the requirement is assessed, where represents the present diversity of the population. Should diversity be judged as poor nrs = 2 solutions are removed from the population and replaced with newly generated solutions. New solutions are computed as a hybrid between the worst performing agent and a random solution. Should diversity be at an acceptable lever agents are generated as a hybrid between the best solution and a random individual.

The hybrid solutions rely on crossover and mutation mechanisms inspired by the genetic algorithm depicted in Figure 3.

Crossover probability for each gene is given as pc. Crossover of two solutions produces two offspring individuals that will replace nrs = 2 solutions from the population, without additional evaluation.

At the start of the algorithm, pc value is set to 0.1, and in each round this parameter is increased by the coefficient of where t is the current ant T maximum number of iterations.

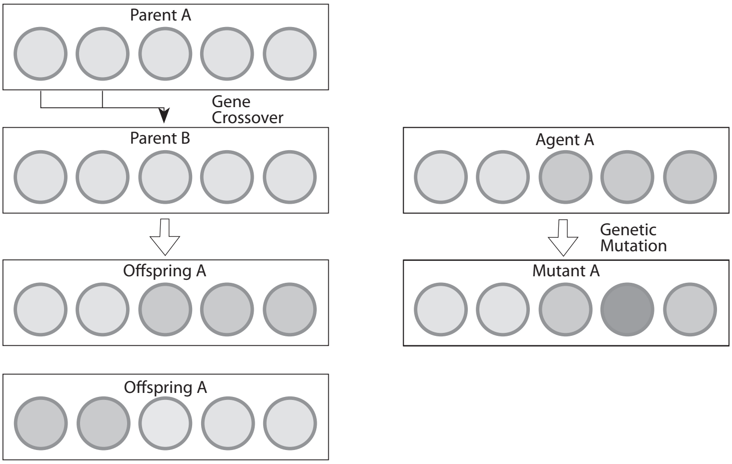

Figure 3. Genetic crossover and mutation mechanisms.

The pseudocode for the version of the modified algorithm is provided in Table 1.

Table 1

Introduced modified DGGFA pseudocode.

		Introduced DGGFA pseudocode
1.	→	Initialized agent population P
2.	→	Initialized ps = 0.1
3.	→	Compute $D_t = 0$ and D_t values
4.	→	**while** (t<T):
5.	→	Rank solutions based on objective function
6.	→	Determine D^p
7.	→	**if** ($D^p < D_t$):
8.	→	Replace nrs solutions with novel agents generated as a
9.	→	combination of the worst and a random agent
10.	→	**else**
11.	→	Replace nrs solutions with novel agents generated as a
12	→	combination of the best and a random agent
13	→	Update pd and D_t
14	→	return best attained agent as solution

To evaluate the proposed approach, experimentation with a publicly available real-world dataset is conducted.

The dataset is available on Kaggle[1] (Realinho, et al., 2021) and has last been accessed on June 15, 2024. The dataset comprised collected student data available to higher education institutions, including marital status, application mode, application order,

[1] https://www.kaggle.com/datasets/thedevastator/higher-education-predictors-of-student-retention

the courses taken by a student, attendance data, previous qualifications, parent qualification and occupation, displacement, special needs, age of enrolment, and number of curriculum units in each semester. Data is appropriately encoded and separated into training and testing portions with 70% of the data belonging to the former and 30% to the latter.

A comparative analysis is conducted between the introduced optimizer, original FA (Yang, & Slowik, 2020). Additional algorithms are included in the analysis such as the PSO (Kennedy & Eberhart, 1995), VNS (Hansen, Mladenović & Moreno Perez, 2010) algorithms. Recently introduced optimizers such as the SCHO (Bai, Li, Zheng, Khatir, Benaissa, Abualigah & Wahab, 2023) and COLSHADE (Gurrola-Ramos, Hernàndez-Aguirre, & Dalmau-Cedeño, 2020) algorithms are also evaluated.

Optimizers are allocated a population of 6 agents and allowed 6 iterations to improve population outcomes. Simulations are repeated 30 times to ensure fair evaluation. Architecture and training parameters of DNN are selected by each optimizer from ranges provided in Table 2.

Table 2
Model parameter constraints for optimization.

Method	Learning Rate	Dropout	Layers	Neurons	Epochs
Upper Bound	0.0001	0.50	3	65	500
Lower Bound	0.0050	0.01	1	35	200

Evaluations are carried out on the testing portion of the dataset. Standard classification metrics are used for evaluations (Ferrer, 2022). Metrics include precision, recall, f1-score, accuracy. Metrics are described in Eq. (17), Eq. (18), Eq. (19), Eq. (20), respectively:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives } + \text{False Positives}} \tag{17}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives } + \text{False Negatives}} \tag{18}$$

$$\text{F1-score} = \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{19}$$

$$\text{Precision} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{20}$$

Additionally, the Cohen's kappa metric (Warrens, 2015) is tracked and used as the objective metric as described in Eq. (21):

$$\text{Cohen's kappa} = \frac{\text{Classification-Expected Classification}}{1 - \text{Expected Classification}} \tag{21}$$

The indicator function tracked during optimization is error rate described Eq. (22):

$$\text{Error rate} = 1 - \text{Accuracy} \tag{22}$$

Following evaluations, the best performing models are subjected to analysis using SHAP and SAGE XAI techniques. Clustering out the analysis outcomes is also performed and discussed later.

Results

Simulations are carried out in two experiments. The first set of experiments focuses on binary classification and tackles separating students from those who have left academia. The second experiment handles a multiclass classification, separating dropouts from enrolled and graduate students. The best performing models are then subjected to interpretation using SHAP and SAGE XAI techniques. Finally, students are clustered to determine subgroups sharing challenges towards graduation.

Binary classification outcomes

Outcomes in terms of objective function for each of the metaheuristics included in the comparative analysis in terms of the best, worst, mean and median results are provided in Table 3. Outcomes suggest that the proposed optimizer constructed the best performing models under all scenarios. Nevertheless, the COLSHADE algorithm demonstrates impressive stability despite not attaining the most desirable outcomes.

Table 3
Objective function outcomes for constructed binary classifiers.

Method	Best	Worst	Mean	Median	Std	Var
DNN-DGGFA	**0.711691**	**0.701916**	**0.706150**	**0.705358**	0.003811	1.45E-05
DNN-FA	0.706097	0.696890	0.702553	0.702547	0.003175	1.01E-05
DNN-PSO	0.708819	0.701169	0.705637	0.707013	0.002943	8.66E-06
DNN-VNS	0.707326	0.693276	0.699004	0.697106	0.004718	2.23E-05
DNN-SCHO	0.710929	0.702099	0.705659	0.703901	0.003467	1.20E-05
DNN-COLSHADE	0.705066	0.700792	0.702968	0.702595	**0.001483**	**2.20E-06**

Outcomes in terms of indicator function for each of the metaheuristics included in the comparative analysis in terms of the best, worst, mean and median results are provided in Table 4. Here, the introduced optimizer attained the best outcome across most scenarios while matching performance in the worst-case execution with the SCHO optimizer. The COLSHADE optimizer attained the highest stability at the cost of overall results.

Table 4
Indicator function outcomes for constructed binary classifiers.

0	Best	Worst	Mean	Median	Std	Var
DNN-DGGFA	**0.123494**	0.127259	**0.125452**	**0.125753**	0.001397	1.95E-06
DNN-FA	0.125753	0.129518	0.126958	0.126506	0.001397	1.95E-06
DNN-PSO	0.124247	0.128012	0.125753	0.125000	0.001580	2.49E-06
DNN-VNS	0.125000	0.130271	0.128313	0.128765	0.001820	3.31E-06
DNN-SCHO	0.123494	0.127259	0.125602	0.126506	0.001460	2.13E-06
DNN-COLSHADE	0.125753	0.128765	0.126958	0.126506	**0.001021**	**1.04E-06**

Comparisons in terms of stability are given in the form of distribution plots provided in Figure 4 and swarm plots provided in Figure 5. The introduced algorithm boasts a comparable stability with the original. However, clear improvement can be observed in terms of solution quality with the best as well as worst solutions outperforming results showcased by the base algorithm. While the COLSHADE optimizers showcases stability, this comes at a cost of solution quality, with many of the solutions presented by this optimizer falling around a suboptimal region.

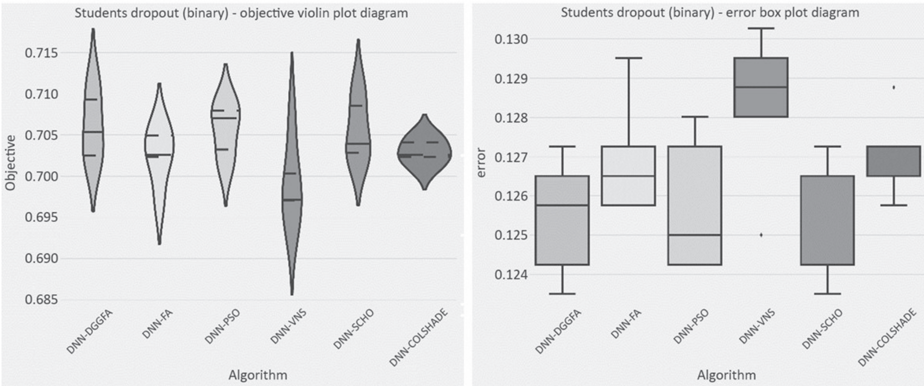

Figure 4. Objective and indicator function distributions for binary classifier models.

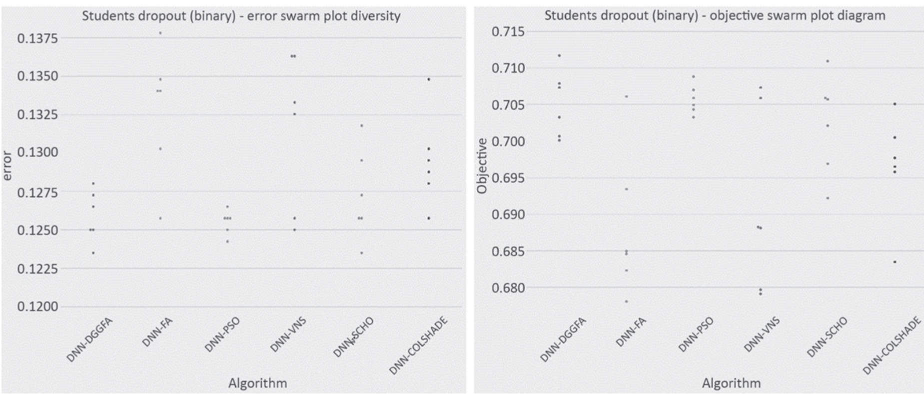

Figure 5. Objective and indicator function swarm plots for binary classifier models.

Detailed metric outcomes for the best performing models constructed by each optimizer are provided in Table 5. The introduced optimizer attained the best outcomes in terms of accuracy, decent recall and f-1 scores in terms of student detection and the best macro and weighted average values in terms of precision. The FA, PSO and SCHO algorithm also demonstrated decent outcomes. This is to be somewhat expected, as stated by the NFL theorem, no single approach is equally suited to all challenges under all metrics.

Table 5
Detailed outcome for the best performing models optimized by each algorithm.

Method	Metric	Student	Dropout	Accuracy	Macro Avg	Weighted Abg
DNN-DGGFA	Precision	0.863054	0.920128	**0.876506**	**0.891591**	**0.881405**
	Recall	**0.972253**	0.674473	**0.876506**	0.823363	0.876506
	F1-score	**0.914405**	0.778378	**0.876506**	0.846392	0.870668
DNN-FA	Precision	0.861220	**0.916667**	0.874247	0.888944	0.879048
	Recall	0.971143	0.669789	0.874247	0.820466	0.874247
	F1-score	0.912885	0.774019	0.874247	0.843452	0.868234
DNN-PSO	Precision	**0.866534**	0.904321	0.875753	0.885427	0.878684
	Recall	0.965594	**0.686183**	0.875753	**0.825888**	0.875753
	F1-score	0.913386	0.780293	0.875753	0.846839	0.870592
DNN-VNS	Precision	0.864222	0.909091	0.875000	0.886656	0.878649
	Recall	0.967814	0.679157	0.875000	0.823485	0.875000
	F1-score	0.913089	0.777480	0.875000	0.845284	0.869486
DNN-SCHO	Precision	0.865938	0.909657	0.876506	0.887798	0.879996
	Recall	0.967814	0.683841	0.876506	0.825827	0.876506
	F1-score	0.914046	**0.780749**	0.876506	**0.847397**	**0.871186**
DNN-COLSHADE	Precision	0.865538	0.901235	0.874247	0.883386	0.877016
	Recall	0.964484	0.683841	0.874247	0.824162	0.874247
	F1-score	0.912336	0.777630	0.874247	0.844983	0.869023
	Support	901	427			

Further details on an algorithm's ability to avoid local minimum traps and focus towards a more promising regions of the search space can be found in the convergence diagrams for the objective and indicator functions provided in Figure 6. While several optimizers focus on sub optimal spaces failing to effectively converge towards a suitable solution, the introduced optimizer manages to overcome these challenges and locate a more promising solution within the given search space outperforming the base optimizer.

Performance details for the best performing binary classification model constructed by the introduced DGGFA optimizer are provided in Figure 7. The confusion matrix and PR curves demonstrate the ability of the best performing models to identify dropout students as opposed to students that are still attending. This is in turn followed by Figure 8 describing the best performing model's architecture. Table 6 provides parameter selections made by each algorithm during optimization that yielded the best performing respective model.

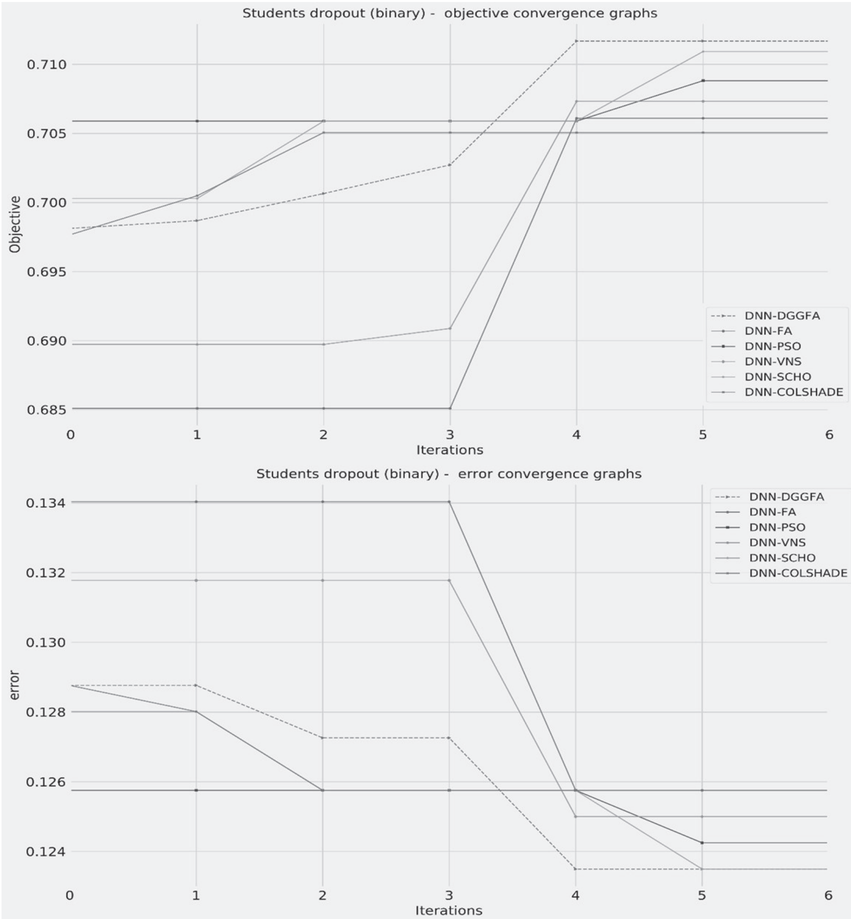

Figure 6. Objective and indicator function convergence diagrams for binary classifier models.

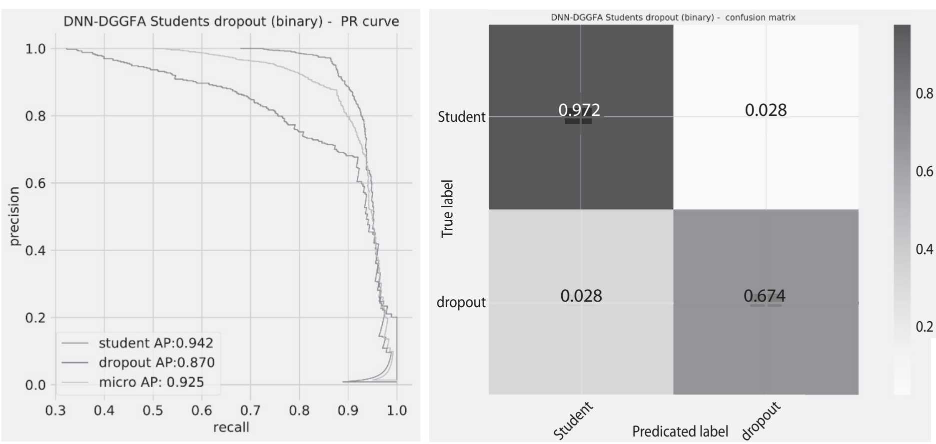

Figure 7. Best performing DGGFA optimizer binary model PR curve and confusion matrix.

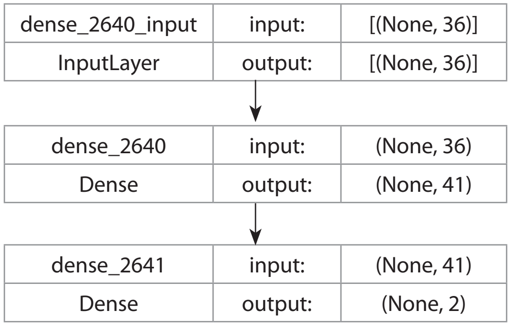

Figure 8. Best performing DGGFA optimizer binary model architecture.

Table 6

Parameter selections for the best performing binary classifiers.

Method	Learning Rate	Dropout	Layers	Epochs	Neurons
DNN-DGGFA	1.50E-04	0.500000	1	41	200
DNN-FA	1.00E-04	0.500000	2	55	200
DNN-PSO	7.00E-04	0.258688	1	65	200
DNN-VNS	1.00E-04	0.500000	2	46	200
DNN-SCHO	4.00E-04	0.368707	1	50	200
DNN-COLSHADE	7.50E-04	0.010000	2	54	200

Multiclass classification outcomes

Outcomes in terms of objective function for each of the metaheuristics included in the comparative analysis in terms of the best, worst, mean and median results are provided in Table 7. The COLSHADE algorithm demonstrates impressive outcomes both in terms of stability as well as outcomes across multiple criteria. However, the best performance is demonstrated by models optimized by the introduced optimizer.

Table 7

Objective function outcomes for constructed multiclass classifiers.

Method	Best	Worst	Mean	Median	Std	Var
DNN-DGGFA	**0.620793**	0.604716	0.612147	0.611545	0.005820	3.39E-05
DNN-FA	0.615526	0.603506	0.608758	0.608824	0.003902	1.52E-05
DNN-PSO	0.615546	0.608432	0.611175	0.610134	0.002428	5.90E-06
DNN-VNS	0.612799	0.601149	0.605685	0.604489	0.004473	2.00E-05
DNN-SCHO	0.612988	0.607231	0.609876	0.610430	0.002205	4.86E-06
DNN-COLSHADE	0.614742	**0.608780**	**0.612498**	**0.612750**	**0.002143**	**4.59E-06**

Outcomes in terms of indicator function for each of the metaheuristics included in the comparative analysis in terms of the best, worst, mean and median results are provided in Table 8. The introduced optimizer attained the best outcomes. However, the COLSHADE optimizer attained the best scores in terms of worst, mean, and median results. The SCHO algorithm attained the highest rate of stability further reinforcing the NFL theorem.

Table 8
Indicator function outcomes for constructed multiclass classifiers.

Method	Best	Worst	Mean	Median	Std	Var
DNN-DGGFA	**0.228916**	0.238705	0.234488	0.236446	0.003768	1.42E-05
DNN-FA	0.231175	0.238705	0.235994	0.237199	0.002591	6.71E-06
DNN-PSO	0.231175	0.236446	0.234940	0.23494	0.002565	6.58E-06
DNN-VNS	0.233434	0.240211	0.237500	0.237952	0.002410	5.81E-06
DNN-SCHO	0.234940	0.236446	0.235994	0.235693	**0.001551**	**2.40E-06**
DNN-COLSHADE	0.231928	**0.235693**	**0.234036**	**0.233434**	0.001743	3.04E-06

Comparisons in terms of stability are given in the form of distribution plots provided in Figure 9 and swarm plots provided in Figure 10.

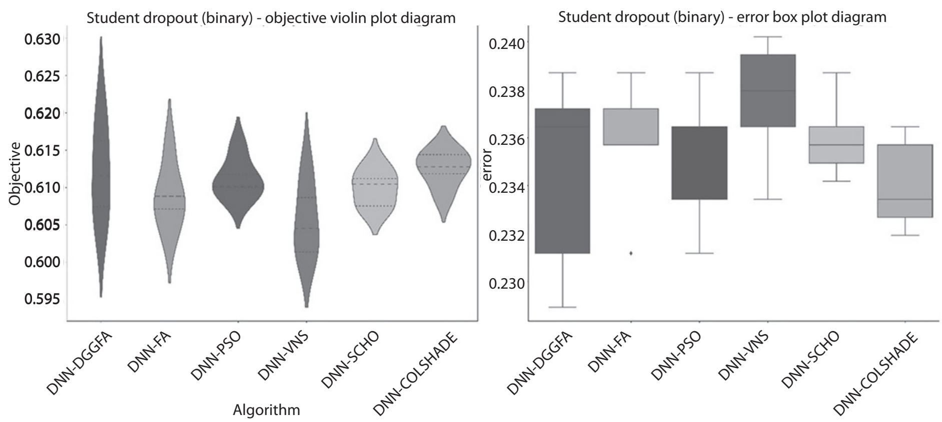

Figure 9. Objective and indicator function distributions for multiclass classifier models

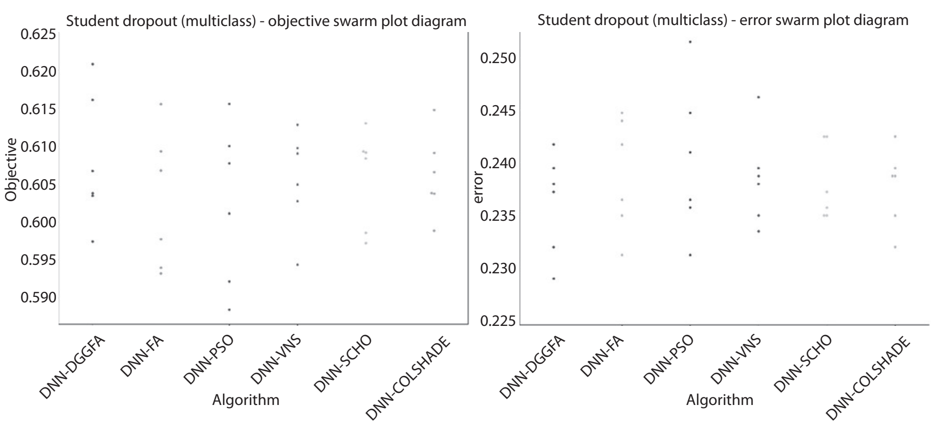

Figure 10. Objective and indicator function swarm plots for multiclass classifier models.

The introduced optimizer showcases better outcomes in comparison to the original. However, this boost in performance comes at a cost in algorithm stability, High stability rates are showcases by the PSO, SCHO and COLSHADE optimizers.

Detailed metric outcomes for the best performing models constructed by each optimizer are provided in Table 9. The introduced algorithm showcases the highest rate of precession for dropout detection as well as the highest accuracy overall with a high rate of graduate detection as well as the highest weighted average outcomes across precision recall and f1-score. Other optimizers attained spotty outcomes demonstrating decent performance across most metrics further enforcing the statements provided by the NFL theorem.

Table 9
Detailed outcome of the best performing multiclass models optimized by each algorithm

Method	Metric	Enrolled	Graduate	Dropout	Accuracy	Macro Avg	Weighted Abg
DNN-DGGFA	Precision	0.796026	0.546448	**0.828205**	**0.771084**	0.723560	**0.761644**
	Recall	0.906486	**0.420168**	0.756440	**0.771084**	0.694365	**0.771084**
	F1-score	0.847673	**0.475059**	0.790698	**0.771084**	**0.704477**	**0.762575**
DNN-FA	Precision	0.785530	0.576000	0.794872	0.768825	0.718801	0.750982
	Recall	0.917044	0.302521	0.798595	0.768825	0.672720	0.768825
	F1-score	0.846207	0.396694	**0.796729**	0.768825	0.679877	0.749738
DNN-PSO	Precision	0.781888	0.618644	0.786385	0.768825	**0.728972**	0.754078
	Recall	**0.924585**	0.306723	0.784543	0.768825	0.671950	0.768825
	F1-score	0.847270	0.410112	0.785463	0.768825	0.680949	0.749051
DNN-VNS	Precision	0.792157	**0.621053**	0.754274	0.766566	0.722494	0.749311
	Recall	0.914027	0.247899	**0.826698**	0.766566	0.662875	0.766566
	F1-score	0.848739	0.354354	0.788827	0.766566	0.663974	0.740873
DNN-SCHO	Precision	**0.818966**	0.553073	0.766004	0.76506	0.712681	0.754284
	Recall	0.859729	0.415966	0.812646	0.76506	**0.696114**	0.765060
	F1-score	0.838852	0.474820	0.788636	0.76506	0.700770	0.757465
DNN-COLSHADE	Precision	0.801862	0.561290	0.783848	0.768072	0.715667	0.752955
	Recall	0.909502	0.365546	0.772834	0.768072	0.682627	0.768072
	F1-score	**0.852297**	0.442748	0.778302	0.768072	0.691116	0.755107
	Support	663	238	427			

Further details on an algorithm's ability to avoid local minimum traps and focus towards more promising regions of the search space can be found in the convergence diagrams for the objective and indicator functions provided in Figure 11. While several optimizers focus on sub optimal spaces failing to effectively converge towards a suitable solution, the introduced optimizer manages to overcome these challenges and locate a more promising solution within the given search space outperforming the base optimizer.

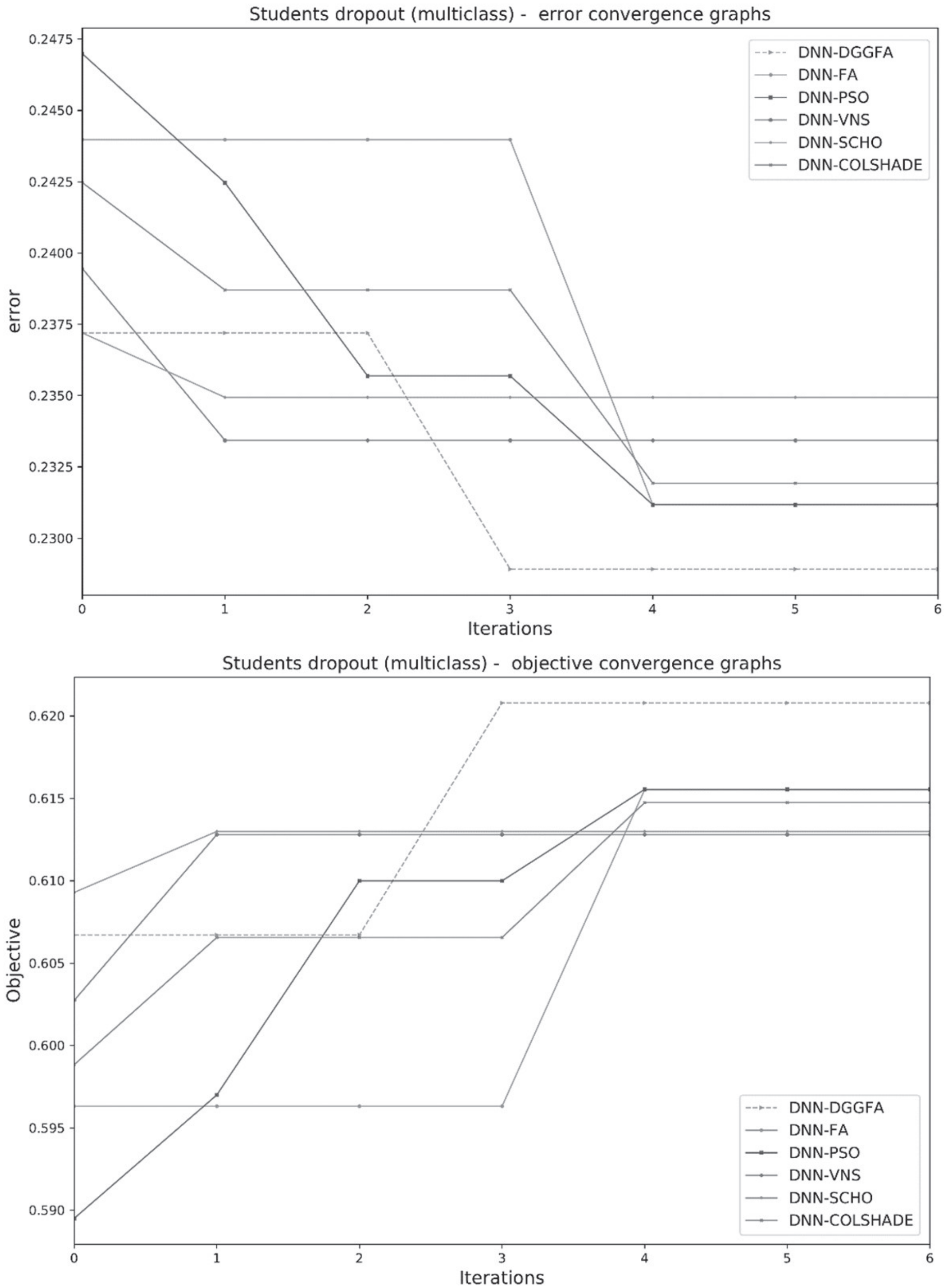

Figure 11. Objective and indicator function convergence diagrams for multiclass classifier models.

Performance details for the best performing multiclass classification model constructed by the introduced DGGFA optimizer are provided in Figure 12. The confusion matrix and PR curves demonstrate the ability of the best performing models to identify dropout students as opposed to students who are still attending. This is in turn followed by Figure 13 describing the best performing model's architecture. Table 10 provides parameter selections made by each algorithm during optimization that yielded the best performing respective model.

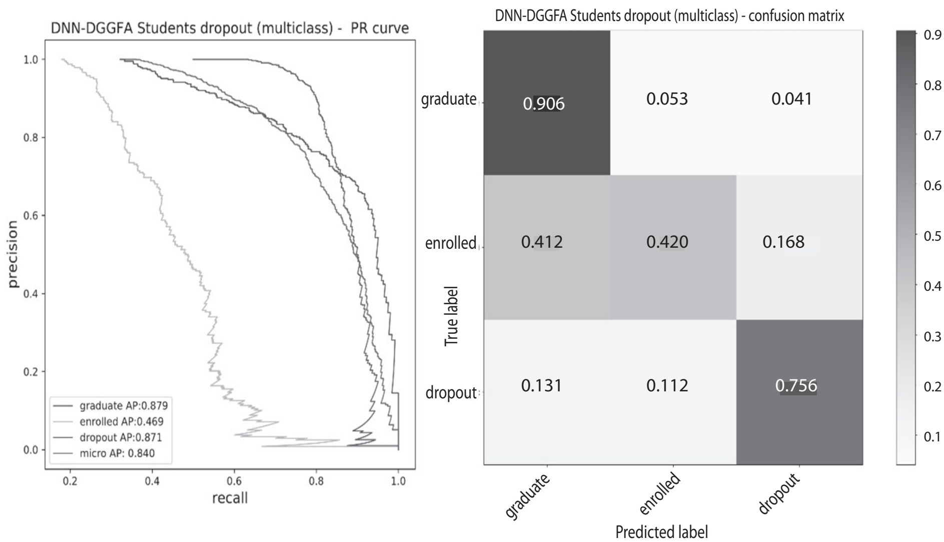

Figure 12. Best performing DGGFA optimizer multiclass model PR curve and confusion matrix.

dense_4710_input	input:	[(None, 36)]
InputLayer	output:	[(None, 36)]

↓

dense_4710	input:	(None, 36)
Dense	output:	(None, 36)

↓

dense_4711	input:	(None, 36)
Dense	output:	(None, 36)

↓

dense_4712	input:	(None, 36)
Dense	output:	(None, 3)

Figure 13. Best performing DGGFA optimizer multiclass model architecture

Table 10
Parameter selections for the best performing multiclass classifiers

Method	Learning Rate	Dropout	Layers	Epochs	Neurons
DNN-DGGFA	1.18E-03	0.012112	2	36	200
DNN-FA	1.00E-04	0.225270	1	53	200
DNN-PSO	1.68E-03	0.018174	1	66	200
DNN-VNS	5.00E-03	0.500000	1	36	200
DNN-SCHO	1.00E-04	0.429243	3	36	200
DNN-COLSHADE	1.15E-03	0.154537	1	48	200

Best performing model interpretation and student clustering

Oftentimes, the reasoning behind model decisions is just as important as the classifications the models make. Understanding student dropout, and the factors that influence model decision can help improve data collection as well as policy to help at risk students. Consequently, this can improve academic performance. Analysis via XAI techniques, SAGE and SHAP is provided for the best performing binary and multiclass models in the following subsections.

Best binary classifier model interpretation

Analysis of the best performing DGGFA optimized binary classifier model using XAI techniques are provided in Figure 14. SHAP feature impact scores are provided on the left, and SAGE feature importance are provided on the right. In both cases the number of approved units in the 2nd semester plays the highest role in the models' decision. This is followed by features concerning curriculum units in the 2nd semester that are graded and units that are approved in the 1st semester. Globally, up-to-date tuition fees as well as holding a scholarship play an important role in classification.

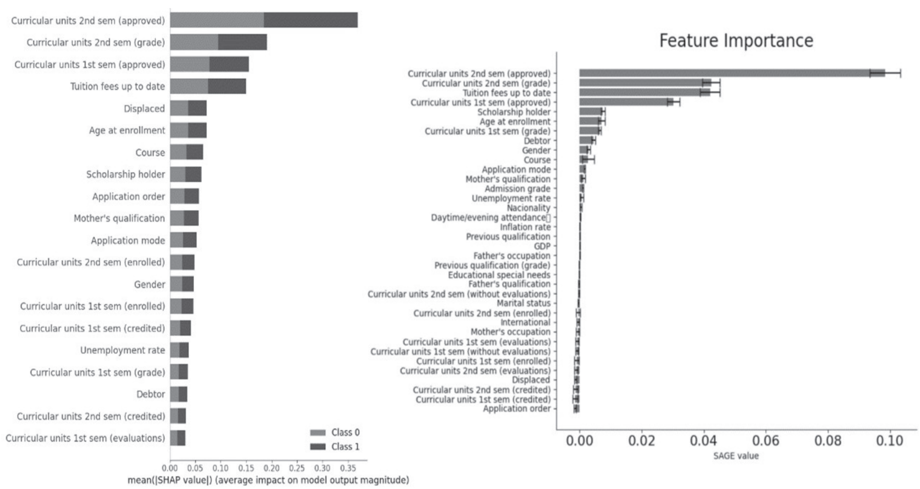

Figure 14. SHAP Feature impact and SAGE feature importance for binary classification.

Best multiclass classifier model interpretation

Analysis of the best performing DGGFA optimized binary classifier model using XAI (Došilović, Brčić, & Hlupić,2018) techniques are provided in Figure 15. SHAP feature impact scores are provided on the left, and SAGE feature importance are provided on the right. In both cases the number of approved units in the 2nd semester plays the highest role in the models' decision. This is followed by features concerning curriculum units in the 2nd semester that are graded and units that are approved in the 1st semester. Globally, up-to-date tuition fees, and holding a scholarship playan important role in the classification. Analysis outcomes somewhat mirror those observed in binary classification which is to be somewhat expected as there is a great similarity between graduate and enrolled students.

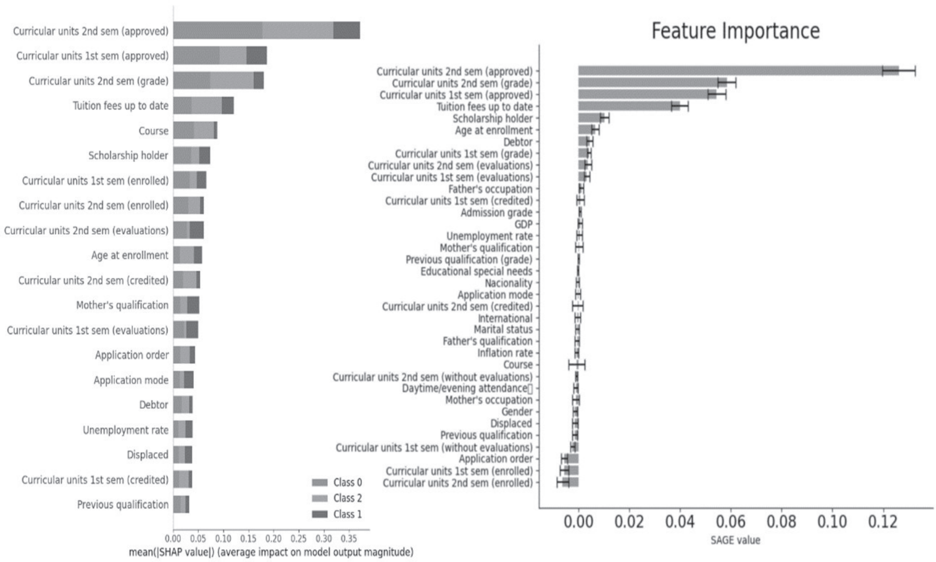

Figure 15. SHAP Feature impact and SAGE feature importance for multiclass classification.

Best binary classifier model SHAP value clustering

Understanding the factors that drive decision-making is a challenging task for institutions. A further challenge is developing strategies that can yield the highest impact in practice. It is important to understand how the factor influence is shared among students. Formulating clusters based on influence factors can help policymakers discern similarities between groups and focus effective efforts where the highest impact is needed.

In Figure 16 student density-based clustering non-parametric algorithm (DBSCAN) (Schubert, Sander, Ester, Kriegel & Xu, 2017) clusters are formed based on local SHAP feature impacts for each, for the visualization Uniform Manifold Approximation and Projection (UMPA) (Leland, John & James, 2018) is used to reduce the dimensionality to two dimensions. To the left, subgroups are formed by the DBSCAN algorithm, while to the right, the students are coloured with respect to their enrolment status. Distinct groupings of dropouts can be seen in several cases. Students in the top left group 6 are highly likely to drop out based on the same factors. Addressing these factors, if possible, could help improve their academic outcomes in an effective manner. Similarly, the lower part of the largest cluster has a low chance of dropping out of education. This information allows policymakers to better allocate resources to have a higher impact on students. Finally, several smaller outliers can be observed. Focusing on outliers with policy can be both challenging and have a lesser impact in practice. It is important to rely on expert opinions when formulating policy to ensure proper and effective implementation.

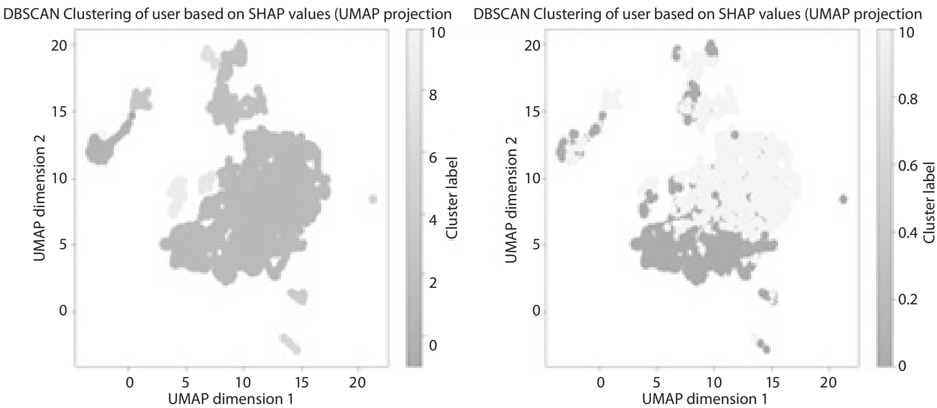

Figure 16. Student clustering based on feature impacts.

Discussion

The study supports the role that education plays in promoting cognitive, knowledge, and skill development—all of which are necessary for long-term financial success. A workforce with a higher education fosters innovation in manufacturing, improves research and development, and supports economic growth. Though its full potential in this area is still untapped, AI has emerged as a promising tool for enhancing academic achievements.

By presenting a DNN model that has been tuned using a particular technique, this study fills this gap. The suggested method is thoroughly tested on a publicly accessible real-world dataset. The findings show that in multiclass settings, the top-performing models get an accuracy of over 89.15% for dropout detection and 77.10% for classification. These high accuracy scores demonstrate how well the suggested technique works to identify students who are at danger of quitting school.

Extensive (XAI) analysis is carried out to further clarify the model's decision-making process. This research reveals the most important elements impacting categorization judgments and offers insights into the major aspects influencing the model's predictions.

Furthermore, local interpretations are subjected to clustering algorithms, which allow pupils to be grouped according to common traits. This method makes it easier to comprehend the main causes of student dropout rates and provides insightful information for developing focused interventions and policies.

Addressing issues with student retention becomes more visible and efficient when AI-driven approaches are combined with XAI-based interpretability. This study offers practical insights for educational institutions to create data-driven strategies targeted at enhancing student retention and academic achievement by identifying important determinants of academic attrition and connecting them to student groups.

Conclusion

Education promotes knowledge, skills, and cognitive development and is essential for societal advancement. It also has a strong correlation with sustained economic success. Education stimulates creativity and the uptake of new ideas by improving the general knowledge and abilities of the population, making human capital a vital component of economic success. An educated labor force makes a substantial contribution to research and development, incorporating innovations into manufacturing and fostering economic expansion. The potential of AI to improve the academic outcomes of students has yet to be explored in literature. This paper seeks to expand on the observed literature gap and introduce an approach based on DNN optimized by a specialized algorithm introduced in this study. Simulations are conducted on a real-world publicly available dataset. The best-optimized models attain accuracy exceeding 89.15% for dropout detection and 77.10% for detection under multiclass simulations. The best models are subjected to extensive XAI analysis to determine the factors that models rely on as well as the features that are deemed important to each classification. Clustering is conducted on local interpretation, and student grouping is connected to better understand the factors that influence the decision to leave academia.

Although the suggested approach shows good predictive accuracy in identifying students who are at risk of dropping out, institutional and contextual variables must be carefully considered when implementing it in practice. To adopt such a model, educational institutions must make sure that the system is incorporated into already-existing frameworks for student assistance and that the proper data protection and ethical standards are in place. To help educators and policymakers identify at-risk adolescents early and customize treatments appropriately, the model should be used as a decision-support tool rather than a deterministic mechanism. Furthermore, because many educational systems have varied structural and socioeconomic factors, the success of any intervention based on these projections depends on domain experience and localized knowledge.

As with any work, certain limitations exist within this study as well. Extensive computation demands of optimization limit the extent of the comparative analysis that can be carried out. Only a small subset of algorithms is included in a comparative study. Furthermore, limited population sizes and limited optimization times are allocated to each algorithm. Future works hope to address these limitations, expand on the introduced methodology, and find novel applications of the introduced algorithm.

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Iskorištavanje metaheuristički optimizirane iskoristivosti klasifikatora za otkrivanje i razumijevanje ispisivanja studenata

Sažetak

Obrazovanje je ključno za društveni napredak, poticanje znanja, vještina i kognitivnoga razvoja te je usko povezano s dugoročnim ekonomskim rastom. Povećanjem općega znanja i vještina stanovništva, obrazovanje potiče inovacije i usvajanje novih ideja, čineći ljudski kapital ključnim pokretačem gospodarskoga razvoja. Dobro obrazovana radna snaga značajno doprinosi istraživanju i razvoju, integrirajući inovacije u proizvodne procese i potičući ekonomski rast. Unatoč opsežnim istraživanjima, održavanje visoke stope upisa i niske stope ispisivanja studenata ostaje izazov. Potencijal umjetne inteligencije (AI) u rješavanju ovoga problema još uvijek nije dovoljno istražen. Ovim radom nastoji se popuniti ta praznina koristeći metaheuristički optimizirane duboke neuronske mreže za otkrivanje studenata koji su u riziku od ispisivanja. U tu svrhu, predstavljena je modificirana verzija algoritma krijesnica (FA) kako bi se zadovoljili specifični zahtjevi optimizacije. Dodatno, tehnike objašnjive umjetne inteligencije (XAI) koriste se za bolje razumijevanje čimbenika koji utječu na odluke studenata, čime se olakšava formuliranje učinkovitih strategija zadržavanja studenata. Predložena metodologija evaluirana je na stvarnom skupu podataka, pri čemu su najbolji modeli postigli točnost veću od 82 % u predviđanju ispisivanja studenata.

Ključne riječi: *akademska zajednica; algoritam krijesnica; duboke neuronske mreže; objašnjiva umjetna inteligencija; pravna regulativa i etička načela*

Uvod

Obrazovanje je temelj i mjerilo napretka svake društvene zajednice. Ono obuhvaća stjecanje znanja, razvoj praktičnih vještina i navika te služi kao osnova za razvoj kognitivnih sposobnosti i vještina (Lajšić, Janjetović i Janjetović, 2014). Povezanost između obrazovanja i dugoročnoga gospodarskog rasta i razvoja očituje se kroz povećanje općega znanja i vještina populacije, čime se osigurava kapacitet za inovacije i prijenos novih znanja i ideja. Gospodarski rast potiču nove ideje i otkrića koja dovode do boljih proizvoda i učinkovitijih proizvodnih tehnologija, što pokazuje da je ljudski kapital ključna pokretačka snaga. Dobro obrazovana radna snaga povećava doprinos istraživanju i razvoju, omogućujući veću apsorpciju inovacija u proizvodnu strukturu, što u konačnici dovodi do gospodarskoga rasta zemlje.

Globalno gledano, ispisivanje studenata postalo je značajan izazov za većinu sveučilišta. Prema nedavnom istraživanju UNESCO-a (UNESCO, 2020), pandemija COVID-19 dovela je 24 milijuna studenata diljem svijeta u rizik od nemogućnosti nastavka obrazovanja. Istraživanjem se naglašava da će visoko obrazovanje vjerojatno doživjeti najvišu stopu ispisivanja, s predviđenim smanjenjem stope upisa za 3,5 %, što bi moglo rezultirati s 7,9 milijuna manje studenata.

Sprječavanje ispisivanja donosi brojne koristi, uključujući povećanje stope diplomiranja, što poboljšava profesionalne i osobne izglede studenata te doprinosi gospodarskom razvoju putem obrazovanije radne snage. Studenti koji završe studij imaju bolje prilike, razvijaju kvalitetniji skup vještina i time značajno doprinose ukupnom društvenom razvoju. Mnogi studenti suočavaju se s različitim izazovima tijekom školovanja, što ih može dovesti do odluke o ispisivanju sa studija (Larsen, Kornbeck, Kristensen, Larsen i Sommersel, 2013). Prikupljanjem i analizom podataka o razlozima ispisivanja, visokoškolske ustanove mogu predvidjeti i spriječiti ispisivanje studenata putem svojih aktivnosti. Istraživači su pokazali potencijal umjetne inteligencije (AI) u rješavanju ovoga problema.

AI modeli mogu analizirati veliki broj podataka o studentima uključujući akademsku uspješnost, prisutnost na nastavi, društvene interakcije i druge relevantne čimbenike. Na temelju tih podataka, umjetna inteligencija može identificirati studente u riziku od ispisivanja te omogućiti sveučilištima poduzimanje preventivnih mjera na vrijeme. Etičke smjernice za razvoj, implementaciju i upotrebu pouzdane i odgovorne umjetne inteligencije (AI) usmjerene su na osiguravanje da se AI razvija na način koji ne ugrožava ljude, životinje i okoliš. Kako bi AI bio pouzdan, siguran i u skladu sa zakonima i etičkim načelima, tri ključne komponente – tehnička pouzdanost, pravna usklađenost i etičke vrijednosti – moraju biti u skladu. Samo tada se AI može ocijeniti kao pouzdan i odgovoran.

U kontekstu zaštite studenata, ove smjernice osiguravaju da su AI alati koji se koriste u obrazovanju usmjereni na poboljšanje njihova iskustva, prepoznavanje rizika i pružanje podrške onima koji su u riziku od ispisivanja. Tako AI pomaže u stvaranju sigurnoga i pravednoga obrazovnog okružja koje poštuje prava i dobrobit svih studenata. Ovaj rad ima za cilj istražiti potencijal AI u rješavanju izazova povezanih s ispisivanjem studenata. Međutim, izvedba algoritama usko je povezana s izborom hiperparametara, a metaheuristički algoritmi primjenjuju se kako bi se poboljšala učinkovitost algoritma za zadani zadatak. Korištenje tehnika objašnjive umjetne inteligencije (XAI) pomaže u razumijevanju čimbenika koji utječu na odluke modela, pružajući bolji uvid u problem, kao i u sam model.

Osim tehničke izvedbe, uspješna primjena takvih modela u obrazovnim okružjima zahtijeva pažljivu integraciju u postojeće okvire studentske podrške. Model bi se trebao koristiti kao alat za pomoć nastavnicima i donositeljima politika, a ne kao automatizirani donositelj odluka, čime se osigurava da ljudska stručnost vodi intervencije. Osim toga, prioriteti bi trebali uključivati etička razmatranja, zaštitu privatnosti podataka i prilagodljivost različitim obrazovnim kontekstima kako bi se osigurala odgovorna i učinkovita implementacija.

Visokoškolske ustanove prikupljaju i pohranjuju veliki broj podataka vezanih uz sudionike obrazovnoga procesa, prvenstveno studente, ali i sam obrazovni proces (Šidlauskas i Limba, 2019). Prema odredbama Zakona o zaštiti osobnih podataka, visokoškolske ustanove poduzimaju sve potrebne korake za pravilno prikupljanje, pohranu i obradu osobnih podataka kandidata za upis na sve razine studija. Potrebno je razumjeti osnovne podatke o voditelju obrade podataka. Pravna osoba odgovorna za ovaj proces je visokoškolska ustanova i njezin zakonski zastupnik kod kojeg se kandidat upisuje. Ovi osnovni podatci omogućuju studentima da budu svjesni tko je odgovoran za obradu njihovih podataka i kome se mogu obratiti za dodatne informacije ili pritužbe.

Svrha prikupljanja i obrade podataka je višestruka. Visokoškolska ustanova vodi evidenciju s ciljem praćenja i poboljšanja kvalitete, učinkovitosti i djelotvornosti svoga rada. Osim toga, obrada podataka služi za unaprjeđenje obrazovne razine studenata, omogućavanje prava na upis u akademsku godinu, provođenje natječajnih i ispitnih rokova, statističku obradu podataka te izdavanje javnih isprava (Stepanović Ilić, Tošković i Krstić, 2020).

Studenti se uglavnom ispisuju zbog četiri glavna razloga: unutarnji razlozi, vanjski razlozi, karakteristike studenata i njihove vještine. Ti razlozi obuhvaćaju podfaktore poput akademske i društvene integracije, financijskoga statusa i osobnih razloga (Lau, 2003). Sveučilišno osoblje, uključujući predavače i pomoćno osoblje, često nije svjesno tih razloga. Glavni izazov za visokoškolske ustanove jest stvaranje i poboljšanje politika koje povećavaju zadržavanje studenata, posebno u ranim godinama studija.

Iako su provedena brojna istraživanja u različitim područjima kako bi se bolje razumjeli studenti i čimbenici koji utječu na njihove odluke, održavanje visoke stope upisa i niske stope ispisivanja ostaje izazov. Potencijal AI u rješavanju ovoga problema i dalje je nedovoljno istražen u literaturi. Nadalje, primjena XAI-a nudi značajan potencijal za dublji uvid i bolje razumijevanje čimbenika koji utječu na odluke studenata. Razumijevanje tih čimbenika temelj je na kojem se mogu graditi politike za poboljšanje zadržavanja studenata. Ovim radom nastoji se popuniti ovu prazninu u literaturi istraživanjem potencijala metaheuristički optimiziranih dubokih neuronskih mreža za otkrivanje studenata u riziku od ispisivanja te analizom XAI tehnika kako bi se osiguralo dublje razumijevanje čimbenika koji utječu na studentske odluke.

Metodologija

Umjetna neuronska mreža (ANN) (Yegnanarayana, 2009) je oblik algoritma umjetne inteligencije koji crpi inspiraciju iz mehanizama zabilježenih u stvarnim biološkim mozgovima. Matematičkim modeliranjem prijenosa informacija između neurona koristeći težine i pristranosti, agregiranjem ulaza i korištenjem aktivacijskih funkcija za obradu agregiranih podataka, neuronske mreže mogu rješavati složene zadatke. Osnovna građevna jedinica ANN-a je neuron. Neuroni su međusobno povezani s drugim neuronima u mreži preko težinskih veza. Te skupne veze mogu se odrediti za svaki neuron prema jedn. (1):

$$\sum_{n=0}^{n} W_i X_i \tag{1}$$

pri čemu w označava težine, a x ulaznu vrijednost, n označava broj ulaza u dani neuron.

Aktivacijska funkcija primjenjuje se na rezultate iz agregacije i koristi se za određivanje izlaza neurona. Postoji nekoliko aktivacijskih funkcija koje su popularne među istraživačima. Neki od značajnih primjera su sigmoidna funkcija jedn. (2) i funkcija rektificirane linearne jedinice (relu) jedn. (3):

$$\sigma(x)= \frac{1}{1+e^{-x}} \tag{2}$$

$$f(x)= \frac{1+|x|}{1+e^{-x}} \tag{3}$$

ovdje ulazna vrijednost (izlaz agregacijske funkcije) označena je kao x, simboli || označavaju apsolutnu vrijednost. Struktura tipičnoga simuliranog neurona može se vidjeti na Slici 1.

Slika 1.

Proces obučavanja ANN-a oslanja se na nekoliko tehnika kao **što** su stohastički gradijentni silaz i propagacija pogreške za prilagodbu mreže danom problemu. Značajna osobina ANN-a je raznolika arhitektura koju mreže mogu imati ovisno o složenosti zadatka koji se rješava. Jednostavni zadatci **često** zahtijevaju jednostavnije mreže, dok složeniji nelinearni problemi zahtijevaju složenije mreže. Neuroni unutar mreža često su organizirani u pojedinačne slojeve. Prvi sloj obično se smatra ulaznim slojem, dok se posljednji sloj smatra izlaznim slojem. Slojevi između ulaznoga i izlaznoga smatraju se skrivenim slojevima. Struktura jednostavne ANN-a prikazana je na Slici 2.

Slika 2.

Stavljanjem više skrivenih slojeva može se stvoriti duboka neuronska mreža (DNN) (Cichy i Kaiser, 2019). Ova arhitektura može rješavati složenije zadatke, ali zahtijeva više podataka za obučavanje i ima veće računarske zahtjeve. Korištenje DNN-a omogućuje rješavanje složenijih problema. Ovaj tip mreže može obraditi složenije i visoko apstraktne podatke.

Primjena i upotreba tehnika umjetne inteligencije postala je sve popularnija za rješavanje mnogih izazovnih problema u stvarnom svijetu. Međutim, kako algoritmi napreduju, istraživači dizajniraju i podešavaju modele kako bi zadržali određeni stupanj fleksibilnosti. U početnom stanju, modeli pokazuju dobru opću izvedbu u velikom broju aplikacija. Međutim, kako bi se postigla željena izvedba algoritama, potrebna su podešavanja hiperparametara. Ovaj proces selekcije često se smatra NP-teškim (Dréo, 2006) zbog velikoga broja mogućih vrijednosti i tradicionalno se rješava metodom pokušaja i pogreške. Usvajanje empirijski vođenoga eksperimentalnog pristupa često se smatra neučinkovitim i napornim. Tehnike koje su sposobne obraditi NP-teške optimizacije primijenjene su za podešavanje hiperparametara.

Metaheuristički algoritmi koriste inherentno nasumičan i iterativan pristup za rješavanje optimizacije. Iako se postignuti rezultati ne mogu matematički potvrditi kao najbolji, prihvatljivo prikladno rješenje može se pronaći u razumnim vremenskim okvirima i na realističnoj računalnoj opremi. Svaka sljedeća iteracija poboljšava mogućnosti da se pronađe prikladno rješenje. Različite izvore inspiracije i oblike optimizatora predlažu istraživači, s dobro etabliranim primjerima kao što su optimizator rojnog čestica (PSO) (Kennedy i Eberhart, 1995), varijabilna pretraga susjedstva (VNS) (Hansen, Mladenović i Moreno Perez, 2010) koji su vrlo popularni među istraživačima za rješavanje optimizacije. Noviji primjeri optimizatora koji su pokazali solidne rezultate primijenjene na izazovne optimizacijske zadatke uključuju Sinh Cosh Optimizer (SCHO) (Bai, Li, Zheng, Khatir, Benaissa, Abualigah i Wahab, 2023) kao i optimizator COLSHADE (Gurrola-Ramos, Hernàndez-Aguirre i Dalmau-Cedeño, 2020).

Optimizatori su učinkovito primijenjeni na podešavanje hiperparametara u nekoliko područja. Neki od značajnih primjera uključuju medicinu (Jovanovic i sur., 2023; Savanović i sur., 2023) kao i kibernetičku sigurnost (Salb i sur., 2023). Hibridni optimizatori pokazali su sposobnost prevladavanja ograničenja osnovnih algoritama i demonstrirali ukupno poboljšanje izvedbe osnovnoga algoritma. Hibridni optimizatori također su pokazali izvrsne rezultate kada se primijene na zadatke podešavanja hiperparametara (Damaševičius i sur., 2024; Stankovic i sur., 2022; Pilcevic i sur., 2023).

S rastućom složenošću algoritama umjetne inteligencije, postalo je važno bolje razumjeti metodologiju funkcioniranja agenata umjetne inteligencije. U većini slučajeva, obučeni modeli smatraju se crnim kutijama koje uzimaju ulaze i daju izlaze temeljem podataka za obuku. Međutim, skrivene pristranosti unutar modela kao i pristranosti u podacima za obuku mogu ostati neprimijećene u modelima. Ključno je razviti skup alata i tehnika koji se mogu iskoristiti za tumačenje crnih kutija i razumijevanje pokretačkih sila iza odluka modela.

Složnost povezanu s DNN-om čini ga teškim za tumačenje pomoću jednostavnih metoda pokušaja i pogreške. Pristranosti i anomalne klasifikacije mogu se teže otkriti i razumjeti u usporedbi s jednostavnijim modelima. Nekoliko tehnika predloženo je u literaturi za rješavanje složenosti tumačenja modela. Ne postoji prihvaćeni standard za model i nekoliko interpretacija treba se uzeti u obzir prilikom procjene modela.

Jedan od značajnih pristupa za tumačenje modela jest korištenje Shapleyovih aditivnih objašnjenja (SHAP) (Lundberg i Lee, 2017) temeljenih na teoriji igara. Ulazi su konceptualizirani kao igrači koji sudjeluju u igri, a ishodi su konceptualizirani kao isplate. Usvajanjem ovoga pristupa temeljenoga na teoriji igara, istraživači mogu odrediti doprinos svakog igrača (ulaza) prema ishodu igre (izlaz modela). Objašnjavajući procjenitelji koriste se za približavanje početnom prediktivnom modelu prema jedn. (4):

$$h(z') = \emptyset_0 + \sum_{i=1}^{N} \emptyset_i Z_i' \tag{4}$$

ovdje h označava model objašnjenja, z' simbolizira značajke, broj ulaza označen je s N, a Ø označava atribuciju značajke. Vrijednost Ø izračunava se prema jedn. (5):

$$\emptyset_i = \sum_{K \subseteq M i} \frac{|K|!\,(N - |K| - 1)!}{N!} [g_x(K \cup i) - g_x(K)] \tag{5}$$

pri čemu označava očekivane vrijednosti za podskup ulaza označen kao K, M je skup svih dostupnih ulaza.

Dok SHAP pokazuje koliko svaka značajka doprinosi pojedinačnim predviđanjima, daljnja analiza je korisna za određivanje koliko model ovisi o svakoj značajki za ukupna predviđanja. To se može ustanoviti korištenjem Shapleyovih aditivnih globalnih važnosti (SAGE) (Covert, Lundberg i Lee, 2020). Iako je potpuno računanje svih uzoraka inherentno eksponencijalno složeno, mogu se koristiti aproksimacije za izračunavanje SAGE vrijednosti. Nasumični podskup značajki $S \subseteq D$ odabire i uzorak marginalne distribucije $X_{\bar{S}}$. U praksi se uzorkovanje provodi u ograničenom iterativnom procesu uz praćenje nekoliko nesigurnosti procjenitelja i detekciju konvergencije. Važnosti se mogu uspostaviti kada algoritam zadovoljava kriterij konvergencije. (6):

$$\max_i \frac{\sigma_i}{\sqrt{n}} < t \left(\max_i \widehat{\phi_i}(v_f) - \min_i \widehat{\phi_i}(v_f) \right) \tag{6}$$

pri čemu ϕ označava izračunate SHAP vrijednosti, σ definira konstantu koja nakon n interakcija zadovoljava uvjet Algoritam tumačenja može se smatrati konvergiranim kada najveća standardna devijacija predstavlja dovoljno nizak udio t (npr. t = 0,01).

Razmatranjem rezultata obiju analiza, SAGE i SHAP, može se postići dublje razumijevanje prediktivnoga modela. Nadalje, skrivene pristranosti u podatcima i predviđanjima mogu se razotkriti. Konačno, razmatranje rezultata analiza može pomoći u poboljšanju prikupljanja podataka za buduća istraživanja.

Potrebna je optimizacija dubokih mreža za učenje. U ovom odjeljku raspravlja se o algoritmu krijesnica (FA) (Yang i Slowik, 2020). Raspravljaju se neka ograničenja izvornoga FA i predstavljaju se potencijalne modifikacije koje mogu pomoći optimizatoru da prevlada ta ograničenja, a uvodi se i izmijenjena verzija algoritma.

Algoritam krijesnica inspiriran je reproduktivnim ponašanjima koja se promatraju kod svjetlećih insekata koji se oslanjaju na bioluminiscenciju kako bi pronašli odgovarajuće partnere. Primijenjena je pojednostavljenja kako bi algoritam bio prikladan za matematičko modeliranje, poput pretpostavke da su sve krijesnice privučene svjetlijim agentima. Atraktivnost krijesnica izravno je proporcionalna svjetlini i temelji se na ciljnoj funkciji. Na kraju, ako dva sredstva imaju istu svjetlinu, obojica se kreću nasumično.

Atraktivnost se upravlja percipiranom svjetlinom (I), koja je približno matematički modelirana prema jedn. (7):

$$I(r) = \frac{I_s}{r^2} \tag{7}$$

pri čemu je svjetlina agenta na izvoru, a r udaljenost između dviju krijesnica. Udaljenost učinkovito smanjuje atraktivnost između agenata u roju. Svjetlina na izvoru određuje se ciljnom funkcijom prema jedn. (8):

$$I_s = f(x_i). \tag{8}$$

Točna funkcija ovisi o problemu i može se odabrati prema tome. Atraktivnost β može se modelirati prema Jedn. (9):

$$\beta(r) = \beta_0 e^{\gamma r^2} \tag{9}$$

pri čemu je atraktivnost pri r = 0 označena kao β_0 a γ je faktor koji se koristi za simulaciju apsorpcije svjetlosti dok se širi kroz medij. Atraktivnost se koristi za motivaciju kretanja agenata u roju. Pozicije se ažuriraju prema jedn. (10):

$$x_i(t+1) = x_i(t)\beta_0 e^{-\gamma r^2}(x_i = x_j) + \alpha\epsilon_i \tag{10}$$

ovdje je kretanje između agenata xi i xj simulirano s), što predstavlja međusobnu privlačnost, a označava parametar koji se koristi za uvođenje faktora randomizacije. Najsjajnija krijesnica u populaciji kreće se u nasumičnom smjeru prema jedn. (11):

$$x_i(t+1) = x_i(t) + \alpha\epsilon_i \tag{11}$$

Izvorni FA (Yang i Slowik, 2020) dobro je uspostavljen kao učinkovit optimizator i poznat je po snažnom mehanizmu objašnjenja. Mehanizam eksploatacije često je uspješno integriran u druge algoritme putem hibridizacije kako bi se ubrzala konvergencija u slučajevima kada je takva modifikacija poželjna. Ipak, ovaj mehanizam može dovesti do prijevremene konvergencije izvornoga algoritma. To može rezultirati smanjenjem ukupne izvedbe pri rješavanju optimizacije. Ovim radom nastoji se predložiti izmijenjenu verziju FA algoritma u kojoj prevladava neki od uočenih nedostataka, povećavajući diversifikaciju. Predloženi algoritam crpi inspiraciju iz genetskoga algoritma (GA) (Mirjalili & Mirjalili, 2019) i nazvan je genetskim GA algoritmom vođenim diversifikacijom (DGGFA).

Za promicanje diversifikacije uveden je L! norm koji uzima u obzir diversifikaciju unutar populacije agenata roja. Parametri norme definirani su prema jedn. (12), jedn. (13) i jedn. (14):

$$\overline{x_j} = \frac{1}{m}\sum_{i=1}^{m} x_{ij} \tag{12}$$

$$D_j^p = \frac{1}{m}\sum_{i=1}^{m\backslash} vline\, x_{ij} - \overline{x}_j \backslash vline \tag{13}$$

$$D^p = \frac{1}{n}\sum_{i=1}^{n} D_j^p\,, \tag{14}$$

ovdje m označava trenutačnu soluciju, a n specifičnu diversifikaciju L1 norme. Parametar predstavlja skup prosječnih pozicija agenata roja preko dimenzija. Parametar označava lokaciju pojedinca kao L1 normu, a je skaler diversifikacije. Veća diversifikacija je poželjna u ranijim fazama optimizacije. Za upravljanje diversifikacijom koristi se L1 norma kroz dinamički parametar praga .

Također je uveden parametar *nrs* koji se koristi za definiranje broja agenata koji se zamjenjuju u svakoj iteraciji optimizacije. Ova vrijednost empirijski je odabrana kao 2 za optimizacijske potrebe ovoga istraživanja. Na početku izvršavanja algoritma, početna vrijednost izračunava se prema jedn. (15).

$$D_{t0} = \sum_{j=1}^{NP} \frac{\left(ub_j - lb_j\right)}{2 \cdot NP}, \tag{15}$$

U svakoj sljedećoj iteraciji ponovo se računa prema jedn. (16):

$$D_{t+1} = D_t - D_t \cdot \frac{t}{T} \tag{16}$$

Dodatno, nakon svake iteracije ocjenjuje se uvjet pri čemu predstavlja trenutačnu diversifikaciju populacije. Ako se diversifikacija smatra slabom, nrs = 2 rješenja uklanjaju se iz populacije i zamjenjuju novim generiranim rješenjima. Nova rješenja izračunavaju se kao hibrid između najslabije performirajućega agenta i nasumičnog rješenja. Ako je diversifikacija na prihvatljivoj razini agenti se generiraju kao hibrid između najboljega rješenja i nasumičnoga pojedinca.

Hibridna rješenja oslanjaju se na mehanizme križanja i mutacije inspirirane genetskim algoritmom prikazanim na Slici 3.

Slika 3.

Vjerojatnost križanja za svaki gen dana je kao lažni kod Križanje dvaju rješenja proizvodi dva potomka koji će zamijeniti nrs = 2 rješenja iz populacije, bez dodatne evaluacije.

Na početku algoritma, vrijednost pc postavljena je na 0,1, a u svakom krugu ovaj parametar se povećava koeficijentom pri čemu t označava trenutačnu iteraciju, a T maksimalni broj iteracija.

Pseudokod za verziju izmijenjenoga algoritma prikazan je u Tablici 1.

Table 1

Introduced modified DGGFA pseudocode.

	Introduced DGGFA pseudocode
1. →	Inicijalizirana populacija agenata roja P
2. →	Inicijaliziran ps = 0,1
3. →	Izračunaj i vrijednosti
4. →	**while** (t<T):
5. →	Rangiraj rješenja na temelju objektivne funkcije
6. →	Odredi
7. →	**if** ():
8. →	Zamijeni nrs rješenja s novim agentima roja generiranim kao
9. →	Kombinacija najlošijega i slučajnoga agenta roja
10. →	**else**
11. →	Zamijeni nrs rješenja novim agentima roja generiranim kao
12 →	Kombinacija najboljega i slučajnoga agenta roja
13 →	Ažuriraj pd i
14 →	**return** najbolje postignuto rješenje kao agenta

Za evaluaciju predloženoga pristupa provedena su eksperimentiranja s javno dostupnim stvarnim skupom podataka.

Skup podataka dostupan je na Kaggleu (Realinho i sur., 2021) i zadnji put je pristupljeno 15. 6. 2024. Skup podataka obuhvaća prikupljene podatke o studentima dostupne institucijama visokoga obrazovanja, uključujući bračni status, način prijave, redoslijed prijave, predmete koje student pohađa, podatke o prisutnosti, prethodne kvalifikacije, kvalifikacije i zanimanje roditelja, preseljenje, posebne potrebe, dob pri upisu i broj kurikula/kolegija u svakom semestru. Podatci su odgovarajuće kodirani i podijeljeni u dijelove za poučavanje i testiranje, pri čemu 70 % podataka pripada prvom, a 30 % drugom dijelu.

Provedena je komparativna analiza između uvedenoga optimizatora, izvornoga FA (Yang i Slowik, 2020). U analizu su uključeni i drugi algoritmi kao što su PSO (Kennedy i Eberhart, 1995), VNS (Hansen, Mladenović i Moreno Perez, 2010). Nedavno uvedeni optimizatori poput SCHO (Bai, Li, Zheng, Khatir, Benaissa, Abualigah i Wahab, 2023) i COLSHADE (Gurrola-Ramos, Hernàndez-Aguirre i Dalmau-Cedeño, 2020) također su evaluirani.

Optimizatori su dodijeljeni populaciji od 6 agenata i dopušteno im je 6 iteracija za poboljšanje rezultata populacije. Simulacije su ponovljene 30 puta kako bi se osigurala poštena evaluacija. Arhitektura i parametri treninga dubokih neuronskih mreža (DNN) odabiru se od strane svakog optimizatora iz raspona navedenih u Tablici 2.

Tablica 2
Ograničenja parametara modela za optimizaciju

Metoda	Brzina učenja	Dropout	Slojevi	Neuroni	Epohe
Gornja granica	0,0001	0,50	3	65	500
Donja granica	0,0050	0,01	1	35	200

Evaluacije su provedene na testnom dijelu skupa podataka. Koristile su se standardne metrike za klasifikaciju (Ferrer, 2022). Metrike uključuju preciznost, odziv, F1-score, točnost. Metrike su opisane u jedn. (17), jedn. (18), jedn. (19), jedn. (20), respektivno:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{17}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{18}$$

$$\text{F1-score} = \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{19}$$

$$\text{Precision} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{20}$$

Dodatno, metrika Cohen's kappa (Warrens, M. J., 2015) pratila se i koristila kao objektivna metrika, kako je opisano u jedn. (21):

$$\text{Cohen's kappa} = \frac{\text{Classification-Expected Classification}}{1 - \text{Expected Classification}} \tag{21}$$

Funkcija indikatora praćena tijekom optimizacije je stopa pogreške opisana u jedn. (22):

$$\text{Error rate} = 1 - \text{Accuracy}$$

Nakon evaluacija, najbolji izvedbeni modeli podvrgnuti su analizi korištenjem SHAP i SAGE XAI tehnika. Izvršena je i klasterizacija rezultata analize o kojoj će se govoriti u daljnjem tekstu.

Rezultati

Simulacije su provedene u dva eksperimenta. Prvi set eksperimenata fokusira se na binarnu klasifikaciju i bavi se odvajanjem studenata od onih koji su napustili akademsku zajednicu. Drugi eksperiment bavi se višeklasnom klasifikacijom, odvajajući studente koji su napustili školovanje od upisanih i diplomiranih studenata. Najbolji izvedbeni modeli zatim su podvrgnuti interpretaciji korištenjem SHAP i SAGE XAI tehnika. Na kraju, studenti su podijeljeni u podgrupe prema preprekama na koje nailaze u preddiplomskom obrazovanju.

Ishodi binarne klasifikacije

Ishodi u pogledu ciljne funkcije za svaki od metaheurističkih algoritama uključenih u komparativnu analizu u pogledu najboljih, najgorih, srednjih i medijanskih rezultata prikazani su u Tablici 3. Ishodi sugeriraju da je predloženi optimizator izradio najbolje performirajuće modele u svim scenarijima. Ipak, COLSHADE algoritam pokazuje impresivnu stabilnost unatoč tome što nije postigao najpoželjnije rezultate.

Tablica 3

Ishodi u pogledu funkcije indikatora za svaki od metaheurističkih algoritama uključenih u komparativnu analizu u pogledu najboljih, najgorih, srednjih i medijanskih rezultata prikazani su u Tablici 4.

Ovdje je uvedeni optimizator postigao najbolje rezultate u većini scenarija, dok je u najgorim slučajevima izjednačio izvedbu s optimizatorom SCHO. COLSHADE optimizator postigao je najveću stabilnost na račun kvalitete ukupnih rezultata.

Tablica 4

Komparacije u pogledu stabilnosti prikazane su u obliku distribucijskih dijagrama prikazanih na Slici 4. i *swarm* dijagrama prikazanih na Slici 5. Uvedeni algoritam pokazuje stabilnost usporedivu s izvornim algoritmom.

Međutim, očito poboljšanje može se primijetiti u pogledu kvalitete rješenja, s najboljim i najgorim rješenjima koja nadmašuju rezultate koje prikazuje osnovni algoritam. Iako COLSHADE optimizatori prikazuju stabilnost, manja je kvaliteta rješenja, pri čemu se mnoga prikazana ovim optimizatorom nalaze oko suboptimalne regije.

Slika 4.

Slika 5.

Detaljni metrički ishodi za najbolje izvedbene modele koje je izradio svaki optimizator prikazani su u Tablici 5. Uvedeni optimizator postigao je najbolje rezultate u pogledu točnosti, pristojnoga odziva i F1 rezultata u pogledu detekcije studenata te najbolje makro i ponderirane prosječne vrijednosti u pogledu preciznosti. FA, PSO i SCHO algoritmi također su pokazali pristojne rezultate. To se može donekle očekivati, kako je navedeno u NFL teoremu, nijedan pristup nije podjednako prikladan za sve izazove prema svim mjerama.

Tablica 5

Daljnje pojedinosti o sposobnosti algoritma da izbjegne zamke lokalnih minimuma i usmjeri se prema obećavajućim područjima pretraživačkoga prostora mogu se pronaći u dijagramima konvergencije za ciljne i indikatorske funkcije prikazane na Slici 6.

Dok se nekoliko optimizatora fokusira na suboptimalna područja ne uspijevajući učinkovito konvergirati prema prikladnom rješenju, uvedeni optimizator uspijeva prevladati ove izazove i pronaći obećavajuće rješenje unutar danoga pretraživačkog prostora, nadmašujući osnovni optimizator.

Slika 6.

Detalji izvedbe za najbolje izvedeni model binarne klasifikacije koji je izradio uvedeni DGGFA optimizator prikazani su na Slici 7. Matrica zabune i PR krivulje prikazuju sposobnost najboljih izvedbenih modela da identificiraju studente koji su napustili školovanje u odnosu na studente koji i dalje pohađaju nastavu. Na Slici 8. prikazana je arhitektura najboljega izvedbenog modela.

Tablica 6. prikazuje odabrane parametre koje je svaki algoritam odabrao tijekom optimizacije, a koji su rezultirali najboljim izvedbenim modelom.

Slika 7.

Slika 8.

Tablica 6

Ishodi binarne klasifikacije

Ishodi u pogledu ciljne funkcije za svaki od metaheurističkih algoritama uključenih u komparativnu analizu u pogledu najboljih, najgorih, srednjih i medijanskih rezultata prikazani su u Tablici 7. COLSHADE algoritam pokazuje impresivne rezultate u pogledu stabilnosti, kao i u pogledu ishoda kroz više kriterija. Međutim, najbolja izvedba prikazana je modelima koji su optimizirani uvedenim optimizatorom.

Tablica 7

Rezultati koji se odnose na funkcije indikatora za svaki od metaheurističkih algoritama uključenih u komparativnu analizu s obzirom na najbolje, najgore, srednje i medijanske rezultate prikazani su u Tablici 8. Uvedeni optimizator postigao je najbolje rezultate. Međutim, COLSHADE optimizator postigao je najbolje rezultate vezano za najgore, srednje i medijanske rezultate. SCHO algoritam postigao je najvišu stopu stabilnosti, dodatno potvrđujući NFL teorem.

Tablica 8

Usporedbe s obzirom na stabilnost prikazane su u obliku distribucijskih dijagrama prikazanih na Slici 9. i *swarm* dijagrama prikazanih na Slici 10.

Slika 9.

Uvedeni optimizator pokazuje bolje rezultate u usporedbi s izvornim algoritmom. Međutim, ovaj porast u izvedbi ujedno znači manju stabilnosti algoritma. Visoke stope stabilnosti prikazali su PSO, SCHO i COLSHADE optimizator.

Slika 10.

Detaljni metrički ishodi za najbolje izvedbene modele koje je izradio svaki optimizator prikazani su u Tablici 9. Uvedeni algoritam prikazuje najvišu preciznost za detekciju studenata koji su odustali od školovanja, kao i najbolju ukupnu točnost s visokom stopom detekcije diplomiranih studenata, te najbolje ponderirane prosječne rezultate vezani za preciznost, odziv i F1 rezultata. Ostali optimizatori postigli su oscilirajuće rezultate, prikazujući pristojne performanse u većini metrika, što dodatno potvrđuje izjave navedene u NFL teoremu.

Tablica 9

Slika 11.

Daljnje pojedinosti o sposobnosti algoritma da izbjegne zamke lokalnih minimuma i usmjeri se prema obećavajućim područjima pretraživačkoga prostora mogu se pronaći u dijagramima konvergencije za ciljne i indikatorske funkcije prikazane na Slici 11. Dok se nekoliko optimizatora fokusira na suboptimalna područja, ne uspijevajući učinkovito konvergirati prema prikladnom rješenju, uvedeni optimizator uspijeva prevladati ove izazove i pronaći obećavajuće rješenje unutar danoga pretraživačkog prostora, nadmašujući osnovni optimizator.

Detalji izvedbe za najbolje izvedeni model višeklasne klasifikacije koji je izradio uvedeni DGGFA optimizator prikazani su na Slici 12. Matrica zabune i PR krivulje prikazuju sposobnost najboljih izvedbenih modela da identificiraju studente koji su odustali od školovanja u odnosu na studente koji i dalje pohađaju nastavu. Na Slici 13. prikazana je arhitektura najboljega izvedbenog modela. Tablica 10. prikazuje odabrane parametre koje je svaki algoritam odabrao tijekom optimizacije, a koji su rezultirali najboljim izvedbenim modelom.

Slika 12.

Slika 13.

Tablica 10

Najbolja interpretacija modela i klasterizacija studenata

Razumijevanje razloga iza odluka modela ključno je za tumačenje klasifikacija koje model donosi. Posebno je važno analizirati studentsko odustajanje i čimbenike koji utječu na odluke modela jer to može poboljšati prikupljanje podataka i oblikovanje politika usmjerenih na podršku studentima u riziku. Posljedično, takav pristup može doprinijeti poboljšanju akademske uspješnosti. U sljedećim pododjeljcima donosi se analiza najboljih izvedbenih binarnih i višeklasnih modela pomoću XAI tehnika, SAGE i SHAP metodologije.

Objašnjenje najboljega binarnog klasifikacijskog modela

Analiza najboljega izvedbenog DGGFA optimiziranoga binarnog klasifikacijskog modela pomoću XAI tehnika prikazana je na Slici 14. SHAP rezultati utjecaja značajki prikazani su s lijeve strane, a SAGE važnost značajki prikazana je s desne strane. U oba slučaja, broj odobrenih kolegija u drugom semestru ima najveću ulogu u odluci o modelima To je praćeno značajkama koje se odnose na ocijenjene kolegije u drugom semestru i položene kolegije u prvom semestru. Globalno, ažurirane školarine, kao i to hoće li student imati stipendiju, igraju važnu ulogu u klasifikaciji.

Slika 14.

Objašnjenje najboljega višeklasnog klasifikacijskog modela

Analiza najboljega izvedbenog DGGFA optimiziranoga binarnog klasifikacijskog modela pomoću XAI (Došilović, Brčić i Hlupić, 2018) tehnika prikazana je na Slici 15.

SHAP rezultati utjecaja značajki prikazani su s lijeve strane, a SAGE važnost značajki prikazana je s desne strane. U oba slučaja, broj odobrenih kolegija u drugom semestru igra najveću ulogu u odluci o modelu To je praćeno značajkama koje se odnose na ocijenjene kolegije u drugom semestru, te na kojegije koji su položeni u prvom semestru. Globalno, ažurirane školarine, kao i to hoće li student imati stipendiju, imaju važnu ulogu u klasifikaciji. Ishodi analize donekle odražavaju one promatrane u binarnoj klasifikaciji, što je donekle očekivano, jer postoji velika sličnost između diplomiranih i upisanih studenata.

Slika 15.

SHAP vrijednosti klasterizacije najboljega binarnog klasifikacijskog modela

Razumijevanje čimbenika koji pokreću donošenje odluka izazovan je zadatak za institucije. Dodatni izazov je razviti strategije koje mogu imati najveći utjecaj na praksu. Važno je razumjeti kako čimbenici utjecaja variraju među studentima. Formuliranje klastera temeljenih na čimbenicima utjecaja može pomoći donosiocima odluka da uoče sličnosti između grupa i usmjere učinkovite napore tamo gdje je utjecaj najpotrebniji.

Na Slici 16 klasteri temeljeni na gustoći studenata korištenjem neparametarskoga DBSCAN algoritma (Schubert, Sander, Ester, Kriegel i Xu, X., 2017) formirani su na temelju lokalnih SHAP utjecaja značajki za svakog studenta. Koristi seUniform Manifold Approximation and Projection (UMPA) (Leland, John i James, 2018) kako bi se postigla dvodimenzionalnost. S lijeve strane formirane su podgrupe pomoću DBSCAN algoritma, dok su na desnoj strani studenti razvrstani prema statusu upisa. Jasno se mogu vidjeti različiti klasteri studenata koji su odustali od školovanja u nekoliko slučajeva. Studenti u gornjoj lijevoj grupi 6 visoko su skloni napustiti školovanje temeljem istih čimbenika. Rješavanje tih čimbenika, ako je moguće, moglo bi pomoći u poboljšanju njihovih akademskih rezultata na učinkovit način. Slično tome, donji dio najvećega klastera ima malu šansu da napusti obrazovanje. Ove informacije omogućuju tvorcima obrazovnih politika da bolje raspodijele resurse za veći utjecaj na studente. Na kraju, mogu se primijetiti nekoliko manjih iznimki. Fokusiranje na iznimke s politikom može biti izazovno i imati manji utjecaj u praksi. Važno je osloniti se na mišljenja stručnjaka prilikom formuliranja politike kako bi se osigurala pravilna i učinkovita implementacija.

Slika 16.

Diskusija

Studija podržava ulogu koju obrazovanje ima u promicanju razvoja kognitivnih sposobnosti, znanja i vještina koje su potrebne za dugoročni financijski uspjeh sveučilišta I veleučilišta. Radna snaga s visokim obrazovanjem potiče inovacije u proizvodnji, poboljšava istraživanje i razvoj te podržava ekonomski rast. Iako je njegov puni potencijal u ovom području još uvijek neiskorišten, umjetni jezik (AI) postao je obećavajući alat za poboljšanje akademskih postignuća.

Predstavljanjem DNN modela koji je podešen korištenjem specifične tehnike, ova studija popunjava tu prazninu u procesu donošenja odluka. Predložena metoda temeljito je testirana na javno dostupnom stvarnom skupu podataka. Nalazi pokazuju da u višeklasnim postavkama najbolji izvedbeni modeli postižu točnost veću od 89,15 % za detekciju napuštanja i 77,10 % za klasifikaciju. Ove visoke ocjene točnosti pokazuju koliko dobro predložena tehnika funkcionira u identifikaciji učenika koji su u opasnosti od napuštanja škole.

Opsežna analiza XAI (eksplainabilne umjetne inteligencije) provedena je kako bi se dodatno pojasnio proces donošenja odluka o produžetku školovanja na osnovu promatranog modela. Ovo istraživanje otkriva najvažnije čimbenike koji utječu na odluke kategorizacije i pruža uvid u glavne aspekte koji utječu na predikcije modela. Nadalje, lokalne interpretacije podvrgnute su algoritmima za klasterizaciju, što omogućuje grupiranje učenika prema zajedničkim značajkama. Ova metoda olakšava razumijevanje glavnih uzroka stopa napuštanja studija i pruža korisne informacije za razvoj ciljnih intervencija i politika.

Rješavanje problema zadržavanja studenata postaje vidljivije i učinkovitije kada se pristupi temelje na AI kombiniraju s interpretabilnošću temeljenom na XAI. Ova studija nudi praktične uvide za obrazovne institucije kako bi razvile strategije temeljenje na podatcima koje imaju cilj poboljšati zadržavanje studenata i akademska postignuća, identificiranjem ključnih čimbenika akademskoga napuštanja i povezivanjem tih čimbenika s grupama studenata.

Zaključak

Obrazovanje promiče znanje, vještine i kognitivni razvoj te je ključno za društveni napredak. Također ima snažnu korelaciju s održivim ekonomskim uspjehom. Obrazovanje potiče kreativnost i prihvaćanje novih ideja poboljšavajući opće znanje i sposobnosti stanovništva, čineći ljudski kapital vitalnim dijelom ekonomskoga uspjeha. Obrazovana radna snaga daje značajan doprinos istraživanju i razvoju, integrirajući inovacije u proizvodnju i potičući ekonomski rast. Potencijal AI za poboljšanje akademskih rezultata studenata još uvijek nije istražen u literaturi. Ovim radom nastoji se proširiti zapaženi literaturni jaz i uvesti pristup temeljen na DNN-u optimiziranom specijaliziranim algoritmom koji je uveden u ovom radu. Simulacije su provedene na javno dostupnom stvarnom skupu podataka. Najbolje optimizirani modeli postižu točnost veću od 89,15 % za detekciju napuštanja i 77,10 % za detekciju u višeklasnim simulacijama. Najbolji modeli podvrgnuti su opsežnoj XAI analizi kako bi se odredili čimbenici na koje modeli ovise, kao i značajke koje su važni za svaku klasifikaciju. Klasterizacija je provedena na lokalnim interpretacijama i grupiranje studenata povezano je s boljim razumijevanjem čimbenika koji utječu na odluku o napuštanju akademskoga okružja.

Iako predloženi pristup pokazuje dobru prediktivnu točnost u prepoznavanju studenata koji su u opasnosti od napuštanja, institucionalne i kontekstualne varijable moraju se pažljivo razmotriti prilikom njegove primjene u praksi. Kako bi usvojile takav model, obrazovne institucije moraju osigurati da je sustav integriran u već postojeće okvire za pomoć studentima i da su postavljeni odgovarajući standardi zaštite podataka i etički standardi. Kako bi pomogao učiteljima i tvorcima obrazovnih politika u prepoznavanju mladih ljudi u opasnosti od napuštanja škole i pravovremenoj rilagodbi obrazovnih postupaka, model bi trebao biti korišten kao alat za podršku odluci o produžetku školovanja, a ne kao deterministički mehanizam. Nadalje, budući da mnogi obrazovni sustavi imaju različite strukturne i socioekonomske čimbenike, uspjeh bilo koje intervencije temeljene na ovim projekcijama ovisi o stručnosti i lokaliziranom znanju.