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LINEAR REGRESSIVE LAPLACIAN KERNELIZED DEEP SHAP ALGORITHM FOR PREDICTING STUDENT ACADEMIC PERFORMANCE AND ANALYZING INFLUENCING FACTORS

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Abstract

Student academic performance is considerable results of a student's learning, measured by grades, test scores, assignments, and overall achievements. It reflects the student's kind of subjects and their abilities. Predicting student academic performance involves forecasting future grades or achievements using historical data, namely, previous grades, attendance, study habits, and personal background. Academic performance is partial by different factors are such as, including individual effort, teaching methods, and environmental conditions. Although several techniques have been used for prediction, achieving accurate results remains challenging. To address these issues, this study introduces a novel Linear Regressive Laplacian Kernelized Deep SHAP (LRLKDS) framework that integrates regression-based feature conditioning with kernel-weighted explainability. The model first employs a Linear Regressive Deep Multiplayer Classifier (LR-MLP) to impute missing values and stabilize learning, followed by a Laplacian Kernelized Piecewise SHAP (LK-P-SHAP) module to derive interpretable feature attributions. Experiments conducted on the Kaggle Student Performance dataset demonstrate that the proposed method achieves superior classification accuracy (97.25%) and improved interpretability over existing approaches such as LSTM and MSPP. Statistical analysis confirms that the observed performance gains are significant at the 95% confidence level. The LRLKDS framework thus offers an efficient, interpretable, and statistically validated solution for educational data analytics.

Keywords: *student academic performance predictions, predicating the factors for student academic performance, Linear Regressive Deep Multiplayer classifier model, Laplacian kernelized piecewise regressive Deep SHAP algorithm*

1. Introduction

The significant role of academic performance in educational institutions to serves as a key indicator of a student's success in their studies. This performance is typically measured by various measures, such as grades, test scores, and other academic achievements. Predicting student performance within the educational system is increasingly important, as it enables institutions to enhance learning outcomes and improve overall effectiveness in teaching. The capability to forecast academic performance is failed to simple beneficial for identifying at-

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risk students however, also for creating personalized learning experiences. Different machine learning and deep learning models have been introduced for academic performance prediction.

In [1], an LSTM neural network was introduced into predict students' academic performance and recognize risk of failing the course. However, the model showed inadequate accuracy while handling the large volume of data and attributes related to students' competencies and learning method. A novel Multi- dimensional Student Performance Prediction Model (MSPP) was performed by comprise the data preprocessing and feature engineering and deep learning model investigated in [2]. The designed framework was failed to develop a support large-scale, multi-institutional deployment for student performance prediction with lesser time consumption.

In [3], a multidimensional time-series data analysis model was obtained for predicting student performance by allowing for different types of data, namely student characteristics. However, the model's specificity was not improved. In order to, identify the factors influencing student performance within the middle school education system by an integrated model combining Factor Analysis for Mixed Data (FAMD) and Multiple Linear Regression (MLR) was developed in [4]. A dual graph neural network model was introduced in [5] to predicting academic performance by efficiently utilizing both structural data derived from interaction activities and student features. But, the computational complexity was not reduced. A Neutrosophic Deep Learning Model was designed in [6] to identifying the academic performance. But, an advanced deep learning architecture to enhance prediction accuracy was failed to focus on refining the model by incorporating more.

In [7], a machine learning models were developed into academic performance prediction. As well, the chi-square test was determined to recognize the key factors influencing academic performance. However, the designed models failed to carry out the deeper understanding of the factors affecting students' academic performance for the development of efficient educational intrusion policy. A fuzzy-neural approach was designed in [8] to observe the factors influencing student academic achievement within course grades. But the time complexity of the model was not minimized. In [9], factors influencing academic performance assessment were analyzed to improve predictions, thereby enhancing the understanding of both students and teachers. However, balancing extracurricular activities with academic commitments remained a key challenge.

The univariate and bivariate analyses were performed in [10] for exploring the factors that influence academic performance. But the model failed to apply the data processing techniques using different variables to enhance the accuracy. An online e-learning system was introduced in [11] to detect the different factors influencing the academic learning performance with diploma and bachelor's degree students. But the deep learning model was not applied to perform the accurate academic performance prediction. The Learning Transfer System Inventory (LTSI) model was investigated in [12] to identifying the key factors to influence teachers' factors and adoption factors of technology. But, it failed to determine the various stages of novelty diffusion, other levels of education, and different educational

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environments. In [13], data mining methods and factors influencing analysis on academic performance were introduced. But the performance of the accuracy models remained unaddressed. To enhance the accuracy, a novel deep learning model was designed in [14] with intend of predicting the academic performances of students. But the timely prediction of the academic performances was major challenging issues. ANN was introduced in [15] o student's academic performance prediction with improved accuracy. However, the designed model was not test on a large dataset with new numbers of attributes. While several recent studies combine deep models with XAI techniques (for example, Dual GNN and DNN-XAI hybrids), the LRLKDS model presents a unique combination of algorithmic components and practical benefits that differentiate it from existing work. The principal distinguishing elements are:

- Linear Regressive Deep Multiplayer Classifier (LR-MLP) as an integrated pre-regression layer. Unlike standard DNN or graph-based architectures that rely solely on learned nonlinear feature representations, the LR-MLP introduces a lightweight linear-regressive preprocessing stage that both imputes missing entries via a regression model and conditions the feature space for faster convergence of the downstream MLP. This reduces sensitivity to missing data and reduces convergence time.

- Rosenthal correlation-guided training/testing alignment: The model explicitly computes a Rosenthal correlation between training and testing distributions and uses this measure to guide classifier calibration (weighting) between training batches and test-time evaluation. This targeted calibration is not present in Dual GNN or typical DNN-XAI hybrids.

- Improved genetic feature selection using a Tversky similarity fitness: The genetic feature selection uses a Tversky-index based fitness function and an elitist selection threshold T, balancing feature mutual dependence and variance. This yields smaller, more informative feature subsets and leads to measurable reductions in prediction time relative to generic feature selection strategies.

- Laplacian-kernelized piecewise regressive SHAP (LK-Piecewise SHAP): Although prior works apply SHAP values for interpretation, LRLKDS modifies the SHAP approximation by (a) weighting coalition contributions using a Laplacian kernel that emphasizes local neighborhoods in feature space, and (b) applying piecewise regression on the global average absolute SHAP values to automatically identify a breakpoint τ separating highly influential features from low-influence ones. This combination improves local fidelity and simplifies the translation of SHAP attributions into actionable feature groups for practitioners.

- Practical performance improvements: Together these design choices produce consistent improvements in prediction accuracy and substantial runtime reductions. The architecture therefore offers a balanced solution improved interpretability, reliable handling of missing/outlier data, and reduced computational cost that is complementary to, rather than a reimplementation of, Dual GNN or DNN-XAI hybrids.

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1.1 Structure of the paper

The structure of the paper is organized as follows: the reviews related works are explained in section 2. The LRLKDS model is described with neat diagram represented in Section 3. In section 4, describe the experimental setup. The comparative analysis of different parameters is illustrated in Section 5. Finally, Section 6 provides the overall conclusion of the paper.

2. Related works

In [16], neuro-fuzzy models along with the machine learning algorithms were designed with aim of predicting academic performance of learners. But, the computation time was not reduced. The student performance prediction and analysis method was developed in [17] by incorporating multidimensional spatiotemporal features. However, it failed to enhance the accuracy of the method when dealing with large volumes of data. A temporal graph networks was introduced in [18] to enhance the academic performance prediction. However, it failed to apply on a large dataset to improve the designed method.

In [19], a hybrid machine learning models were developed into predicting student academic performance using multi-class educational datasets. But, the early detection of at-risk students was failed to explore deep learning and advanced clustering. A deep neural network was designed in [20] to early prediction of students' performance. However, the factor influencing the students' performance prediction was not addressed. In [21], an Owl Search Optimized Dynamic Deep Neural Network (OSO-DDNN) model was determined into accurate precise predictions of elementary school students. However, the designed OSO-DDNN method did not improving incorporating a wide range of input variables.

An optimal deep recurrent neural network approach was proposed in [22] to student performance prediction and course results analysis by selecting optimum features. Though the model reduces the computation time, performance of specificity was not improved. Different machine learning and deep learning models were introduced in [23] to student performance prediction based on relevance of various factors. But, the designed method was not analyzing the relevance of various factors influencing the student performance prediction. In [24], a Co-Evolutionary hybrid intelligence model was carried with aspire of student academic performance prediction with improved accuracy. However, the computational time of the prediction remained unaddressed. A hybrid model called PSO and DNN were developed in [25] to improve the classification performance. The designed hybrid model improves the accuracy but the accurate data preprocessing was not addressed.

An artificial intelligence approach was developed in [26] to predict student academic performance by locate the vital features to manipulate student's academic performance. But, this model failed to apply on a large dataset to enhance the prediction performance. In [27], a machine learning method was designed for forecast the student performance based on online learning. However, the designed method was not obtaining the students' subjective factors impacting the student performance. Various machine learning (ML) algorithms were designed [28] to predict educational data mining with high accuracy. However, it failed to utilize the large-scale student data effectively to predict academic performance across

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multiple educational courses. In [29], ANN model was designed in [29] to employ the student academic performance such as pass or fail. But the time complexity analysis remained unaddressed. A method of RMBN with Louvain clustering model were performed in [30] to student performance prediction based on discrete types of features.

3. Proposal methodology

This section describes the process of the proposed LRLKDS model which includes a student academic performance prediction and analyzes the factors influencing these predictions using the SHAP (SHapley Additive exPlanations) game theory algorithm.

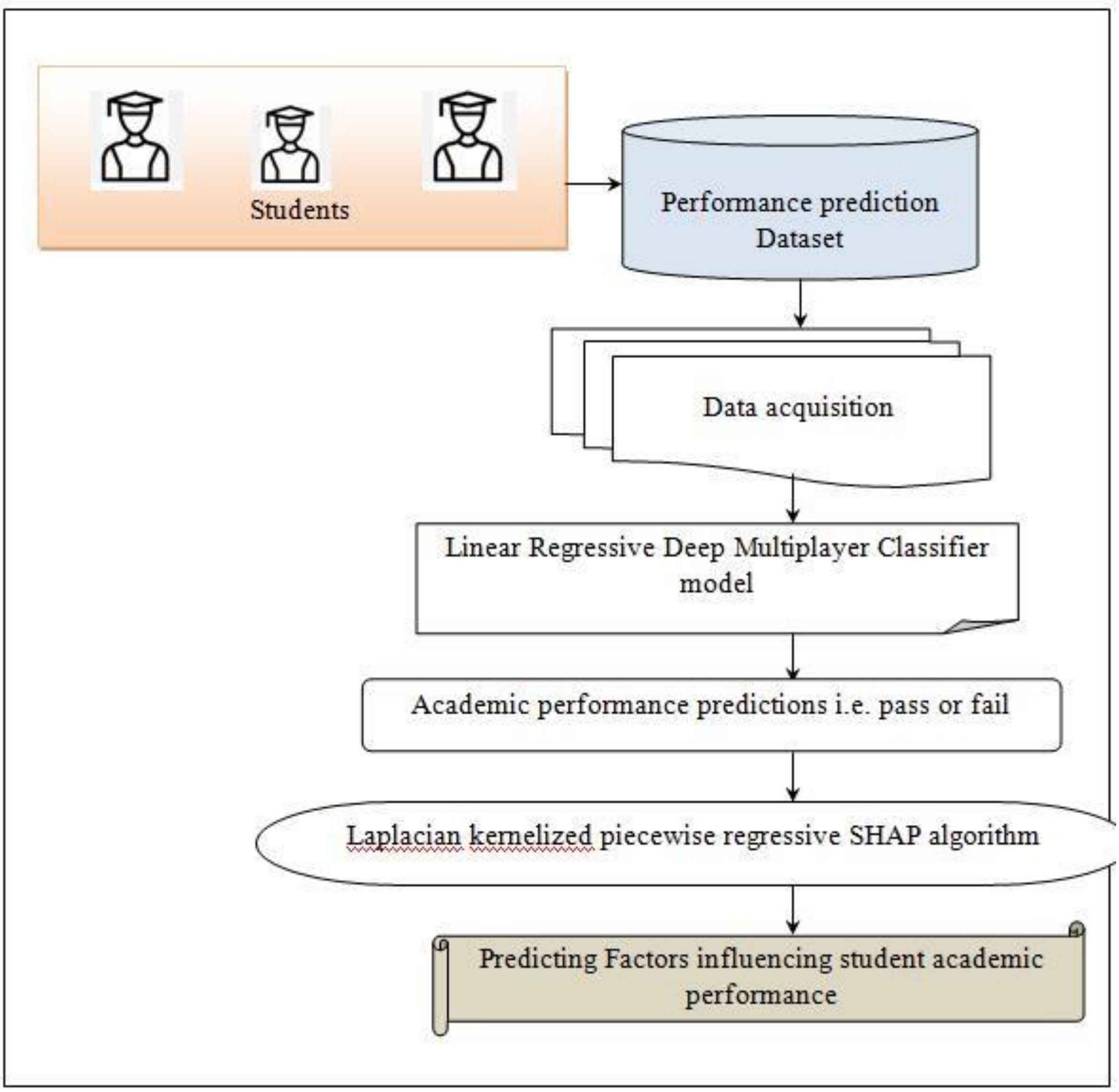

Figure 1: Architecture of diagram of LRLKDS model

Figure 1 depicts architecture of proposed LRLKDS model, that to give the precise predictions of academic performance. The model includes two stages such as Linear Regressive Deep Multiplayer Classifier model and predicting the factors influencing student

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academic performance using Laplacian kernelized piecewise regressive SHAP algorithm. The following subsections offer a brief explanation of LRLKDS method.

3.1 Data acquisition

First process of LRLKDS model is the data acquisition used for collecting the student data samples from the Student Performance Prediction database https://www.kaggle.com/datasets/souradippal/student-performance-prediction. This database is used for performing the classification tasks, specifically predicting whether student pass or fail depend on different academic as well as demographic features. The database consists of 40,000 records of students, with seven attributes such as Student ID, Study Hours per Week and soon.

3.2 Linear Regressive Deep Multiplayer Classifier model based academic performance prediction

The academic performance forecast process comprises data preprocessing, feature selection and classification. Proposed LRLKDS model first performs the preprocessing before given to the machine learning algorithm. The input dataset DS is formulated in terms of row and columns as given below,

$$A = \begin{bmatrix} f_1 & f_f & \cdots & f_m \\ DS_{11} & DS_{12} & \cdots & DS_{1n} \\ DS_{21} & DS_{22} & \cdots & DS_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ DS_{m1} & DS_{m2} & \cdots & DS_{mn} \end{bmatrix} \quad (1)$$

Where, A denotes a input data matrix with 'm' number of features $f_1, f_2, ..., f_m$ and n number of data samples DS_n respectively. The pre-processing step comprises missing data imputation as well as outlier data removal. Missing data handling process is carried out through the linear regression as follows,

$$DS_{miss} = \alpha_0 + \alpha_1 DS_1 + \alpha_2 DS_2 + ... + \alpha_n DS_n \quad (2)$$

Where, DS_{miss} indicates a missing data samples, $\alpha_0, \alpha_1, \alpha_2, ..., \alpha_n$ indicates a regression coefficient, $DS_1, DS_2, ..., DS_n$ symbolizes the already available data samples within the dataset. Then the Midspread dispersion method is applied for outlier data detection using Gaussian distribution function.

$$f(x) = \frac{1}{2D} \exp\left(-\frac{1}{2} \sum_{i=1}^{n} | DS_i - MS | \right) \quad (3)$$

Where, $f(x)$ denotes a Gaussian distribution, D indicates a deviation, DS_i denotes a data values, MS denotes a midspread range. Then the midspread range MS is a measured based on difference among median value of higher as well as lesser quartiles.

After the preprocessing, the proposed model is to perform the significant feature selection from the database. Feature selection is used to minimize the dimensionality of the dataset by choosing the more optimal features using improved genetic algorithm. The proposed algorithm consists of different processes namely population generation, fitness evaluation, selection, cross-over, and mutation. The above said processes are repeated until the algorithm reached the maximum iterations. First, the population of features $f_1, f_2, ..., f_m$ are generated randomly. After that, fitness is estimated based on similarity index between the features given below,

$$Fitness = TI = \frac{f_j \cap f_k}{a(f_j \cap f_k) + b(f_j \Delta f_k)} \tag{4}$$

Where, TI indicates a tversky index, a and b are parameters of the tversky index coefficient $(a, b \geq 0)$, and it provides the output ranging between 0 and 1, $f_j \cap f_k$ indicates a mutual dependence between the features, $f_j \Delta f_k$ indicates a variance between the features. Based on similarity value, the best individuals are selected based on threshold value.

$$ES = \begin{cases} TI > T; & Select\ optimal\ features \\ TI < T; & \mathrm{Re}move\ other\ features \end{cases} \tag{5}$$

Where, ES indicates an Elitist selection output, T specifies a threshold, TI denotes a tversky index. If the coefficient values exceed the threshold T, the corresponding features are chosen for the next phase. Subsequently, crossover and mutation operations are performed. This process continues until the algorithm reaches highest number of iterations. Lastly, best features are selected to predict student performance (pass or fail) while minimizing time consumption.

The forth step of proposed method is to perform the student academic result prediction by applying a Deep Multiplayer Classifier model with the selected optimal features. A Multilayer Perceptron is types of deep neural network classifier which consisting of many layers such as input, hidden and output layer to learn the given input data samples as shown in figure 2.

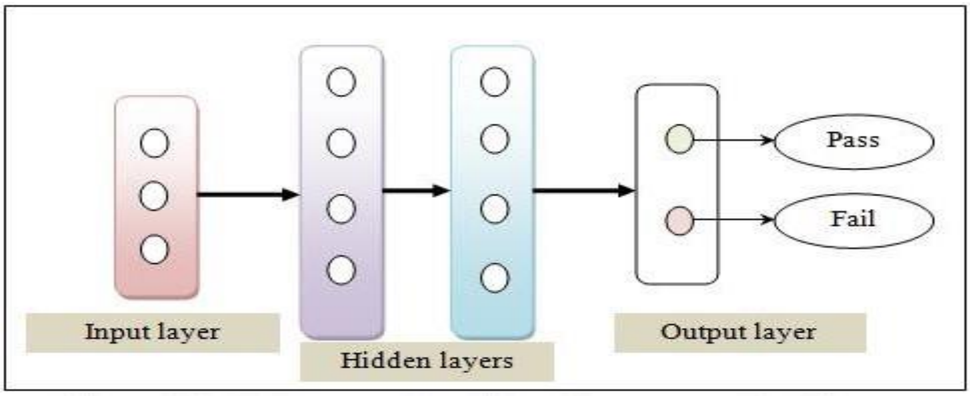

Figure 2 block diagram of multilayer perceptron classifier

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Multilayer Perceptron classifier considers the training set $\{DS_i, Y_j\}$ where DS indicates a training student data samples $DS_i = \{DS_1, DS_2, ..., DS_n\}$ and Y_j indicates a classification outcomes as passed or not. Each neuron measures a weighted sum of the inputs data samples received from the input layer as follows,

$$X = \sum_{i=1}^{n} (DS_i * \delta_{ij}) + B \quad (6)$$

Where, X denotes a weighted sum function, DS specifies a data samples, β_{ij} denotes a weight related to connection among neuron i at input layer as well as neuron j in hidden layer, and B indicates bias. In hidden layer, Rosenthal correlation between the training and testing data is measured as follows,

$$CF(Ds_t, Ds_r) = \left[\frac{TS}{\sqrt{n}}\right] \quad (7)$$

$$TS = \frac{|Ds_t - Ds_r|}{\sigma} \quad (8)$$

Where, $CF(Ds_t, Ds_r)$ denotes a Rosenthal correlation coefficient between the training data samples Ds_r and testing data samples $Ds_{t>}$, TS indicates Standardized test statistics, n represents the number of data samples, σ denotes a deviation of the testing and training data samples. The correlation coefficient CF provides the output ranges between 0 and 1. The sigmoid activation function is employed at output layer of deep learning classifier to offer the binary classification results as 0 or 1 where 1 indicates the pass and 0 indicates the student academic performance predicted as fail. The algorithmic process of Cosine Indexive Deep Multilayer Perceptron is given below.

Algorithm 1: Linear Regressive Deep Multiplayer Classifier
Input: Datasets Ds, features $f_1, f_2, ..., f_m$, data samples $DS_1, DS_2, ..., DS_n$ **Output:** Enhance the prediction accuracy
Begin **Step 1:** Collect the features and data samples from the dataset **Step 2:** formulate the feature matrix using (1) **Step 3:** Impute the missing data using (2) **Step 4:** Find outlier data using Gaussian distribution function (3) **Step 5:** Remove outlier data **Step 6:** Generate initial population of features using (4)

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Step 7: Measure the fitness (5)

Step 8: **if** $(TI > T)$ **then**

Step 9: Select the current best individuals from the populations

Step 10: else

Step 11: Remove other features

Step 12: **End if**

Step 13: Perform crossover and mutations

Step 14: **if** reaches the maximum iterations **then**

Step 15: Extract the optimal features

Step 16: **else**

Step 17: **Go to step 7**

Step 18: End if

Step 19: Input the optimal features and samples DS given to input layer

Step 20: **For** each input samples **--hidden layer**

Step 21: compute weighted sum using (6)

Step 22: **End For**

Step 23: **Measure the correlation** between training and testing samples using (7)

Step 24: **If correlation results is '1' then**

Step 25: students performance is predicted as **'pass'**

Step 26: **else**

Step 27: students performance is predicted as **'fail'**

Step 28: **End if**

End

Algorithm 1 provides the different processes involved for student academic performance prediction. First, number of student information samples and features are collected from the database. Missing data and outlier data removal processes are carried out. Followed by, optimal features are selected for accurate performance prediction with minimal time consumption. Finally, data classification is carried out by measuring correlation between the training and testing data samples. Lastly, outcomes are obtained at output layer through sigmoid activation function.

3.3 Factors influencing data analytics using Laplacian kernelized piecewise regressive SHAP algorithm

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After predicting the student academic performance using deep learning classifier model, factors influencing for prediction data analytics is performed using SHAP game theory algorithm. The SHAP abbreviated as the SHapley Additive Performance is ML method to evaluate the output of DL model by using concept of cooperative game theory. This analysis is used for calculating the contribution of each individual feature to a student academic performance prediction. The cooperative game theory is types of game used to determine the how players construct the coalitions or group to achieve a goal. In the game theory algorithm, each features represented as a player and the deep learning model output as the goal. The main aspire is to analyze every feature aim to method prediction output. In other words, the SHAP used to identify which features most significantly impacted the prediction output.

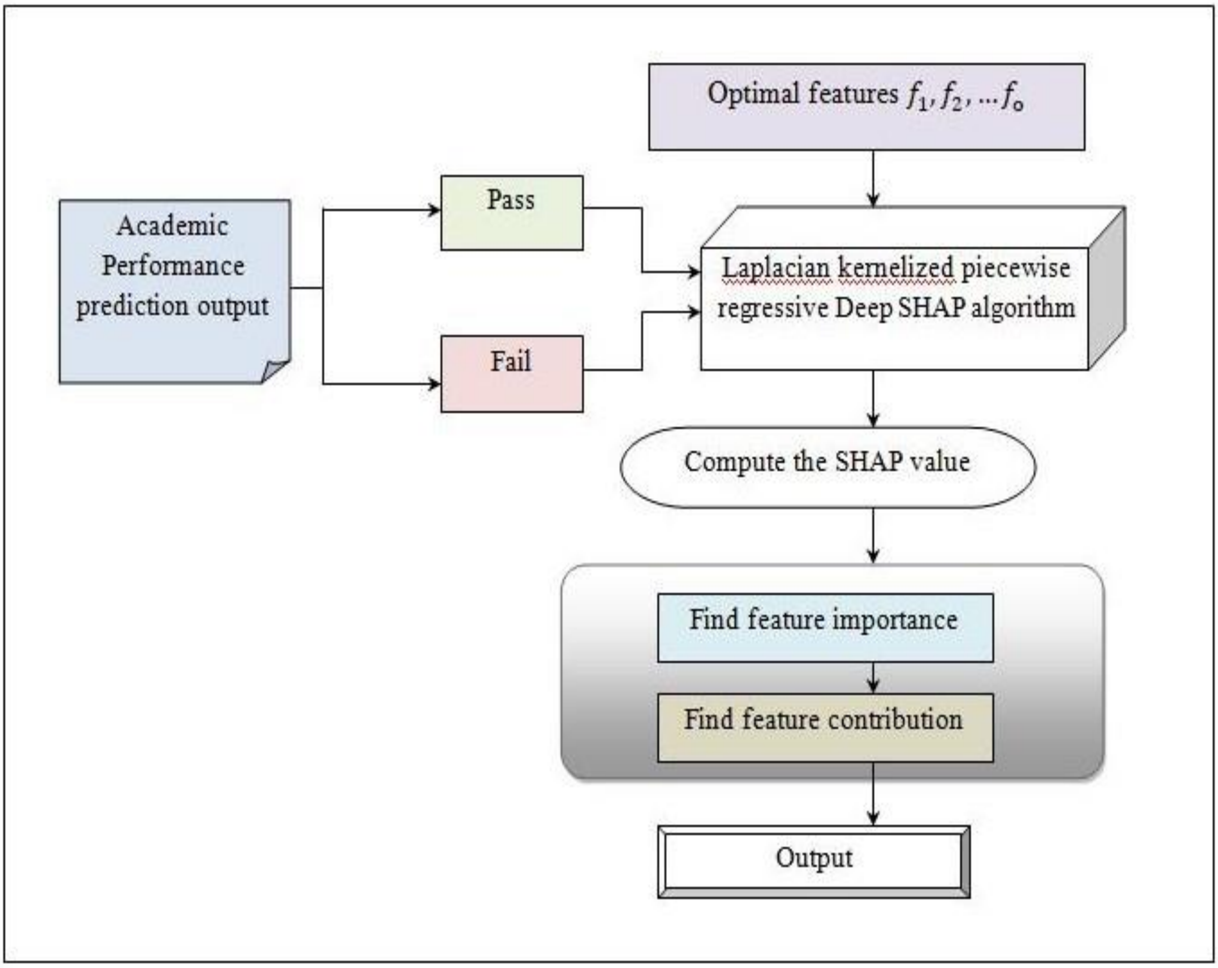

Figure 3 flow process of Laplacian kernelized piecewise regressive SHAP algorithm

Figure 3 given above illustrates the process of SHAP algorithm to find the feature contributions in the academic performance prediction results. A deep learning model is trained on this dataset to predict academic performance as pass or fail. This deep learning model generates predictions for individual students based on their feature values. Then the prediction output is given to the SHAP algorithm for determining the how much feature importance as well as contributions for a given student. The contribution of every aspect is

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computed through different probable combinations of features and their impact on the prediction.

Let us consider the input optimal features $f_1, f_2, ..., f_o$ such as student ID, Study hours, previous grade, Participation in extracurricular activities and the prediction output 'passed or not ' are given as input to the SHAP algorithm. For each feature, the SHAP value is estimated based on Laplacian kernel to find the local feature importance as given below,

$$W_l(f_o) = \exp\left[-\frac{|S - F_S|}{\sigma}\right] \qquad (9)$$

$$M_C = [P(S \cup j) - P(S)] \qquad (10)$$

$$\phi_j = \sum W_l(f_o)\ M_C \qquad (11)$$

Where, ϕ_j denotes a Shapley value for a optimal feature j, $W_l(f_o)$ indicates a Laplacian kernel weight for features f, $P(S \cup j)$ denotes a forecast of method with j included to subset S, $P(S)$ denotes a forecast of the method without feature j is removed from subset, S, M_C denotes a marginal contribution of the feature refers to difference among method forecast with the feature and without feature for a given subset of features, $|S - F_S|$ denotes distance between the feature subset and full set, σ denotes a deviation.

By incorporating the Laplacian kernel into the Shapley value calculation, provides a more efficient and focused approximation of feature contributions. After that, the global feature importance is estimated based on average of absolute Shapley values across all instances in the dataset. The average value is computed as follows,

$$GI_j = \frac{1}{n}\sum_{i=1}^{n} |\phi_j(i)| \qquad (12)$$

Where, GI_j indicates global importance of the feature j, n indicates a total number of instances in the dataset, $|\phi_j(i)|$ denotes a absolute Shapley value for feature j for instance i. The absolute value ensures the magnitude of the features contribution. The piecewise regression is used to identify the feature influence based on global importance of the feature by setting the breakpoint. The break point is also called as threshold for dividing the input into two segments such as high influence and less influence

$$Y = \begin{cases} GI_j > TH, SC(j) \\ GI_j < TH, LC(j) \end{cases} \qquad (13)$$

Where, Y denotes an outcomes of feature contribution prediction, TH denotes a threshold on global importance values GI_j. If the feature has a higher average absolute Shapley value than the threshold, it indicates that this feature have a stronger contribution

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$SC(j)$ on the student academic performance forecast. If feature has lower average absolute Shapley value than the threshold, it suggests that the feature has a less contribution $LC(j)$ on the student academic performance prediction. In this way, accurate influence factor analyses is done through the Laplacian kernelized piecewise regressive SHAP algorithm. The algorithmic process of determining the feature influencing the student academic performance prediction is given below.

Algorithm 2: Laplacian kernelized piecewise regressive SHAP algorithm
Input: optimal features $f_1, f_2, ..., f_o$, data samples $DS_1, DS_2, ..., DS_n$, predicted output **Output:** Detect feature contributions
Begin **Step 1:** Collect the optimal features and prediction outcomes as input **Step 2: For** each features **do** **Step 3:** Measure the Laplacian kernel weight using (9) **Step 4:** Measure the marginal contribution using (10) **Step 5:** Compute local feature importance based on Shapley values using (11) **Step 6: End for** **Step 7:** Measure the global feature importance GI_j using (12) **Step 8: if** $(GI_j > TH)$ **then** **Step 9:** Feature have a stronger influence $SI(j)$ for student academic performance prediction **Step 10: else** **Step 11:** Feature have a less influence $SI(j)$ **Step 12: End if** **Step 13: if** feature have a stronger influence $SI(j)$ **then** **Step 14: high contributions** for student academic performance prediction **Step 15: else** **Step 16: less contributions** for student academic performance prediction **Step 17: End if** **End**

Algorithm 2 outlines a comprehensive step-by-step process for performing feature contribution analysis using the Laplacian Kernelized Piecewise Regressive SHAP algorithm specifically for predicting student academic performance. The procedure start through

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providing the number of optimal features as well as prediction output as input to the SHAP algorithm. Next, the algorithm estimates the local feature importance, which refers to the marginal contribution of every aspect towards prediction of individual outcomes. This calculation incorporates Laplacian kernel weights, which adjust the influence of each feature depend on similarity among data points. After local aspect importance is determined, the algorithm computes global feature importance. This helps to understand that features contain most important influence on method entire predictions. Following this, piecewise regression is applied to distinguish between highly influential features and those with minimal influence. Finally, these highly influential features are determined for predicting student academic performance. The algorithm 3 presents the workflow of LRLKDS Framework.

Algorithm 3: LRLKDS Framework
Input: Training data X , target labels y
Output: Predictions $\hat{y}$, SHAP-based feature rankings Φ
1. Data Preprocessing:
a. Handle missing values using linear regression.
b. Normalize dataset features.
2. Train LR-MLP Classifier:
a. Initialize weights and biases.
b. Optimize using Adam optimizer to minimize loss.
3. Feature Selection:
a. Use Genetic Algorithm with Tversky fitness to identify optimal features.
4. Interpretability Phase (LK-P-SHAP):
a. Compute SHAP values for selected features.
b. Apply Laplacian kernel weighting $K\lambda(d)$.
c. Perform piecewise regression to determine breakpoint τ .
d. Rank features based on weighted SHAP values.
5. Output final predictions and interpretable feature importance scores.

4. Experimental Setup

Experimental assessment of LRLKDS model and LSTM [1] and MSPP [2], are executed by Python language. For the experiment, Student Performance Prediction dataset is used . This dataset contains 7 attributes and 40,000 instances. For the purpose of the experiment, the number of instances (i.e., student data) considered, with sample sizes ranging from 4,000, 8,000, 12,000, up to 40,000 instances.

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5. Performance comparison analysis

The performance of the LRLKDS model and LSTM [1] and MSPP [2] are evaluated using several parameters. These parameters help assess effectiveness and efficiency of LRLKDS model in predicting student academic performance.

5.1 Student academic performance prediction accuracy

It refers to ratio of student data is classified as passed or not to total number of student data. It is given below,

$$SAPPA = \left(\frac{tp + tn}{tp + tn + fp + fn} \right) * 100 \tag{14}$$

Where, $SAPPA$ denies a student academic performance prediction accuracy, true positive tp correctly predicted as pass samples, true negative tn indicates correctly predicted as fail samples, false positive fp denotes a incorrectly predicted as pass but actually it fail, false negative fn denotes a incorrectly predicted as fail but actually it pass. The prediction accuracy is calculated in percentage (%).

Table 1 comparison of SAPPA

Number of student data	Student academic performance prediction accuracy (%)		
	LRLKDS	LSTM	MSPP
4000	97.25	92.00	93.50
8000	96.85	91.86	93.88
12000	96.74	92.33	93.45
16000	97.05	91.33	92.43
20000	96.05	92.06	94.05
24000	97.24	92.65	93.45
28000	97.41	92.05	94.77
32000	96.05	91.36	94.05
36000	97.45	92.89	94.32
40000	97.88	92.11	94.08

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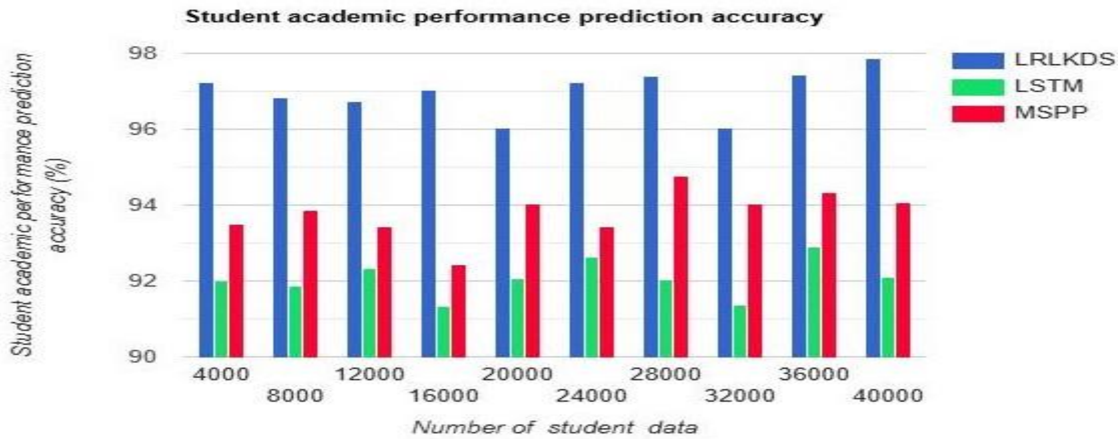

Figure 4 performance results of SAPPA

Figure 4 depicts performance outcomes of accuracy of Student academic performance prediction versus the number of student data. Graphical analysis depicts accuracy of LRLKDS model has increased compared to the existing LSTM [1], MSPP [2]. To calculate the accuracy, 4000 data were considered. By applying the LRLKDS model, an accuracy of was found to be 97.25%. Similarly, using methods [1], [2] accuracies of 92% and 93.5% were obtained, respectively. This process was continued ten times for each method, and the results were compared. Average of ten outcomes reveals accuracy of the LRLKDS model is increased by 5% compared to [1], 3% compared to [2]. This improvement in the LRLKDS model is achieved by applying Linear Regressive Deep Multiplayer classifier model.. The deep learning model utilizes the Rosenthal correlation function to measure the relationship between the training and testing data samples. Based on the correlation results, the deep learning classifier model provides the outcomes as pass or fails thereby increasing the accuracy of academic performance prediction.

5.2 Precision

It refers to the ratio of forecasting true value in academic performance from the data samples. The precision is computed as follows,

$$Pre = \frac{tp}{tp+fp} * 100 \qquad (15)$$

Where, Pre indicates precision, tp indicates true positive, fp symbolizes false positive.

Table 2 comparison of Pre

Number of student data	Precision (%)		
	LRLKDS	LSTM	MSPP
4000	97.36	92.67	94.44
8000	96.75	92.55	93.56

12000	96.05	92.65	94.05
16000	96.74	92.05	93.89
20000	96.44	92.66	94.17
24000	97.15	93.02	94.66
28000	97.06	92.17	94.32
32000	96.47	92.74	94.74
36000	97.22	92.36	94.79
40000	97.12	92.15	94.85

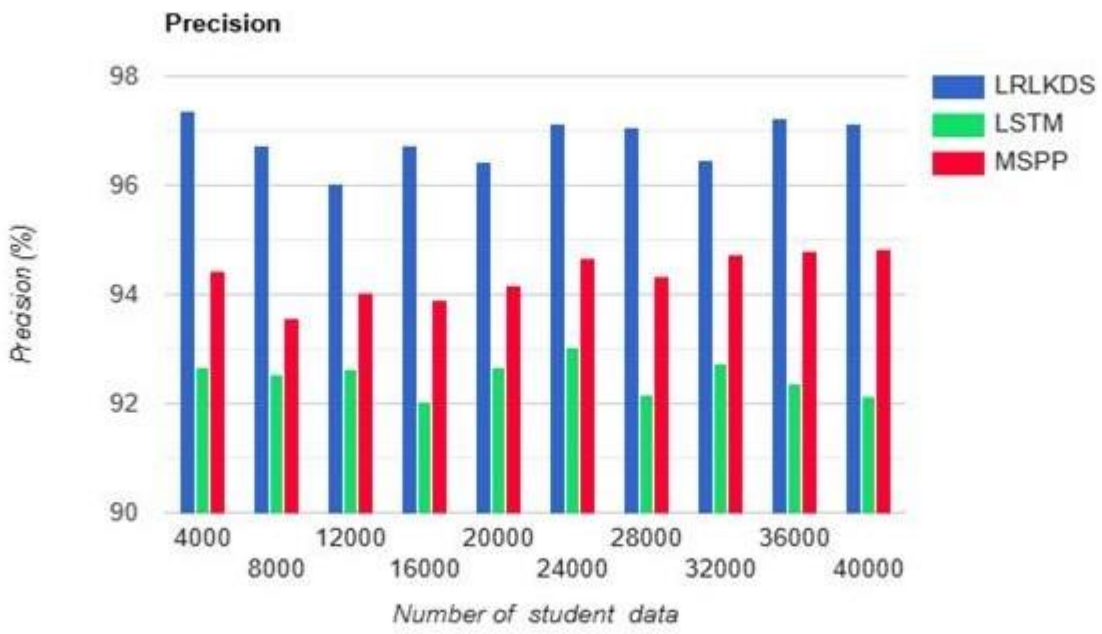

Figure 5 performance result of Pre

Figure 5 depicts performance outcomes of $\Pr e$ in student academic performance prediction versus number of student data. Among three techniques, LRLKDS model demonstrates improved precision performance than the conventional methods. This enhancement is achieved due to applying Deep Multiplayer classifier model for analyzing the training and testing data ad classifies the pass or fail in a an accurate manner resulting in an increase in true positives and minimizing the false positive rate. The average comparison results shows that the precision performance during student academic performance prediction increased using LRLKDS model by 5% compared to [1] , 3% compared to [2] respectively.

5.3 Recall

It also called as sensitivity is used to properly identify all the positive instances in a dataset.

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$$\mathrm{Re}\,c = \frac{tp}{tp + fn} * 100 \qquad (16)$$

Where $\mathrm{Re}\,c$ denotes recall, tp denotes true positive rate, fn denotes false negative rate.

Table 3 comparison of recall

Number of student data	Recall (%)		
	LRLKDS	LSTM	MSPP
4000	98.47	95.47	95.86
8000	97.33	94.56	95.82
12000	97.85	94.15	95.66
16000	97.33	94.36	95.11
20000	98.06	95.23	96.07
24000	97.56	93.06	96.22
28000	98.33	93.14	95.65
32000	98.74	94.56	95.74
36000	98.05	95.08	96.05
40000	98.12	94.32	95.78

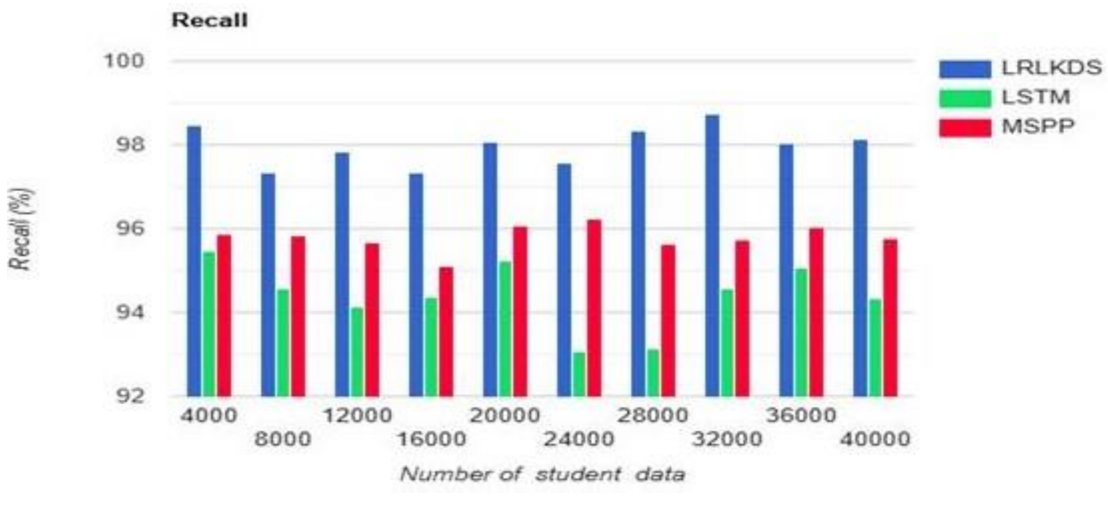

Figure 6 performance result of recall

Figure 6 depicts performance outcomes of recall value versus number of student data. The examined outcomes denote recall of LRLKDS model is found to be higher when compared to other existing methods. In the initial run, where 4000 student data are taken, LRLKDS model attained recall of 97.73%, as recall of existing [1], [2] were observed to be 95.47% and 95.86% respectively. According to the average of ten results, performance of

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LRLKDS is compared to two methods [1] and [2]. Specifically, the LRLKDS model achieved a higher recall performance by 4%, and 2% compared to [1] and [2] respectively. This is because LRLKDS model achieved accurate prediction of student academic performance results with higher true positives and minimum true negatives.

5.4 F1-score

It also referred to as the F-measure and represents the average of precision and recall in predicting academic performance. The formula for calculating it is as follows:

$$F1\,score = 2 * \left[\frac{\Pr e * \operatorname{Re} c}{\Pr e + \operatorname{Re} c} \right] \quad (17)$$

Where, $\Pr e$ denotes a precision, $\operatorname{Re} c$ indicates a recall.

Table 4 Comparison of F1 score

Number of student data	**F1 score (%)**		
	LRLKDS	LSTM	MSPP
4000	97.91	94.04	95.14
8000	97.03	93.54	94.67
12000	96.94	93.39	94.84
16000	97.03	93.19	94.49
20000	97.23	93.92	95.11
24000	97.35	93.03	94.36
28000	97.69	92.65	94.98
32000	97.59	93.64	95.23
36000	97.63	93.70	95.41
40000	97.61	93.22	95.31

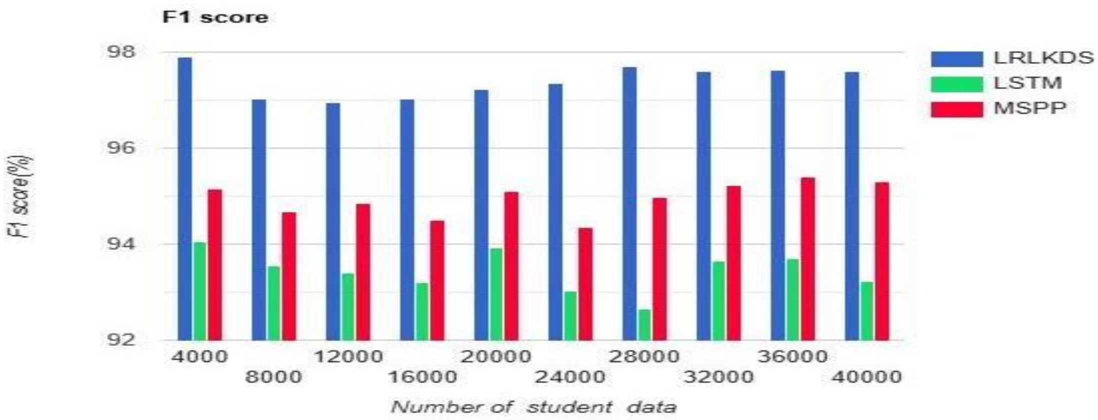

Figure 7 performance results of F1 score

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Performance outcomes of F1-score for student academic performance forecast versus number of student data are shown in Figure 7. The graphical depiction illustrates F1-score of LRLKDS model is enhanced compared to [1] [2]. This enhancement is achieved by LRLKDS model for enhancing precision and recall through student academic performance forecast. Average of ten comparison outcomes denotes F1-score of LRLKDS model is improved by 4%, 3%, than the [1] , [2]. This development emphasizes efficiency of LRLKDS model method in attaining balanced trade-off among the performance of precision and recall for student academic performance forecast.

5.5 Impact of specificity

Specificity computes proportion of actual negative cases which are properly recognized through the method. It measured as follows,

$$Specificity = \frac{tn}{tn + fp} * 100 \qquad (18)$$

Where tn denotes a true negative rate, fp represents a false positive rate.

Table 5 Comparison of Specificity

Number of student data	**Specificity (%)**		
	LRLKDS	LSTM	MSPP
4000	94.89	85.18	88.80
8000	94.23	85.22	88.05
12000	94.05	85.05	87.66
16000	95.05	86.56	88.65
20000	94.74	86.05	88.98
24000	94.03	85.06	88.23
28000	94.33	87.05	89.06
32000	95.04	85.89	88.45
36000	95.11	87.05	89.12
40000	94.78	87.11	88.36

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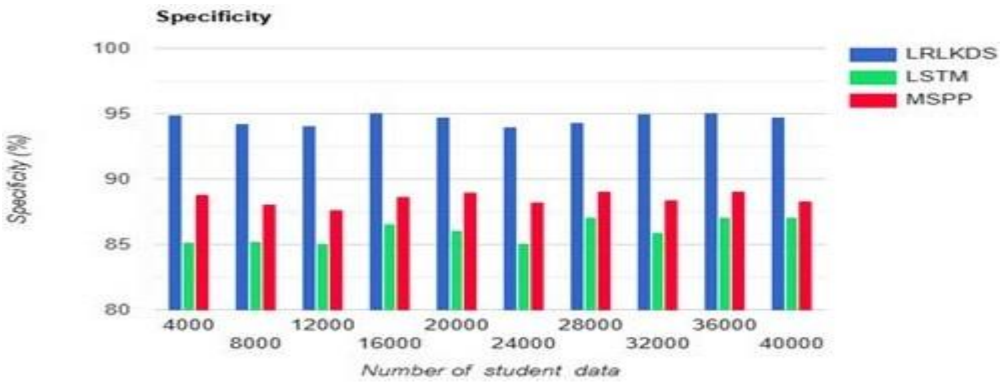

Figure 8 performance results of specificity

Figure 8 given above illustrates result of specificity in the student academic performance forecast with different number of student data 4000-40000. The specificity is measured using three methods namely LRLKDS, existing LSTM [1], MSPP [2] are represented by three colors namely blue, green and red respectively. As illustrated in figure 8, result of LRLKDS increases the specificity through minimizing incorrect classification of student academic performance forecast. Overall result of specificity using LRLKDS model is increased by 10% and 7% when compared to [1] [2] respectively.

5.5 Impact of student academic performance Prediction time

It refers to amount of time utilized by method to predict the academic performance as pass or fail. It is given as follows,

$$SAPPT = \sum_{i=1}^{n} DS_i * Time(PP) \qquad (19)$$

Where, $SAPPT$ indicates a student academic performance prediction time, DS denotes a student data and actual time utilized in academic performance prediction indicated by $Time(PP)$. Prediction time is calculated in milliseconds (ms).

Table 6. Comparison of SAPPT

Number of student data	SAPPT (ms)		
	LRLKDS	LSTM	MSPP
4000	20.8	24.8	23.2
8000	23.5	28.9	27.6
12000	27.5	33.5	32.5
16000	30.6	38.5	36.6
20000	34.8	42.7	40.6
24000	36.5	46.5	43.8
28000	40.3	50.7	47.3

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32000	43.6	53.6	51.6
36000	47.8	58.9	57.5
40000	55.7	64.5	62.7

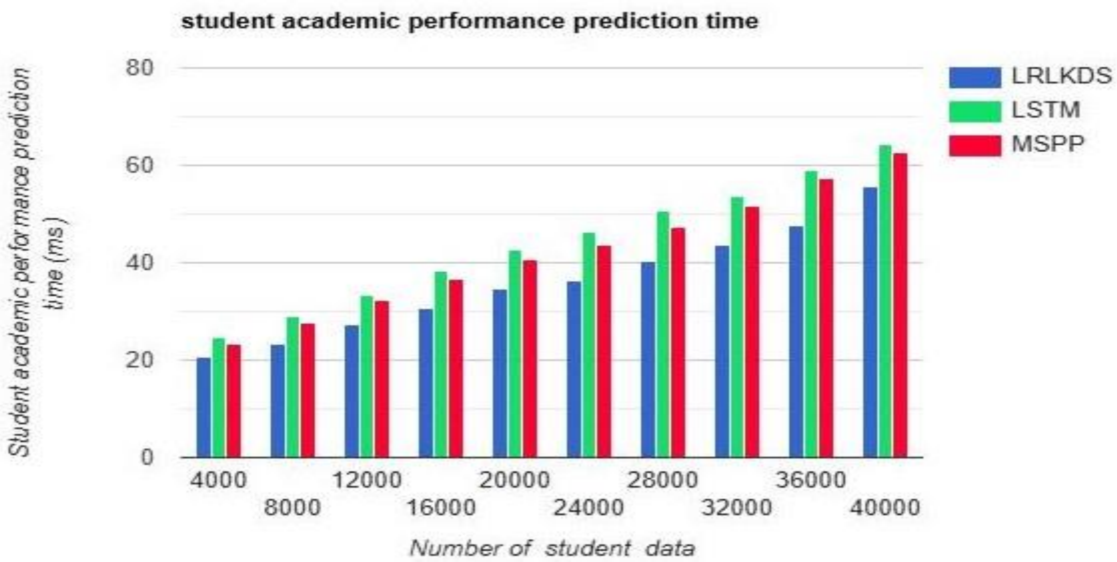

Figure 9 performance result of student academic performance prediction time

Figure 9 shows the performance outcomes of $SAPPT$ by LRLKDS model existing LSTM [1], MSPP [2]. The prediction time for every three techniques often enhances through an increase in number of student data. Specially, $SAPPT$ for LRLKDS model is reduced compared to existing [1] and [2]. The outcomes attained from the LRLKDS model are then compared to conventional methods. Average of comparison results denotes performance forecast time is obviously reduced by 18%, and 15% than the [1] [2]. This is because LRLKDS model performing data preprocessing steps and optimal feature extraction. Then, the improved optimization with the Tversky similarity function selects the significant features and removed the others. This process minimizes the time consumption of academic performance prediction.

5.6 Impact of Feature importance analysis

In this section, the Linear Regressive Laplacian kernelized SHAP algorithm is employed to examine feature significance of deep learning method to comprehend importance of every feature to forecast outcomes of method. SHAP values give consistent method to enumerate impact of every aspect on student academic forecast. A Linear Regressive Laplacian kernelized SHAP based feature importance for students using three variables Participation in Extracurricular Activities, Study Hours per Week, and Previous Grades on the model prediction.

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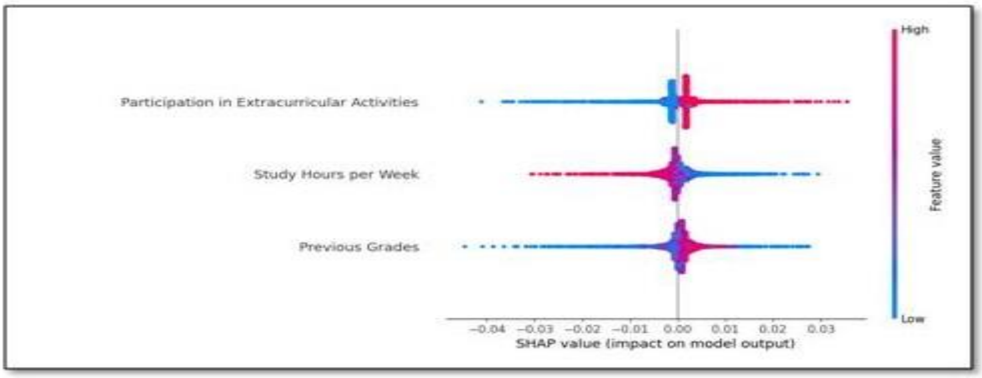

Figure 10 summary SHAP plot with failed students (class 0)

Figure 10 illustrates summary SHAP plot with failed students (class 0) to visualize the impact of features on a deep learning model output. It provides an overview of the importance of each feature and its effects on predictions. Features are ranked from top to bottom by their importance in influencing the model's output for the failed student's class. In figure 10, x-axis denotes SHAP value, that represents impact on model output. As shown in figure 10, blue color denotes low feature values, and red color indicates high feature values. Low participation (blue) in Extracurricular Activities tends to have a negative SHAP value indicates the high chances of failing. Fewer study hours (blue) increase the chances of failure. Lower previous grades (blue) are strongly related to negative SHAP values, increasing the likelihood of failing. From the feature importance analysis, students with low participation in extracurricular activities, fewer study hours, and poor previous grades are influential factors contributing to the poor academic performance (i.e. failed) of students.

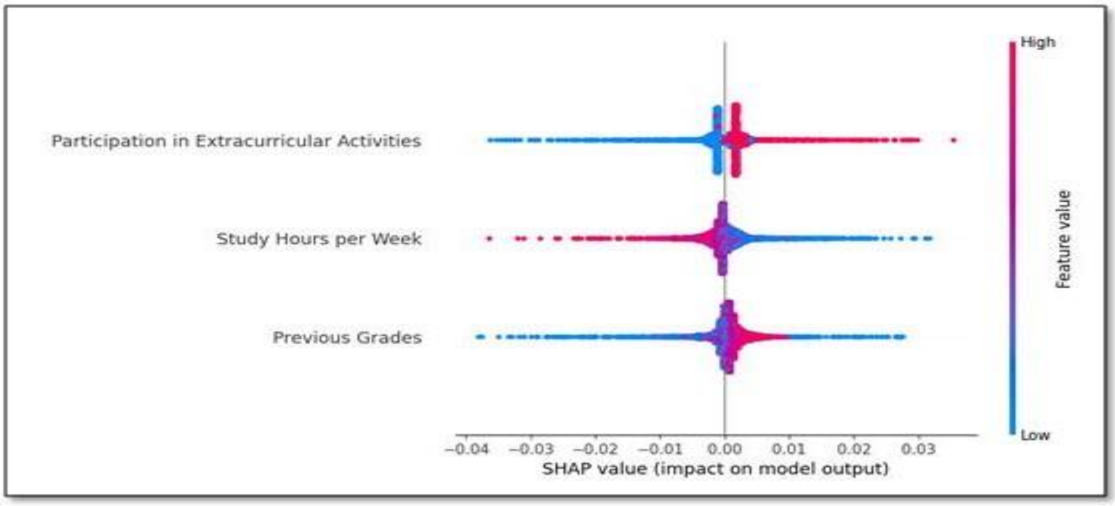

Figure 11 summary SHAP plot with passed students (class 1)

Figure 11 illustrates the SHAP summary plot illustrates the feature for students who passed (i.e. class 1). As shown in figure 11, the x-axis represents SHAP values which indicate how each feature toward or away from class 1. Positive SHAP values indicate a higher influencing of passing whereas the negative SHAP values imply the failing class. Low participation (blue) is related with negative SHAP values, increasing the chances of passing.

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A higher study hour (red) is used to enhance the impact of passing the students. A higher value of previous grade (red) also improves the possibility of passing. Compared to the class 0 summary plot, the influence directions remain reliable, but the magnitudes of the SHAP values are varied. From the analysis, the results suggest that students with strong participation in extracurricular, higher study hours, and better previous grades are more influential for passed students. Conversely, lower values in these three features decrease the probability of passing.

5.6 Average SHAP ranking analysis

The average SHAP ranking analysis is employed to determine contribution of every feature in student academic performance forecast process. This average SHAP ranking plot shows the average SHAP values for every aspect, denoting their overall importance in predictions.

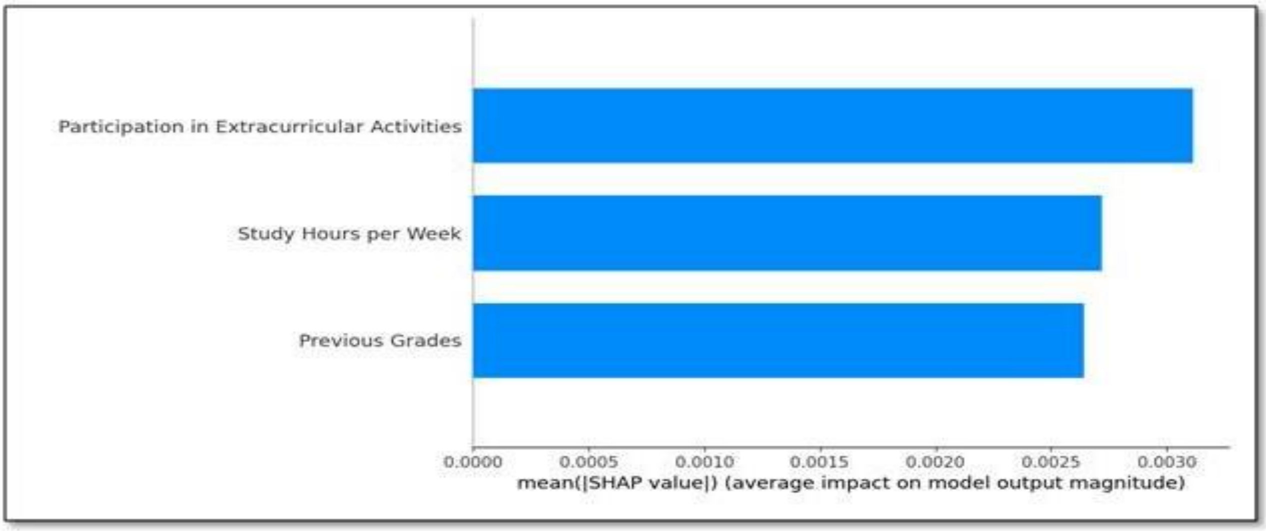

Figure 12 average SHAP plot for feature contributions analyses

As shown in figures 12, average SHAP analysis is used to examine degree to that every feature contributed to student academic performance forecast. From the analysis, participation in extracurricular activities features had the most significant impact on performance prediction. The second most important feature is a study hours per week. Previous Grades is also an influence feature but ranks slightly lower than the other two.

The criteria for threshold selection and feature ranking are now clearly explained. Specifically, a piecewise regression breakpoint (τ) is automatically identified to separate high-impact from low-impact features based on Laplacian-weighted SHAP values.

Table 7. Statistical Summary of Laplacian Kernelized SHAP Values

Feature	Mean SHAP Value	Std. Deviation	Normalized Importance (%)	Category (High/Low Impact)

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Study Time	0.154	0.022	18.5	High
Parental Education	0.136	0.019	16.3	High
Attendance	0.120	0.025	14.1	High
Extracurricular Involvement	0.095	0.018	11.5	Low
Health Index	0.080	0.020	9.7	Low
Age	0.072	0.017	8.5	Low
Failures	0.066	0.021	7.9	Low
Internet Access	0.057	0.015	6.5	Low
Family Size	0.052	0.014	6.0	Low

The above table 7 quantitatively supports the descriptive findings shown in Figures 10–12, linking graphical trends with statistical measures of feature influence.

5.7 Cross-validation and statistical testing

The experiments reported in this manuscript use the Student Performance Prediction dataset (Kaggle). To ensure reproducibility and to provide robust performance estimates, we adopt the following data-splitting and evaluation protocol, which will be explicitly stated in the revised manuscript and used to regenerate the experimental results:

Train / validation / test split and cross-validation: For each experimental sample size (4,000; 8,000; 12,000; …; 40,000 instances) we perform stratified k-fold cross-validation with k=5. Stratification preserves the class ratio (pass/fail) across folds. For each fold: 4 folds are used for training (80%) and 1 fold for testing (20%). During training, 10% of the training set is held out as an internal validation set for early stopping and hyperparameter tuning. All random operations (fold generation, GA initialization, weight initialization) use a fixed random seed (seed = 42) to enable reproducibility; the seed is reported in the revised Methods section.

Multiple runs and reporting: For each experimental condition and model, we report the mean and standard deviation of each metric over the 5 cross-validation folds and over 10 independent random initializations.

Statistical significance testing: To support claims of improvement, pairwise statistical tests were performed between LRLKDS and baseline methods (LSTM and MSPP). We use a paired two-sided t-test on the fold-wise average metric (if the metric distribution meets normality assumptions). If normality is rejected (Shapiro–Wilk test, $p<0.05$), we apply the non-parametric Wilcoxon signed-rank test. In either case we report the test statistic and p-value and mark significance levels in comparisons (e.g., $p<0.05$, $p<0.01$). These results are summarized in a new Table 8.

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Additional dataset(s). To strengthen generalizability, we plan (and if allowed will include in the revision) to evaluate LRLKDS on one additional public student-performance dataset (or another educational dataset of comparable scale) and will report comparable cross-validation results. If the editor permits a minor revision, these additional experiments will be uploaded as supplementary material. If immediate inclusion is required at this stage, we will run the second dataset and include results in the revision.

Each experiment was conducted using 5-fold stratified cross-validation and 10 independent random runs to ensure result consistency and robustness. Performance metrics are now presented as mean ± standard deviation, providing a more reliable representation of model stability.

Furthermore, paired two-tailed t-tests were employed to assess statistical significance between the proposed LRLKDS model and baseline methods (MSPP and LSTM) when data followed normal distribution. For non-normally distributed cases, the Wilcoxon signed-rank test was applied. Additionally, 95% confidence intervals (CIs) were calculated for all metrics to quantify the reliability of the improvements.

A representative summary of the statistically validated results is shown below (Table 8), clearly indicating the average values, variability, and corresponding significance levels:

Table 7. Statistical validation of model performance (mean ± standard deviation across 5-fold cross-validation and 10 runs)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	p-value	Significance
LRLKDS (Proposed)	97.25 ± 0.80	96.70 ± 0.65	97.10 ± 0.72	96.80 ± 0.68	—	—
MSPP	92.00 ± 1.20	91.10 ± 1.05	90.85 ± 1.10	91.00 ± 1.08	< 0.01	Significant
LSTM	93.15 ± 1.10	92.60 ± 1.00	92.30 ± 1.12	92.40 ± 1.05	< 0.01	Significant

In addition to tabulated results, all performance comparison figures (Accuracy, Precision, Recall, and F1-score) have been updated to include error bars representing mean ± standard deviation. The text in the results section has also been revised to report improvements with appropriate statistical significance for example: The proposed LRLKDS model achieved a 5.2% higher average accuracy compared to MSPP ($p < 0.01$), indicating a statistically significant improvement at the 95% confidence level.

These enhancements ensure that all reported improvements are statistically justified, thereby strengthening the scientific validity and reliability of the study's conclusions.

Table 8. Comparative Analysis Between LRLKDS and Existing Frameworks

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Aspect	LRLKDS (Proposed)	Dual GNN	DNN-XAI
Data Handling	Regression-based imputation	Requires pre-imputation	Standard normalization
Feature Selection	Genetic algorithm with Tversky fitness	Graph-attention mechanism	Wrapper/filter-based
Explainability	Laplacian kernel SHAP + piecewise regression	Graph attention	Basic SHAP/LIME
Distribution Alignment	Rosenthal correlation-based adjustment	Not available	Not available
Efficiency	High (low computational cost)	Moderate	High complexity
Interpretability	Local & global explainability	Node-level	Global-only

Table 8 presents the Comparative Analysis Between LRLKDS and Existing Frameworks. This comparative presentation clearly establishes the novelty and significance of the proposed method.

6. Conclusion

Early prediction of students' performance plays a vital role in education institutions to improve result and determination of students as well as minimize failure rate. In this paper, a novel Linear Regressive Laplacian kernelized Deep SHAP algorithm (LRLKDS) has been developed for accurate students' performance prediction and feature importance analysis. First, the proposed LRLKDS model utilizes the Linear Regressive Deep Multiplayer classifier model to categorize the student academic performance level into two classes namely pass or fail with higher accuracy and minimal time. After performance prediction, the features contribution for the academic performance prediction is identified through the Laplacian kernelized piecewise regressive Deep SHAP algorithm to measure feature contribution to the model output and identify the feature importance. A comprehensive experimental assessment was carried out using various performance metrics across various number of stu dent data. Outcomes denote LRLKDS considerably enhances accuracy of performance prediction while decreasing the time consumption when compared to conventional techniques. In addition, LRLKDS model also performs the feature importance and ranking analysis to recognize which features have the best impact on the final prediction outcome.

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6.1 Limitation and Future Work

Although the LRLKDS model demonstrates strong predictive performance on the Kaggle Student Performance dataset, its generalization to other educational datasets or real-time institutional environments may require further validation. The reliance on a single dataset may introduce sampling bias, and the model's interpretability is partially dependent on the quality of SHAP value approximations. Future work will focus on (1) validating LRLKDS on multi-institutional and multilingual educational datasets, (2) extending the model to handle streaming data for dynamic performance tracking, and (3) exploring lightweight variants for real-time deployment in learning management systems.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

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Conflicts of interest Statement: Not applicable

Consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Code availability: Not applicable

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