Enhancing Students' Academic Performance Classification in E-Learning Using Hybrid Model (Random Forest and Deep Neural Network)

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Abstract— This study investigates how a hybrid model that combines Random Forest (RF) and Deep Neural Networks (DNN) might improve the classification of academic performance in e-learning environments. The study makes use of sophisticated data processing methods like feature selection and normalisation, drawing on the xAPI-Edu dataset, which comprises demographic and behavioural information from 480 students. With accuracies ranging from 68% to 92%, prior research has demonstrated the efficacy of several algorithms, including XGBoost and Logistic Regression, in forecasting student performance. These studies, however, frequently encountered difficulties with multi-class categorisation, which our model resolves by separating low, medium, and high performance with a noteworthy 80% accuracy. Crucially, the study shows that tri-class data has a detrimental effect on algorithm performance, as seen by the outcomes. With an accuracy of up to 96% in binary classifications, the hybrid model demonstrates its potential to enhance educational data mining and facilitate well-informed decision-making in academic settings.

Keywords— *e-learning RF, Deep neural network*

I. Introduction

(Cameron Hashemi-Pour). Unlike classic methods, e-learning allows employees and students to learn without geographical boundaries and has developed to include multidirectional interaction using interactive tools, giving learners the freedom to choose how they receive and engage with information. E-learning is a modern educational approach conducted via the Internet or internal networks, allowing learners to access courses anytime and anywhere through a browser. The importance of e-learning lies in its crucial role in academic education and professional skill development, especially with rapid technological advancements requiring continuous training to keep up with changes, such as quantum computing, which will impact programming and cybersecurity fields. Companies are increasingly relying on Learning Management Systems (LMS) to train employees and enhance their skills, while educational institutions integrate these technologies both inside and outside classrooms. According to a 2022 McKinsey survey, 65% of higher education students prefer retaining some aspects of e-learning even after the pandemic. (Connolly, 2023). Automation and AI are transforming the e-learning landscape, with the potential to automate up to 30% of tasks in 60% of jobs, according to a 2023 McKinsey report. AI can enhance eLearning by analyzing large data sets, personalizing learning experiences, automating grading, and providing virtual tutoring. AI systems can monitor student progress, adapt learning activities, and provide real-time support. While AI won't replace human teachers, it can reduce administrative tasks, allowing educators to focus more on teaching. AI's integration in education promises to improve efficiency and support learning at scale.

(McCarthy, 2007). Artificial intelligence (AI) is a field that aims to develop intelligent machines capable of mimicking human abilities, primarily through computer programming. Intelligence is based on computational abilities to achieve goals, but there is still no precise definition of it. AI research began after World War II, with Alan Turing being one of the first to propose its development through programming. AI branches into various fields, such as logical reasoning, learning from experience, planning, and pattern recognition, enabling its application in areas like gaming, speech recognition, natural language processing, and expert systems. Despite significant advancements, AI still faces challenges, including the difficulty of reaching true human-level intelligence and ethical concerns related to its use and impact on jobs and society.

(Kumar, Last updated on Jan 22, 2025). Artificial Intelligence (AI) is classified based on capabilities, functionalities, and technologies. In terms of capabilities, Narrow AI (Weak AI) performs specific tasks like facial recognition, General AI (Strong AI) has human-like cognitive abilities, and Superintelligent AI (a future concept) surpasses human intelligence. Based on functionalities, Reactive Machines respond without memory, Limited Memory AI learns from past data, Theory of Mind AI aims to understand emotions, and Self-aware AI (still theoretical) would have consciousness. Regarding technologies, AI includes Machine Learning (ML) for self-improvement, Deep Learning for complex pattern recognition, Natural Language Processing (NLP) for human language understanding, Computer Vision for image interpretation, Robotics for autonomous machines, and Expert Systems for domain-specific problem-solving.

II. Research Contribution

Creation of a Hybrid Model: To improve classification accuracy, Random Forest and Deep Neural Network algorithms were combined.
Student Data Analysis: Made use of an extensive dataset (xAPI-Edu) that included behavioural and demographic data.
Data Processing Methodology: To maximise model performance, strategies including feature selection and normalisation were put into practice.
High Accuracy Achievement: The hybrid model classified academic performance into binary categories with 96% accuracy.
Determining the Limitations of Multi-Class Classification acknowledged the difficulties in dealing with tri-class data, and in this case, achieved 80% accuracy.

III. Literature Review

(Cohausz, Tschalzev, Bartelt, & Stuckenschmidt, 2024)"Investigating Demographic Features and Their Connection to Performance, Predictions, and Fairness in EDM Models." The xAPI-Edu dataset, which contains demographic and behavioural information on 480 Arab students enrolled in online courses, was the main focus of this investigation. Students were divided into three performance levels, low, medium, and high, by the researchers using XGBoost and Generalised Linear Models (GLM) in a multiclass classification problem. According to the results, XGBoost performed best when all features (demographic and study-related) were used, with an F1-score of 0.78, as opposed to 0.74 when study-related features were used alone. This suggests that predicted accuracy was not considerably increased by demographic characteristics. Further investigation, however, showed that models continued to rely on demographic characteristics when they were accessible, which raised questions about fairness to the impact of sensitive variables on forecasts.

(Qian, Chen, Zhao, Li, & Huai, 2024) The research paper titled "Exploring Fairness in Educational Data Mining in the Context of the Right to be Forgotten" examines how model fairness in educational settings is affected by selective forgetting. To forecast academic achievement, the study makes use of the xAPI-Edu-Data collection, which includes behavioural and demographic data about students. Classification algorithms like Multi-Layer Perceptrons (MLP) and Logistic Regression (LR) were used. Three classification classes, high, medium, and low performance, are used in this work. In addition to demonstrating a notable increase in fairness gaps (e.g., by gender) with the application of unlearning, experimental results demonstrated that the models obtained high accuracy, reaching up to 84.12% with the MLP-2 model under partial unlearning situations.

(Liu, Wang, Du, & Yuan, 2022) " The paper titled "A Predictive Model for Student Achievement Using Spiking Neural Networks Based on Educational Data" explains how to use the xAPI-Edu-Data database, which has data on 480 students. The data was analysed and divided into three groups: low (L), medium (M), and high (H) using algorithms like logistic regression, decision trees, and XGBoost. Both binary and multi-class classification were used in the investigation. In binary classification, the model's accuracy was 81.4% for category A (Excellent) and 92% for category B (Good). The accuracy in multi-class classification was 68% for the high category (H) and 84.375% for the medium category (M). These outcomes demonstrate how well the model works to increase the precision of student achievement predictions made from educational data.

(Cohausz, Tschalzev, Bartelt, & Stuckenschmidt, 2023) In the research paper titled "Investigating the Importance of Demographic Features for EDM-Predictions," The xAPI-Edu-Data dataset, which includes information on 480 students' academic performance as well as several metrics about their study habits, was used. Generalised Linear Models (GLMs) and XGBoost were among the techniques used in the study. Using a three-class categorisation approach, performance was divided into three classes: 0-69, 70-89, and 90-100. According to the results, the model's recorded accuracy was 0.76 (76%), demonstrating how well it predicted student performance using the information at hand.

(Farhood, Joudah, Beheshti, & Muller, 2024)"Evaluating and Enhancing Artificial Intelligence Models for Predicting Student Learning Outcomes." The xAPI-Edu-Data dataset, which comprises student data from 14 nations, was the main focus of this investigation. Binary classification (Pass/Fail) was used to predict student results, with "Low" performance being classified as "Fail" and "Middle" and "High" performance as "Pass." Three deep learning models and seven machine learning models were put to the test. Using k-fold cross-validation, the Random Forest model had the highest accuracy of any machine learning technique (92.70%), while the Gradient-Boosted Neural Network (GBNN) was the best deep learning model with an accuracy of 91.44%. Lasso feature selection increased the accuracy of a number of models, particularly kNN and logistic regression.

(Tsiakmaki, Kostopoulos, & Kotsiantis, 2024) The scientific paper titled "Exploiting the Regularized Greedy Forest Algorithm Through Active Learning for Predicting Student Grades: A Case Study" offers a fresh method for forecasting student achievement. The xAPI-Edu-Data dataset, which was gathered by the researchers using the Kalboard 360 learning management system, includes behavioural, academic, demographic, and parental participation data for 480 children. Using an active learning framework, the study implemented the Regularised Greedy Forest (RGF) method and evaluated its performance against popular classification algorithms as C4.5 Decision Tree, Naïve Bayes, Artificial Neural Networks (ANN), Bagging, Boosting, and Random Forests. Three classes were used for the categorisation exercise, which sought to classify student performance as poor, medium, or high. With an accuracy of 81.60%, the results demonstrated that the suggested RGF-based model performed better than any other approach, demonstrating its usefulness in educational data mining and early risk assessment of students.

(Roslan & Chen, 2022)"Educational data mining for student performance prediction: feature selection and model evaluation." The xAPI-Edu-Data database, which includes detailed information about 480 students, including social and academic traits as well as classroom behaviours, was used in this study. The Extreme Gradient Boosting (XGBoost) technique was used for classification, and the Adaptive Sea Horse Optimisation (ASHO) approach was used for feature selection. Based on their academic performance, pupils are divided into two groups: "Successful" and "Unsuccessful" under the binary categorisation type. With a 92.3% accuracy rate, the model demonstrated how well the strategies employed to forecast student performance and improve educational outcomes worked.

(Sengupta, 2023)The paper titled "Towards Finding a Minimal Set of Features for Predicting Students' Performance Using Educational Data Mining" provides a thorough analysis to improve machine learning models' ability to predict student success. The Xap-Edu-Data dataset, which gathers data on student interactions within a Learning Management System (LMS), was used in the study. The study used a number of methods, such as Random Forests (RF), Support Vector Machines (SVM), and Decision Trees. Academic performance was used as the basis for classification, and both binary and multi-class analyses were used to ascertain the correlations between various characteristics. Significant predictive accuracy was demonstrated by the results, with some models reaching accuracies of up to 89% in binary classification and 85 multi-classification, demonstrating the efficacy of the algorithms employed in enhancing comprehension of student performance. This study's methodical data analysis aids in the creation of more effective teaching methods.

IV. CRITICISM OF PREVIOUS STUDIES

Although the data is based on a three-class categorisation scheme, prior research has demonstrated that the algorithms used to analyse student performance data, which includes behavioural, academic, and demographic attributes, have obtained relatively low classification performance. This finding prompted enquiries on whether the complexity of tri-class classification presents a problem that impairs the effectiveness of conventional algorithms. Thus, the purpose of this study is to assess the suggested hybrid model utilising tri-class labelled data by adopting a particular data preprocessing methodology that entails breaking the dataset up into smaller groups and examining each group separately, as explained in the methodology section. This method aims to improve classification accuracy and evaluate the hybrid model's efficacy in contrast to conventional methods.

V. METHODOLOGY

This study's technique combines an applied and quantitative experimental approach. The RF-led (performance) mechanism is introduced in the methodology. Shown is the first suggested model's architecture. A description of the RF implementation mechanism is given. A flowchart of a deep neural network is also included. An innovative deep neural network featuring a layer for adaptive attention. The methodology part also presents the architecture of the second suggested model, the DNN implementation mechanism, dataset collection, data processing, data reduction, data conversion, and data normalisation.

VI. RANDOM FOREST PERFORMANCE MECHANISM (FLOW CHART)

Figure 1 below demonstrates the flowchart of the modeling process of this proposed model. The historical data, Preprocessing of Historical data, and loading of historical data are illustrated in the first and second steps. The third step is to define the initial SVM parameters and the kernel function that will be used in the proposed model. Then, the training process is demonstrated in the fourth step. The historical data are split into v parts. One subset is used as a validation part, and the remaining is used to train the model in the fifth step. Then, the trained model and unseen data are explained in the sixth step. A proposed model of the forecasting process is described in the seventh step.

This flowchart represents the process of building a Random Forest model, which is an ensemble learning technique based on constructing multiple decision trees and averaging their predictions. Here's a step-by-step explanation:

1- Select "K" random data points: Randomly select K data points from the training dataset. This introduces diversity into the model.

2- Construct a decision tree: Build a decision tree using the selected data points. Each tree is trained on a different subset of the data.

3- Choose the number of trees (N): Determine how many decision trees (N) will be built to form the forest. A higher number of trees generally improves accuracy.

4- Predict *y* 1 y 1 for all trees: Each decision tree makes a prediction (*y* 1 y 1) based on its training data.

5- Average *y* 1 *S* y 1 S: The final prediction is made by averaging the predictions from all the decision trees (for regression) or using a majority vote (for classification).

6- END: The process ends with the final prediction or decision.

This method reduces overfitting and improves prediction accuracy by combining multiple weak models (decision trees) into a strong, reliable model.

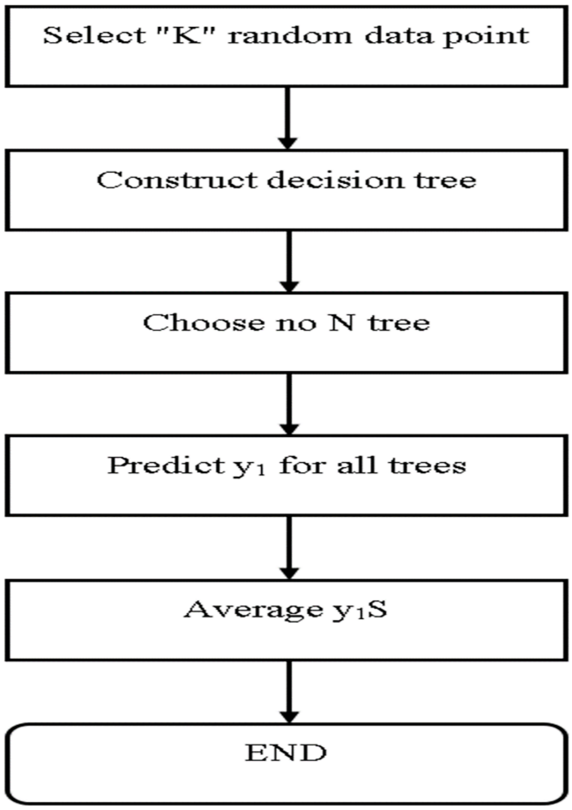

Figure 1: Demonstrates a Random Forest Flow Chart

Random Forest Implementation Mechanism

The R F Implement Mechanism is based on various elements such as:

1. Import the libraries: the main libraries include Scikit-learn, Pandas, NumPy 1.17.4, and Matplotlib.
2. Upload the dataset: Load the breast cancer dataset from the Kaggle machine learning repository.
3. Split the dataset into X and Y: X represents 12 features except for the Class features. Y represents one feature called Class has three categories: Medium, Low, and High.
4. Split the X and Y dataset into the training set and test set: in this case, the given 80% for the Training and 20% for the test.
5. Perform normalizations for features: in this case, transfer numbers over two between 0 and 1.

6. Fit the proposed model to the training set.
7. Predict the test set results: this case determines the performance of the model based on three categories, Medium, Low, and High. Also, two categories, Low and High, respectively.
8. Make the confusion matrix: this case depends on TP, FP, FN, and TN.
9. Visualization of the test set results: In this paper use an Excel tool to visualize the results.

Deep Neuron Network Flowchart

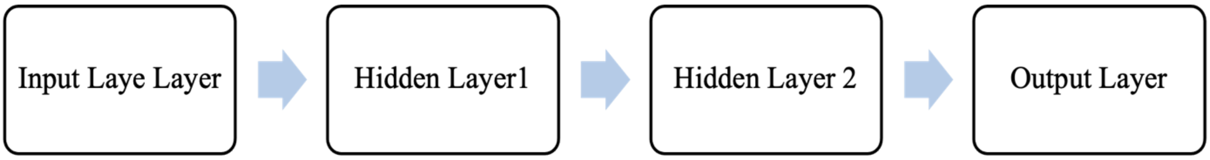

Figure 2: Deep Neuron Network Flowchart

Figure 2 above demonstrates a flow chart for deep neuron networks such as the input layer in Stage One and Stage Two, Three demonstrates the hidden layer including the Rectified Linear Unit function, and finally, the output layer includes the Sigmoid and softmax function if the output is true or false or 0,1 and include SoftMax function if the class label has more than Two patterns shown in Stage Four.

A novel Deep Neural Network with Adaptive Attention Layer

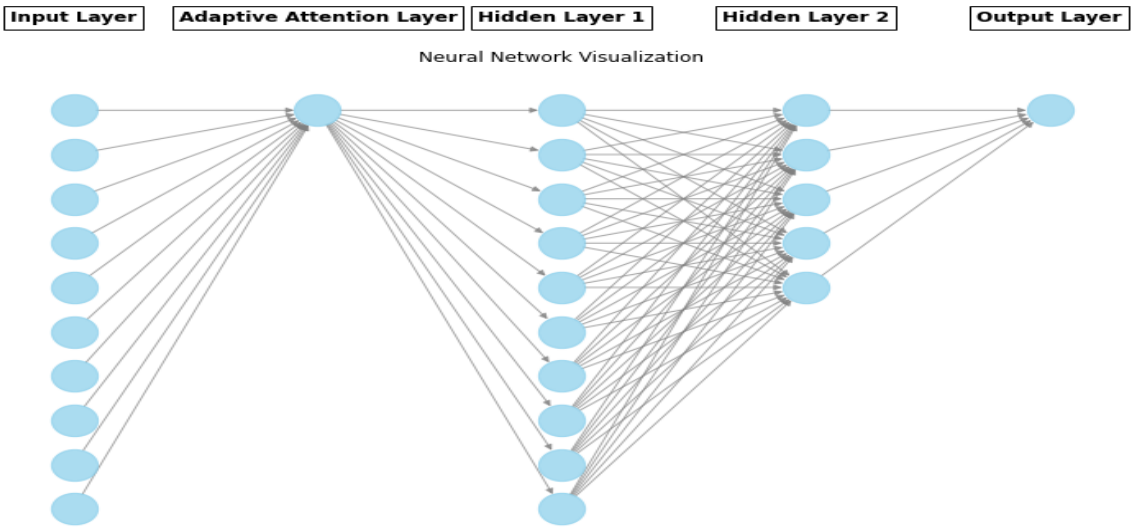

Figure 3: A novel Deep Neural Network with Adaptive Attention Layer

Figure 3 above demonstrates a flow chart for expanding deep neuron networks such as the input layer in Stage One, the adaptive attention layer in Section Two, and Stage Three, Four demonstrates the hidden layer, including the Rectified Linear Unit function, and finally, output layer includes the Sigmoid function if the output is true or false or 0,1 and include SoftMax function if the class label has more than Two patterns shown in Stage Five.

A Novel Deep Neural Network Work Mechanism for Every Epoch

Adaptive Attention Layer

Data is then supplied to the neural network, which assigns a weight to each input. Each input is given a relative priority based on the weights' exponential values. To make sure the weights are scaled correctly, these values are then normalized by dividing each exponential value by the sum of all exponential values. The relative influence of each input on the network is then calculated by multiplying it by its normalized weight.

The input layer is represented by x^i and weights by w^i

e^{wi}--------(1)

$\frac{e^{wi}}{\Sigma e^{wi}}$--------(2)

$\frac{e^{wi}}{\Sigma e^{wi}} * x^i$ This equation represents weighted inputs.--------(3)

$\sum \frac{e^{wi}}{\Sigma e^{wi}} * x^i$-----------(4)

Equations 1 to 4 represent to intelligence vector used to make an algorithm achieve high performance.

Forward Propagation

In this case, the state outputs are computed using the following procedure: the weighted inputs are added together with a bias term, and the result is then run through the Sigmoid activation function, which assurances that the output values stay between 0 and 1. The outputs are then compared with the target values, and the error is determined by the difference between them.

$\Sigma x^i w^i + b.$

Sigmoid $= \frac{1}{1+e^{-last\ node\ value}}$.

The result is passed through the **Sigmoid activation function** to limit the output between 0 and 1.

Calculate Error =0.5 * (Target- output value)^2.

The error is computed as the difference between the actual and target values.

$$\text{Softmax} = \frac{1}{1+e^{-last\ node\ value}}$$

VII. Backpropagation

After determining the mistake, the network begins using backpropagation to fix it. Initially, the final node's error gradient is calculated using the difference between the expected and actual output. The error gradient for earlier nodes is then computed using their values. Lastly, the weights are modified based on the learning rate, gradually decreasing the error by modifying the previous weights. The neural network's predictions become more accurate as a result of repeating this process over several epochs until the error is reduced.

To modify the weights and reduce error throughout the neural network, backpropagation is utilized.

$\delta\ lastnode\ = output(1 - output) * (target - output).$

$\delta\ lastnode - 1 = lastnode - 1\ value(1 - lastnode - 1\ value).$

Calculate new weights

New weights last node, last node-1 = old weight $+ \eta * \delta\ lastnode * lastnode - 1\ valu.$

VIII.DNN Implementation Mechanism

The Deep Neuron Network Implementation Mechanism is based on various elements such as:

1. Import the libraries: the main libraries include Scikit-learn, Pandas, NumPy 1.17.4, and Matplotlib.
2. Upload the dataset: Load the CIC-IDS dataset from the Kaggle machine learning repository.
3. Processing dataset
4. Split the dataset into X and Y:
5. Fit the proposed model to the training set.
6. Predict the test set results: this case determines the performance of the model based on three categories, Medium, Low, and High. Also, two categories, Low and High, respectively.
7. Make the confusion matrix: this case depends on TP, FP, FN, and TN.
8. Visualization of the test set results: In this research, an Excel tool is used to visualize the results.

The Architecture of the Proposed Hybrid Model

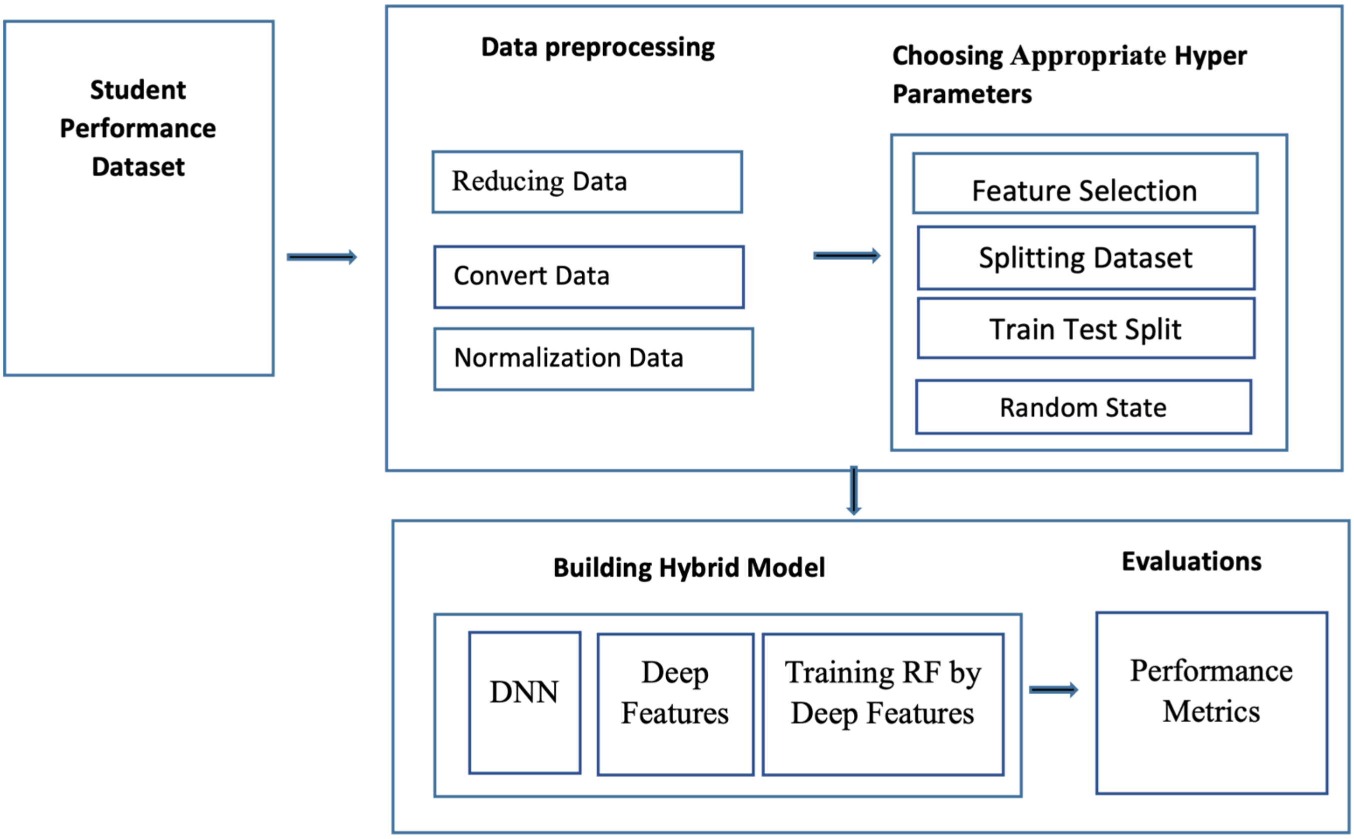

Figure 4: Architecture of the Proposed Hybrid Model

The general architecture of the proposed model consists of four phases, which are illustrated in Figure 4 above. These phases are data collection, data processing, hyperparameters, the proposed hybrid model (DNN, RF), and evaluation of the applied model.

Dataset Collection

480 records and 17 attributes make up the Students' Academic Performance Dataset (xAPI-Educational Mining Dataset), which was obtained from Kaggle and offers thorough information about students in an online learning environment. Along with academic identifiers like stage ID, grade ID, and section ID, the collection also contains demographic information like gender, nationality, and place of birth. The subject and semester being studied are also

specified. The "Relation," "ParentAnsweringSurvey," and "ParentSchoolSatisfaction" elements all represent parental participation and relationship. Metrics like raised hands, resource visits, announcement views, and discussion involvement are used to gauge how engaged students are. The "StudentAbsenceDays" portion of the dataset also keeps track of attendance. Three levels of academic achievement are distinguished by the goal variable, "Class," which is divided into low, middle, and high. The main purpose of this dataset is to evaluate and forecast student involvement and performance in online learning settings.

Table 1:Demonstration Dataset with All Features

Features name
Gender
Nationality
PlaceofBirth
StageID
GradeID
SectionID
Topic
Semester
Relation
raisedhands
VisITedResources
AnnouncementsView
Discussion
ParentAnsweringSurvey
ParentschoolSatisfaction
StudentAbsenceDays
Class

Data Processing

Data processing involves converting and normalizing data for analysis, while data reduction is about simplifying and minimizing the dataset to enhance algorithm performance.

Data Reducing

The dataset initially contains 17 features, but after the data reduction process, the number of features was reduced to 13. The features reduced Nationality, PlaceofBirth, Grade ID, and Section ID.

Table 2: Before and after conversion.

Data after conversion	Data before conversion	Feature name	Data after conversion	Data before conversion	Features name	Data after conversion	Data before conversion	Features name
1	Good		9	Spanish	Topic	1	Male	Gender
0	Under-7	StudentAbsenceDays	10	Quran		0	Female	
1	Above-7		3	History		1	lower level	StageID
2	L	Class	6	Biology		2	middleschool	
1	M					3	HighSchool	
3	H					1	IT	Topic
			0	F	Semester	2	Math	
			1	S		2	Arabic	
			1	Father	Relation	9	Science	
			0	Mum		8	English	
			0	No	ParentAnsweringSurvey	10	French	
			1	Yes		4	Geology	
			2	Bad		5	Chemistry	

Table 3 above contains a set of features used for data analysis, where textual values are converted into numerical values to facilitate processing and analysis. For example, the "Gender" feature is converted into numerical values: Male is represented by 1, and Female by 0. Similarly, "Student Absence Days" is categorized into two classes: students absent for fewer than 7 days (Under-7) are assigned 0, while those absent for more than 7 days (Above-7) are assigned 1. The "StageID" feature represents the education level, where the lower level is assigned 1, middle school is assigned 2, and high school is assigned 3. The same conversion applies to other features like "Semester," "Relation" (Father = 1, Mum = 0), "Parent Answering Survey" (Yes = 1, No = 0), and

"Topic," where different subjects such as Math, Science, and IT are assigned specific numerical values. This transformation helps in data processing and machine learning applications.

Data Before Normalization

Table 1: Illustrates Data Before Normalization

Features	Data before normalization
Gender	1
StageID	1
Topic	1
Semester	0
Relation	1
Raised hands	15
VisITedResources	16
AnnouncementsView	2
Discussion	20
ParentAnsweringSurvey	1
Parent School Satisfaction:	1
StudentAbsenceDays	0
Class	1

Data After Normalization

Table 2 demonstrates the Data After Normalization

Features	Data normalization
Gender	1.0
StageID	0.0
Topic	0.0
Semester	0.0
Relation	1.0
Raised hands	0.15
VisITedResources	0.161616
AnnouncementsView	0.020408
Discussion	0.193878
ParentAnsweringSurvey	1.0
Parent School Satisfaction:	0.0
StudentAbsenceDays	0.0
Class	1

Tables 4 and 5 above show data before and after normalization. In the "before normalization" dataset, the values represent raw, unprocessed data. For example, the "Raised hands" feature has a value of 15, and "VisitedResources" has a value of 16. Other features, like "Gender" and "StageID," are represented using binary values (0 or 1). After normalization, the values are scaled to a range between 0 and 1 to ensure consistency and comparability. For instance, "Raised hands" is normalized to 0.15, and "VisitedResources" becomes approximately 0.1616. Binary values such as "Gender" and "ParentAnsweringSurvey" remain unchanged at 1.0, while others like "Semester" and "ParentSchoolSatisfaction" are represented as 0.0. Normalization is typically applied to enhance the performance of machine learning algorithms by reducing the effect of varying scales in the dataset.

Features Selection

Following data preparation, Table 2 displays the important attributes selected for student performance analysis during the Feature Selection stage. Demographic information like gender, stage ID, topic, and semester is among these features. Variables like raised hands, VisitedResources, AnnouncementsView, and Discussion also show how engaged students are. Additionally, StudentAbsenceDays shows how many days a student was absent, while ParentAnsweringSurvey and ParentSchoolSatisfaction record parental involvement. Class, which stands for the student's overall performance level, is the target variable for classification.

Table 5: Dataset After Processing

Features name
Gender
StageID
Topic
Semester
Relation
raisedhands
VisITedResources
AnnouncementsView
Discussion
ParentAnsweringSurvey
ParentschoolSatisfaction
StudentAbsenceDays
Class

Splitting Dataset

The dataset was divided into multiple performance groups: students with high and low performance were included in the first category; students with high and medium performance were included in the second category; students with medium and low performance were included in the third; and students with pass and fail performance were included in the fourth. Following the data's classification into these groups, each group was entered independently into the suggested model, enabling the tracking and examination of the outcomes from each category separately. This procedure helps to improve learning strategies and provide suitable support for students in each group by assisting in the comprehension of how academic performance levels affect the model's outcomes.

Binary Categories (Low, High) Dataset

Table 3: Dataset with Binary Categories (High, Low)

Gender	**: Represents the student's gender (1 for male, 0 for female).**
StageID	The educational stage (e.g., Primary, Middle, or High School
Topic	The subject of study, represented by a numerical value
Semester	The semester of the academic year (0 or 1).
Relation	The student's relationship with their parents (1 for a good relationship, 0 otherwise).
Raised hands	The number of times the student raised their hand to participate
VisITedResources	The number of resources the student visited

AnnouncementsView	The number of announcements the student viewed
Discussion	The number of discussion contributions made by the student
ParentAnsweringSurvey	Whether the parent answered the school survey (1 for Yes, 0 for No).
Parent School Satisfaction:	Parental satisfaction with the school (1 for satisfied, 2 for unsatisfied).
StudentAbsenceDays	Number of absence days (0 for low absence, 1 for high absence).
Class	The student's performance classification (1: Low, 2: High).

Table 6 above: Binary Categories (High, Low). This table includes a set of features that describe student performance and their relationship with the school. Gender is represented by a number (1 for male, 0 for female), and it includes information about the educational stage, subject of study, semester, student-parent relationship, number of times the student raised their hand to participate, resources visited, and number of announcements viewed. It also includes the number of discussion contributions, whether the parent answered the school survey, parental satisfaction with the school, number of absence days, and the student's performance classification (1: Low, 2: High).

Binary Categories (Medium, High) Dataset

Table 10: Dataset with Binary Categories (High, Low)

Gender	**: Represents the student's gender (1 for male, 0 for female).**
StageID	The educational stage (e.g., Primary, Middle, or High School
Topic	The subject of study, represented by a numerical value
Semester	The semester of the academic year (0 or 1).
Relation	The student's relationship with their parents (1 for a good relationship, 0 otherwise).
Raised hands	The number of times the student raised their hand to participate
VisITedResources	The number of resources the student visited
AnnouncementsView	The number of announcements the student viewed
Discussion	The number of discussion contributions made by the student
ParentAnsweringSurvey	Whether the parent answered the school survey (1 for Yes, 0 for No).
Parent School Satisfaction:	Parental satisfaction with the school (1 for satisfied, 2 for unsatisfied).
StudentAbsenceDays	Number of absence days (0 for low absence, 1 for high absence).
Class	The student's performance classification (1: Medium, 2: High).

Table 7 above: Binary Categories (Medium, High). This table is similar to Table 1 but focuses on classifying student performance into three categories: Medium and High. It retains the same features as mentioned in Table 1, with the performance classification adjusted to include (1: Medium, 2:High).

This table offers additional insights into student performance in the medium and high categories.

Binary Categories (Medium, Low) Dataset

Table 11: with Binary Categories (High, Low)

Gender	**: Represents the student's gender (1 for male, 0 for female).**
StageID	The educational stage (e.g., Primary, Middle, or High School
Topic	The subject of study, represented by a numerical value
Semester	The semester of the academic year (0 or 1).
Relation	The student's relationship with their parents (1 for a good relationship, 0 otherwise).
Raised hands	The number of times the student raised their hand to participate
VisITedResources	The number of resources the student visited
AnnouncementsView	The number of announcements the student viewed
Discussion	The number of discussion contributions made by the student
ParentAnsweringSurvey	Whether the parent answered the school survey (1 for Yes, 0 for No).
Parent School Satisfaction:	Parental satisfaction with the school (1 for satisfied, 2 for unsatisfied).
StudentAbsenceDays	Number of absence days (0 for low absence, 1 for high absence).
Class	The student's performance classification (1: Medium, 2: Low).

Table 8 above: Binary Categories (Medium, Low). This table complements the previous categories, focusing on classifying student performance into (Medium and Low). It retains the same features as in the previous tables, with the performance classification adjusted to include (1: Medium, 2: Low). This table aims to provide a comprehensive view of student performance in the low and medium categories. Each table assists in analyzing data related to student performance and their relationships with the school, facilitating informed educational decisions, and Table 9 below illustrates the binary category Pass and Fail. Pass includes high performance and medium performance; fail includes low performance..

Binary Categories (Pass, Fail) Dataset

Table 12: with Binary Categories (High, Low)

Gender	**: Represents the student's gender (1 for male, 0 for female).**
StageID	The educational stage (e.g., Primary, Middle, or High School
Topic	The subject of study, represented by a numerical value
Semester	The semester of the academic year (0 or 1).
Relation	The student's relationship with their parents (1 for a good relationship, 0 otherwise).
Raised hands	The number of times the student raised their hand to participate
VisITedResources	The number of resources the student visited
AnnouncementsView	The number of announcements the student viewed
Discussion	The number of discussion contributions made by the student
ParentAnsweringSurvey	Whether the parent answered the school survey (1 for Yes, 0 for No).
Parent School Satisfaction:	Parental satisfaction with the school (1 for satisfied, 2 for unsatisfied).
StudentAbsenceDays	Number of absence days (0 for low absence, 1 for high absence).
Class	The student's performance classification (1: Pass, 2: Fail).

Three Categories Dataset

Table 4: Dataset with Three Categories (High, Medium, Low)

Gender	**: Represents the student's gender (1 for male, 0 for female).**
StageID	The educational stage (e.g., Primary, Middle, or High School
Topic	The subject of study, represented by a numerical value
Semester	The semester of the academic year (0 or 1).
Relation	The student's relationship with their parents (1 for a good relationship, 0 otherwise).
Raised hands	The number of times the student raised their hand to participate
VisITedResources	The number of resources the student visited
AnnouncementsView	The number of announcements the student viewed
Discussion	The number of discussion contributions made by the student
ParentAnsweringSurvey	Whether the parent answered the school survey (1 for Yes, 0 for No).
Parent School Satisfaction:	Parental satisfaction with the school (1 for satisfied, 2 for unsatisfied).
StudentAbsenceDays	Number of absence days (0 for low absence, 1 for high absence).
Class	The student's performance classification (1: Low, 2: Medium, 3: High).

Train Test Split Function

In this paper, a single function is used to execute training and testing for the algorithm, namely, the splitting data 80-20.

Random State

This variable is used to shuffle the data and then enter the data into the model for examination to ensure the performance of the model, and this operation continues until the best accuracy is achieved. This paper used values random state=42, 7 achieved high accuracy.

IX. Building a Hybrid Model

The suggested model is a hybrid approach that improves classification performance on educational data from the xAPI-Edu dataset by combining the Random Forest classifier with Deep Neural Networks (DNN). Preprocessing, which includes feature normalisation and target label encoding, is the first step in the procedure. After that, the input data is run through the DNN, which has a final Softmax output layer and hidden layers with ReLU activation. Deep features are taken from the DNN's penultimate layer after training. The Random Forest algorithm then uses these acquired features as inputs to get the final classification. This hybrid method makes use of Random Forest's robust classification capabilities and the DNN's capacity to learn abstract feature representations. Model performance is assessed using a confusion matrix and accuracy.

Performance Evaluation

This case demonstrates the experimental setup and experimental result for the proposed algorithm.

Experimental Setup

The algorithms are implemented using Python. Experiments are performed on a Device named LAPTOP-CDTI2F87. Processor Intel(R) Core (TM) i7-1065G7 CPU @ 1.30GHz 1.50 GHz Installed RAM 8.00 GB (7.77 GB usable) System type 64-bit operating system, x64-based processor. We used different sizes of text files in our experiments.

Accuracy:

The percentage of correctly classified objects used to calculate the classifier's accuracy is calculated accuracy is explained by Equation (1) as follows:

$$= (\frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Negative + False\ Positive} \quad (1)$$

X.RESULTS

Table 5: Demonstrates Proposed Hybrid Model

Model	Dataset Used	Category	Confuse Matrix				ACC
			TP	FP	FN	TN	
Hybrid Model	Binary Category Dataset(L,H)	Binary	29	0	2	23	0.96
Hybrid Model	Binary Category Dataset(M,L)	Binary	27	4	1	36	0.93
Hybrid Model	Binary Category Dataset(H,M)	Binary	33	14	6	27	0.75
Hybrid Model	Binary Category Dataset(Pass,Fail)	Binary	26	0	6	64	0.94
Hybrid Model	Three Category Dataset(L,H,M)	H, L, M					0.80

A thorough assessment of the suggested hybrid classification model applied to a variety of binary and multi-class datasets drawn from educational data is provided in Table 8: Demonstrates the Proposed Hybrid Model. The table displays the overall accuracy (ACC) for each classification scenario along with key performance indicators based on the confusion matrix: True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN). The model demonstrated good precision and dependability with an accuracy of 0.96 in the binary classification of (Low, high) and no false positives. Despite a minor rise in false positives, the model continued to perform well for the (Medium, Low) binary classification, maintaining an accuracy of 0.93. The accuracy dropped to 0.75 in the (High, Medium) binary case, indicating a higher level of confusion between these two classes, possibly as a result of overlapping features. The model demonstrated strong results with 0.94 accuracy and no false positives when analysing the (Pass, Fail) binary classification, proving its efficacy in differentiating academic outcomes. Finally, the model achieved an accuracy of 0.80 in the three-category classification, including Low, Medium, and High. Given the added complexity of multi-class classification, this result is deemed acceptable even if it is marginally lower than in the binary situations. Overall, Table 8 shows how well the model performs in binary classification and how the kind of classification—binary versus multi-class—affects the model's accuracy and predictive dependability in educational data mining.

Comparison Between Previous Studies and the Proposed Hybrid Model

Table 6: Demonstrates Comparison between previous studies and Proposed Hybrid Model

Researcher(s) (Year)	Algorithm(s) Used	Dataset	Classification Type	Accuracy / Performance
Cohausz et al. (2024)	XGBoost, GLM	xAPI-Edu	Multiclass (Low, Medium, High)	F1-score: 0.78 (XGBoost with all features)
Qian et al. (2024)	Logistic Regression, MLP	xAPI-Edu-Data	Multiclass (High, Medium, Low)	Accuracy: 84.12% (MLP-2 under partial unlearning)
Liu et al. (2022)	Spiking NN, Logistic Regression, Decision Trees, XGBoost	xAPI-Edu-Data	Binary & Multiclass	Accuracy: 92% (Binary), 84.38% (Medium), 68% (High)
Cohausz et al. (2023)	XGBoost, GLM	xAPI-Edu-Data	Multiclass (0–69, 70–89, 90–100)	Accuracy: 76%
Farhood et al. (2024)	Random Forest, GBNN, Lasso, kNN, Logistic Regression	xAPI-Edu-Data	Binary (Pass/Fail)	Accuracy: 92.70% (RF), 91.44% (GBNN)
Tsiakmaki et al. (2024)	RGF, C4.5, Naïve Bayes, ANN, Bagging, Boosting, Random Forest	xAPI-Edu-Data	Multiclass (Low, Medium, High)	Accuracy: 81.60% (RGF)
Roslan & Chen (2022)	ASHO (Feature Selection), XGBoost	xAPI-Edu-Data	Binary (Successful/Unsuccessful)	Accuracy: 92.3%
Sengupta (2023)	Decision Trees, SVM, Random Forest	xAPI-Edu-Data	Binary & Multiclass	Accuracy: 89% (Binary), 85% (Multiclass)
Our work	Proposed Hybrid Model	xAPI-Edu-Data	Binary Category Dataset(L,H)	96%
Our work	Proposed Hybrid Model	xAPI-Edu-Data	Binary Category Dataset(M,H)	75%

Our work	Proposed Hybrid Model	xAPI-Edu-Data	Binary Category Dataset(L,M)	93%
Our work	Proposed Hybrid Model	xAPI-Edu-Data	Binary Category Dataset(Pass, Fail)	94%
Our work	Proposed Hybrid Model	xAPI-Edu-Data	Triple Category Dataset(M, L, H)	80%

A thorough academic comparison between earlier research and the suggested hybrid model is shown in Table 9, with an emphasis on student performance analysis using the xAPI-Edu-Data dataset. The table is organised into five primary columns: Accuracy/Performance, Dataset, Classification Type, Algorithm(s) Used, and Researcher(s) and Year. The information demonstrates how different machine learning algorithms, such as XGBoost, GLM, Logistic Regression, MLP, Random Forest, Naïve Bayes, SVM, and others, were used in earlier research. The classification methods included multiclass schemes (e.g., Low, Medium, High) and binary classifications (e.g., Pass/Fail or Successful/Unsuccessful). Performance varied by study. For instance, Liu et al. (2022) obtained 92% accuracy for binary classification and 68% accuracy for the "High" class in multiclass classification; Cohausz et al. (2024) used XGBoost with all characteristics and obtained an F1-score of 0.78. The suggested hybrid model performed better than a lot of current techniques, especially when it came to binary classification problems. It was able to differentiate between Low and High categories with 96% accuracy, Pass/Fail with 94%, Low/Medium with 93%, and Medium/High with 75%. The suggested model achieved an accuracy of 80% for the multiclass categorisation of (Low, Medium, High). The table concludes by showing that the suggested hybrid model performs noticeably better than earlier methods, particularly in binary classification scenarios, proving its usefulness in student performance prediction and educational data mining.

XI.CONCLUSION

This study uses the xAPI-Edu-Data dataset to analyse and forecast students' academic performance using a sophisticated hybrid model that combines Deep Neural Networks (DNN) and the Random Forest (RF) method. To guarantee ideal model performance, a thorough ؤcertain methodological approach comprising feature selection, data preparation, and normalisation was used. The efficiency of the suggested hybrid model in more straightforward, binary classification scenarios was highlighted by its high accuracy in binary classification tests, which included 96% accuracy in the Low/High category and 93% accuracy in the Low/Medium category. However, while working with multi-class (three-category) data, the study also identified a significant drawback. In particular, the model's accuracy in the Low/Medium/High classification job decreased to 80%. Given the increasing class overlap and difficulty in differentiating between similar performance levels, this reduction suggests that three-class classification has a detrimental effect on the model's predictive power. In comparison to binary-class data, the results demonstrate that tri-class data presents additional difficulties for machine learning algorithms and results in lower model efficiency. In contrast to earlier research that used more conventional methods like logistic regression, XGBoost, and multi-layer perceptrons, the suggested hybrid model produced better accuracy and dependability results in binary classification tasks. These outcomes highlight how well the model may be used to predict student performance and mine educational data. To further enhance decision-making processes in educational institutions, future research should concentrate on strengthening interpretability and the model's ability to handle multi-class classification more successfully.

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