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Research Article

Intelligent Prediction of EFL Student Performance in Higher Education Using Ensemble Machine Learning Techniques

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Abstract – *Digital technologies have rapidly changed teaching and learning, forcing educators to use novel methods to improve student engagement and academic performance. EFL Student Performance in Higher Education has shown that gamification may motivate and engage students in language learning on computer and mobile platforms. Due to the richness and diversity of educational data, predicting student success is difficult. This article provides an intelligent prediction framework using the ResXGR hybrid model to address this issue. Preprocessing the educational dataset with Data Cleaning and Z-Score Normalisation improves data quality and consistency. HCFS is then used to extract the most important student performance features. The ResXGR architecture uses SE attention mechanisms to capture high-dimensional academic characteristics and the Jaya optimisation algorithm to optimise model hyperparameters for predictive accuracy and computing efficiency. Experimental results show that the proposed model outperforms conventional ML and contemporary prediction algorithms with 96.28% prediction accuracy, faster convergence, and lower processing overhead. These findings demonstrate that the proposed framework is scalable, robust, and efficient for predicting EFL Student Performance in HE, enabling timely academic interventions, informed educational decision-making, and improved student learning outcomes in technology-enhanced EFL environments.*

Keywords— *Hierarchical Contextual Feature Scoring (HCFS), Mutual Information (MI), English as a Foreign Language (EFL), Higher Education (HE), Rectified Linear Unit (ReLU), Squeeze-and-Excitation (SE).*

INTRODUCTION

Academic success for students learning English as a foreign language (EFL) depends on a lot of different things. Affective elements are among the most important for their academic performance [1]. Acquiring proficiency requires the ability to speak and understand the English language. These abilities can be categorised as either productive or receptive. A person's productive abilities include writing and speaking, whereas their receptive abilities include reading and listening. Students develop their listening, speaking, and reading abilities through exposure to spoken and written language. To understand the receptive material, students must first understand its meaning. It is impossible to overstate the significance of reading as a linguistic competency. One of the most important ways to get knowledge, particularly for schoolwork, is through this medium [2]. Students need to develop several skills in order to succeed in today's classrooms, but critical thinking is one of the most important. Critical thinking, which is essential for solving problems in real life, needs to be developed early on in a student's educational path. In order to foster students' critical thinking abilities, educators must employ fresh, imaginative, and engaging educational approaches. They must also be skilled at choosing strategies that are in line with the characteristics of today's learners' [3].

Fundamental changes in human lifestyle and worker profiles have resulted from the fast evolution and change in information technology, the internet, and the nature of data this century. Because of these shifts, people in the 21st century—which is also characterised by increased accessibility and new forms of innovation—need to improve their skill sets in order to thrive in educational institutions and businesses [4]. The use of learning management systems (LMS), which provide a centralised virtual environment for the development and administration of online courses, has been expanding rapidly in the field of education, both as an adjunct to and a replacement for more conventional classroom settings. As the COVID-19 pandemic began, the adoption of learning management systems like Moodle went from being voluntary to obligatory or even mandatory. As a result of this shift, there has been increased academic and pedagogical curiosity about the pros and cons of moving education online [5].

This article's section is organised in the following way: 'Related Work' begins with a thorough examination of previous research, drawing attention to pertinent studies and their conclusions. In "Proposed Methodology," they go over the approaches that were used and give a full rundown of the tests that were performed. The purpose of "Result and Discussion" is to provide detailed experimental results and encourage insightful conversations about them. Finally, by summarising important findings and their consequences, the final part captures the core of the proposed system.

RELATED WORKS

Intelligent tutoring systems (ITS) are one area where RL has been particularly useful in education, allowing for substantial progress. To maximise engagement and effectiveness, these systems use RL algorithms to personalise instructional content based on learner profiles [6]. In game-based learning settings, RL plays a crucial role in facilitating active and personalised learning through adaptive engines that change the difficulty of tasks and feedback in real-time. Reasons why RL is still relevant in modern educational settings include its connection with constructivist pedagogical approaches [7]. By simplifying the handling of complicated, high-dimensional data, Deep Reinforcement Learning (DRL), a state-of-the-art combination of RL and neural networks, has expanded its educational applications [8]. By enabling dynamic difficulty adjustment methods in e-learning platforms, DRL makes it possible to personalise tasks according to learners' real-time evaluations. To further address ethical concerns in AI-driven education technology, RL incorporates Explainable AI (XAI) to guarantee transparency and equity [9].

In order to forecast a college student's performance, researchers looked at the efficacy of deep neural network learning transfer [10]. Machine learning techniques are useful in this setting for solving supervised optimisation problems by creating models that match input data with expected target values. Two of the most common ML models used for classification are RF and DT [11]. DT are tree-structured categorisation models that are easy to understand and use, regardless of the user's degree of experience [12]. A number of DT classifiers work together in RF, an ensemble approach. When it comes to producing predictions about numerical (regression) and nominal (classification) target properties, random forests are great tools [13].

Modern ML algorithms make heavy use of logistic regression, decision trees, and other complex statistical models and approaches. Bayesian models, which include Hidden Markov Models (HMM), are particularly useful for sequential pattern recognition [14]. Classification statistics models that have recently seen the most use are Deep Neural Networks (DNNs) and Support Vector Machines (SVMs). Classification problems in many different fields have been effectively addressed using the support vector machine (SVM) technique [15]. The authors employed ML methods to foretell how well students will do in class. According to their claims, this methodology can single out struggling pupils who can benefit from extra help. Decision Tree (DT) with the C4.5 algorithm, ANN with Multi-Layer Perceptron (MLP), Support Vector Machine (SVM) with Sequential Minimal Optimisation (SMO), Bayesian Network (BN) with Naîve Bayes (NB), Lazy Learners with incremental learning, and 1-Nearest Neighbourhood (1-NN) were the ML algorithms utilised for classification [16].

By examining performance patterns using the suggested ResXGR model, this study adds to the body of knowledge on academic management. By offering consistent and accurate estimates, the framework guarantees fairness, transparency, and integration preparedness. Here is a brief overview of the main contributions:

- To address the shortcomings of manual and conventional school administration systems, this research introduces ResXGR, an interpretable and extensible ML framework. Keeping computational complexity in mind, the model is optimised for use with educational datasets.
- Addressing important difficulties such class imbalance, incomplete data, and skewed distributions, ResXGR ensures solid prediction of student performance. In order to increase prediction consistency across varied educational environments, the study proposes standardised modelling approaches.
- To improve accuracy and computing performance, ResXGR incorporates advanced feature representation techniques. This makes it a good fit for instructional deployment and decision-making in the real world.

METHODLOGY

College students' lack of proficiency in reading English literature is a major issue for teachers since it reflects the students' overall performance in school. Students who struggle with reading and comprehension are likely to encounter numerous obstacles both in and out of the classroom. Acquiring proficiency requires the ability to speak and understand the English language. There are two types of these abilities: receptive and productive.

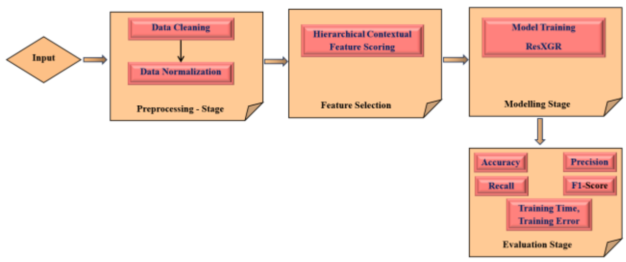

Fig. 1. The Proposed Methodology Higher-Level Visualization

Figure 1 is a schematic of the suggested approach for EFL scholastic achievement in HE [17]. Five primary steps make up the methodology: pre-processing data, selecting features, modelling data, and evaluating the models.

This dataset contains detailed information about 500 college students enrolled in English courses. Information gathered from students includes their age, gender, major, and academic year as well as their chosen learning style, method, pace, and English proficiency scores (TOEFL, IELTS) [18]. It also keeps tabs on students' final grades, competency levels (beginner, intermediate, and advanced), and engagement levels (hours per week, participation, and quiz scores).

A. Data Preprocessing:

An essential part of ML is the first stage, where the data set is prepared to be passed to the prediction algorithm. A number of preprocessing operations were performed:

1) Step for Data Cleaning:

Records of pupils having grades of 0 or -1 are included in the collected data. Course discontinuation or entry error could explain the grades. This process involves removing records that are deemed noisy data due to their failure to reflect the true academic circumstances of the students. On top of that, the data set includes classes that a handful of students took over the course of five years. It is possible that these classes are replacements for ones that the student has already dropped from their specialisation curriculum. Because new students cannot enrol in courses that have already been taken, this action will also eliminate any courses that have been taken by less than 50 students. Consequently, including them in the matrix is superfluous.

2) Z-Score Normalization:

To make all of our data more comparable in scale without changing the dispersion of our scores, we used Z-score normalisation. When it comes to categorisation tasks, these strategies are great. By taking the average and standard deviation from each student's grade column, the Z-score method of normalisation may be determined. Here is the normalised value P_k for student grade E_k in the grade column in Equation (1):

$$P_k = \frac{E_k - Avg(Grade)}{std(Grade)} \tag{1}$$

B. Feature Selection:

1) Hierarchical Contextual Feature Scoring:

HCFS takes into account context, predictive capacity, and the elimination of duplicate features while selecting features, which is an innovative approach. Independently predicting attributes and their correlations with other important traits allows it to choose data appropriately [19]. Ratings could be enhanced by incorporating grouped or hierarchical relationships of qualities. Starting with each characteristic, the HCFS approach finds its Mutual Information (MI). It uses MI to assess Z feature data. The equation (2) is as follows:

$$MI(v_l, z) = \int\int n(v_l, u)\, log \frac{n(v_l, z)}{n(v_l)n(z)} bv_l bz \tag{2}$$

Although the individual features' marginal probability distributions are $n(v_l)$, the aggregate distribution of these features' probabilities v_l is $n(v_l)$. More associations are associated with higher MI-scored attributes, which improves the relevance of the goal. In contrast to MI-based feature selection, HCFS takes contextual relevance into account during the second assessment.

In this context, $n(v_l, z)$ denotes the joint probability distribution of feature v_l and target z, while $n(v_l)$ and $n(z)$ denote the respective stochastic distributions. Element scores with a higher MI are better since they belong to the target more closely. HCFS reevaluates the impact of context, unlike earlier MI-based feature selection approaches in Equation (3).

$$CIS(v_l, D_l) = \frac{1}{|D_l|} \sum_{v_i \in D_l} MI(v_l, v_i) \qquad (3)$$

With respect to D_l, the quantity of features is denoted as $-|C\_l|-$ and the measure of the MI between features v_l and v_i is $MI(v_l, v_i)$. This means that HCFS have a better chance of finding advantageous characteristics and attributes.

Redundancy Penalisation (RP) is a part of HCFS that helps prevent recurrent trait selection. A diversified and non-redundant set of features is achieved by penalising characteristics that produce the same results. Equation (4) is used to determine the RP for feature v_i:

$$RP(v_l) = \sum_{v_i \in Q} MI(v_l, v_i) \qquad (4)$$

The set of features Q is measured by $MI(v_l, v_i)$, where v_l and each v_i in the set are variables. By reducing the number of identical features, this redundancy reduction phase improves the model's performance by avoiding overfitting.

Incorporating these computations into an HCFS for every feature is the last step of HCFS. The score is comprised of contextual interaction, feature MI, and the redundancy penalty in Equation (5):

$$HCFS(v_l) = MI(v_l, z) + \mu_1 CIS(v_l, D_l) - \mu_2 RP(v_l) \qquad (5)$$

The weighting variables μ_1 and μ_2 determine the relative significance of the redundancy penalty and the contextual engagement score. The features with the greatest HCFS scores are used by the model. Instead of focusing on linear feature correlations, as is the case with traditional FS methods, HCFS prioritises contextual interactions. By categorising attributes and examining their relationships, it is able to more accurately represent the complexity of multidimensional data. Overfitting is prevented at every phase of the redundancy penalty procedure, which maintains the model efficient. By taking into account students' academic, behavioural, emotional, and environmental factors, educational data mining is able to effectively utilise HCFS in complex datasets. To put facts about thoughts, feelings, and actions into perspective, HCFS is a great tool to have. To lessen redundancy, it ranks the best predictors and adjusts for overlapping features. The relevance and diversity of the feature sets offered enhance the performance of the model.

C. Model Training:

1) Data Exploration and Analysis:

In this study, they undertake extensive exploratory data analysis to fully understand the dataset and derive meaningful insights. It was the main goal of EDA to use visual analysis and mapping techniques to find connections between category data and other parameters. Initiating a working exploration process involves visually analysing the multiple links and linkages within the data utilising mapping tools [20]. The relationships, ratios, and distribution of categorical variables were better understood as a result of this research. The ever-changing relationships between different types of data were better conveyed through the use of visual aids like graphs, charts, and contingency tables. Significant findings are reached and valid judgements are developed throughout the inquiry.

2) Proposed ResXGR Method:

For the purpose of predicting how well students will do in school, the ResXGR model stands as an elaborate and flexible framework. Combining the SE attention model's systematic learning and contextual grasp with the ResXGR architecture's outstanding feature extraction capabilities, the aforementioned framework achieves a remarkable result. Figure 2 displays the internal structure of the ResXGR Model.

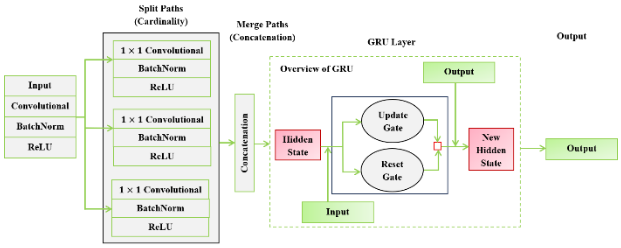

Fig 2. ResXGR Model Architecture

The first step is to use the ResXGR architecture to provide multiple parallel pathways for the student performance data. In order to extract useful features from the input, each path performs a sequence of procedures, including convolution, batch normalisation, and ReLU activation. Because there are many pathways, the model is able to keep varied representations after merging these characteristics by concatenation. The aggregated features are then passed into a parallel modelling layer that is based on SE. To comprehend temporal patterns, the model learns from previous performance levels using gated processes. As a result, the model is able to better anticipate student outcomes over time by concentrating on the most important data and ignoring irrelevant signals.

a) ResXGR Mechanism for Extracting Features:

Predictions are based on information about students' initial performance in the subject. This data goes through a number of transformations inside the ResXGR component. Methods for every possible path k in the extracting features, ResXGR blocks look like this:

- Convolutional Layer: $Conv_k$ = Convolutional Layer $k(v)$.
- Batch_Norm: BN_k =Batch_Norm $i(Conv_k)$.
- Activation Trigger using Function ReLU: $ReLU_k = ReLU(BN_k)$.

The input data representing student performance is represented by v in this scenario. In this context, $Conv_k, BN_k, ReLU_k$" all refer to different variables: the layer of convolution output, the batch normalisation result, and the result of applying the activated ReLU function to the group-normalized output for path k.

b) The Principle of Cardinality and Concatenation:

To give a model the ability to acquire diverse properties, the data was carefully separated into multiple pathways according to cardinality. Each path undergoes independent processing by the ResXGR architecture. Equation (6) combines the outputs of multiple paths, each of which is enriched with unique data, to create a comprehensive feature depiction:

$$Patch\_Concate = \begin{bmatrix} func_R eLU1, func_R eLU2, \\ func_R eLU3, func_R eLU4 \end{bmatrix} \quad (6)$$

The four outputs $func_R eLU_k$ from the paths were merged by the concatenation operator.

c) SE based Parallel Monitoring:

Following the merging stage, the merged features make their way via the parallel modelling layer that relies on squeezing and excitement. With this layer, the model may continue to use the ResXGR architecture while analysing student achievement data for temporal dependencies and sequential linkages.

$$c = \beta(O_c \cdot [\text{Path\_Concate}, d_{r-1}] + d_c \quad (7)$$

$$d = \beta(O_d \cdot [\text{Path\_Concate}, d_{r-1}] + d_d \quad (8)$$

$$\tilde{a}_r = \alpha(C \cdot [\text{Path\_Concate}, c \cdot d_{r-1}] + g \quad (9)$$

$$a_r = (1 - d) \cdot d_{r-1} + d \cdot \tilde{a}_r \quad (10)$$

In these equations $(7) - (10)$, the workings of the ResXGR framework's SE-based parallel modelling layer are explained, where 'c_t' denotes the hidden state at time 't,' and gates 'a' and 'b' control the data flow via adaptive scaling procedures.

3) Hyperparameter Tuning:

Hyperparameters are critical parameters set before the training phase that greatly affect the algorithm's convergence, generalisation, and overall efficacy. To forecast students' performance using the suggested ResXGR model, they calibrated the hyperparameters in Table 1:

TABLE I. RESXGR HYPERPARAMETER AND CORRESPONDING VALUES

HYPERPARAMETER	ASSIGNED VALUES
Train Epochs	75
Ration of Squeeze-and-Excitation	16
Block Configuration of ResXGR	Depth: 48, No. of Block: 5, Width: 5
Rate for Dropout	0.25
Size of Batch	32
Factor for Regularization	0.0002
Rate of Learning	0.002

Model performance and computational efficiency were greatly enhanced by optimising the hyperparameters in Table 1 utilising the JA. All of the steps are described in Algorithm 1.

Algorithm 1: ResXGR Model Classification for Student Performance Predicting	
1.	**Preprocessing**
2.	Resolve outliers and missing variables using strong imputation methods.
3.	Eliminate redundant polynomial elements.
4.	Employ the ResXGR technique to identify significant attributes.
5.	**EDA**
6.	Organise information utilising descriptive statistics.
7.	Transform categorical variables by index mapping.
8.	Imagine patterns and trends via graphical examination.
9.	**Hyperparameter Algorithm for JA**
10.	Establish a varied collection of potential solutions (students) utilising arbitrary hyperparameters.
11.	Assess every candidate utilising the ResXGR feature selection methodology.
12.	Select the most effective prospects for the forthcoming iteration.
13.	Implement mutation and crossover to generate diversity.
14.	Systematically adjust hyperparameters through an initial warm-up period.
15.	Repeat the procedure for a predetermined number of generations to improve efficacy.
16.	**Model Training and Evaluation**
17.	Divide the dataset into Train and Test segments.
18.	Utilise the training dataset to instruct the ResXGB model.
19.	Evaluate the efficacy of the model through diverse assessment indicators.
20.	Conduct statistical evaluation to corroborate the findings.
21.	Choose the most effective configuration as the ultimate contender.
22.	**Output:** A hybrid classification framework (ResXGR) refined for forecasting student achievement.

RESULT AND DISCUSSION

Lately, the flipped classroom model has been all the rage among educators. The fundamental premise of this strategy is to reverse the traditional classroom-to-video-lesson model and have students view introductory films on the material before class. This allows more time during class for activities that are designed to engage students and promote active learning. In spite of its widespread use, research on the flipped classroom model has mostly concentrated on academic institutions and disciplines with heavy reliance on lecture, such STEM (science, technology, engineering, and mathematics).

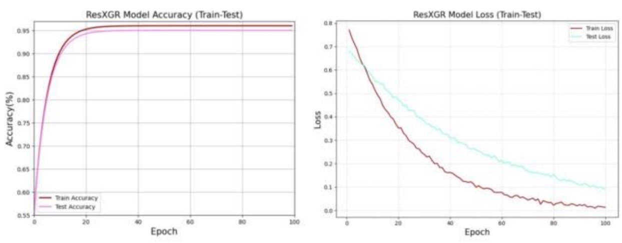

Fig 2. Training and Validation Accuracy and Loss

Fig. 2 shows the accuracy and loss of the ResXGR model over 100 training and testing epochs. The accuracy of the training and testing models is shown in the left subplot. With time, the training accuracy rises to 96.28%, showing that the model is learning from the data it has been fed. The model's testing accuracy increases to 95.02% in the last epoch, indicating that it generalises effectively to extra data. Training and testing losses are shown in the right subplot. From 0.8 to 0.001, the training loss improves the model's accuracy. Confirming good model-to-data and test-set performance, the testing loss falls to 0.09. The image clearly demonstrates that the ResXGR model is capable of making accurate predictions about students' early performance on both the testing and training sets with minimal loss values.

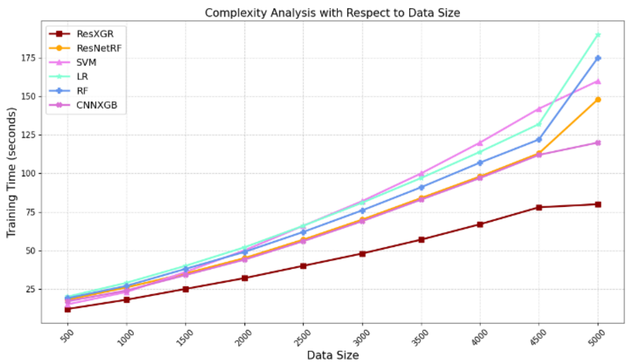

Fig 3. Training Time Comparison with Data Size

Fig. 3 displays the results of a complexity analysis of various ML methods applied to ever-growing datasets. From 500 to 5000 examples, the training times (in seconds) of LR, RF, SVM, ResNetRF, CNNXGB, and ResXGR are compared in the graph. Regardless of the size of the data, the graphic shows that ResXGR achieves the fastest training times.

TABLE II. PERFORMANCE METRIC (%)

Metric	**LR**	**RF**	**SVM**	**ResNetRF**	**CNNXGB**	**ResXGR**
Accuracy	78.09	82.17	86.30	90.16	93.42	96.28
Precision	76.40	80.34	84.21	88.52	91.60	94.48
Recall	74.37	78.46	82.68	86.28	89.45	92.67
F1-Score	78.65	82.88	86.75	90.84	93.97	96.91
Training Time	190	175	160	148	120	80
Training Error	0.8	0.48	0.5	0.35	0.19	0.06

The suggested LR, SVM, RF, ResNetRF, CNNXGB, and ResXGR are compared in Table 1. Accuracy, recall, precision, F1 score, training time, and training error are displayed in the table for each model's early student performance prediction. Based on the data in the table, ResXGR has superior predictive power, with an accuracy of 96.28%, which is much higher than any other competing methods.

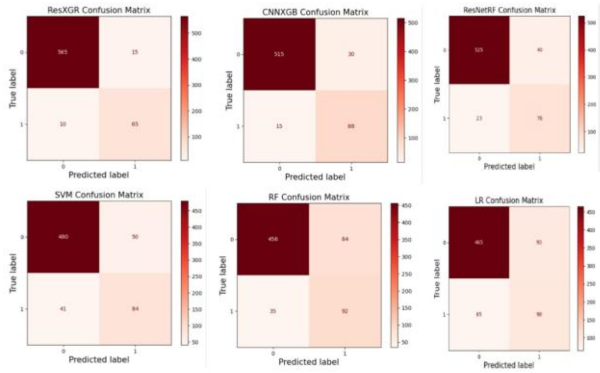

Fig 4. Confusion Matrix

The confusion matrix and performance indicators are shown in Fig. 4, which shows that the Predicted and true labels are quite close to each other. With a total evaluation accuracy of 96.28%, the suggested ResXGR model surpasses prior state-of-the-art methods. Notably, compared to earlier methods, the ResXGR model significantly reduces the number of FP and FN. Academic decision-making relies heavily on accuracy and reducing misclassification.

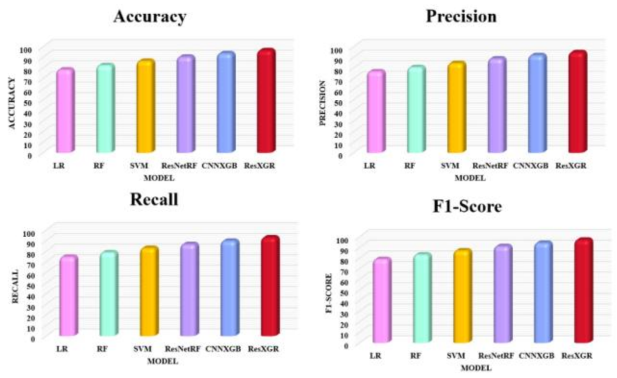

Fig 5. Performance Comparison Over Traditional vs Proposed Model

Since the ResXGR model outperformed all baseline models in this investigation, it displayed top-tier accuracy, precision, recall, and F1-Score levels of 96.28%, 94.48%, 92.67%, and 96.91%, respectively in Fig. 5.

Fig 6. Comparison of Training Error

Fig. 6 show an error rate of only 0.06, a ResXGR model proved to be incredibly accurate and reliable in its predictions. There were 0.8, 0.5, and 0.19 errors produced by LR, SVM, and CNNXGB, respectively, compared to 0.48 and 0.35 mistakes produced by Random Forest and ResNetRF models. By combining several algorithmic prediction powers, the ResXGR model improves classification accuracy and achieves its smallest error rate.

CONCLUSION

The degree to which second language learners are successful is heavily dependent on their self-efficacy, self-concept, and self-regulation. Consequently, the purpose of this research was to assess college students' academic self-concept, self-efficacy, and self-regulation abilities in regards to academic performance and self-assessment, and secondarily to probe the link between academic self-perception, self-confidence, and self-control. Data cleaning and Z-Score normalisation were two of the preprocessing approaches required by a Kaggle dataset. HCFS is a feature selection method that is commonly used. An unique hybrid model called ResXGR is proposed in this work. It combines the ResXGR architecture with SE attention mechanisms. To improve prediction accuracy and computational efficiency, the model uses the Jaya optimisation method to tune hyperparameters. Simulations and comparisons show that XSEJNet is superior to both older and more modern ML models and methods, including LR, RF, SVM, ResNetRF, and CNNXGB. With a scalable and realistic solution, this model achieves a high prediction accuracy of 96.28% and shows faster convergence and lower processing overhead. It is thus ideal for real-world educational situations.

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Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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