Indian Engineering Journal
ISSN: 2984-9047
Vol 4 Issue 2 (2026)

A Hybrid Probabilistic Local Robust Expectile Graph Attention Network for Student Academic Performance Prediction with Mental Health Indicators

M.Thenmozhi[1], J. Vandarkuzhali[2]

[1]PG and Research Department of Computer Science, Erode Arts and Science College (Autonomous)
Erode, India.
mthenmozhimsc@gmail.com

[2]PG and Research Department of Computer Science, Erode Arts and Science College (Autonomous)
Erode, India.
j.vandarkuzhali@easc.ac.in

Abstract:

Student academic performance prediction has become important one for educational institutions with support systems. Student academic performance is influenced by both cognitive abilities and psychological well-being. Mental health affects the student academic performance and impacts the physical and mental development, social interaction and future careers. Different machine learning and deep learning techniques are employed to compute relationship between mental health conditions and academic performance. But, the inaccurate prediction was carried out by existing methods as mental health changes frequently over time.

In addition, the existing methods failed to identify the most relevant psychological indicators. In order to address these issues, a new intelligent hybrid predictive model called Probabilistic Local Robust Expectile Graph Attention Network (PLRExGAN) is introduced. The designed PLRExGAN model integrates the mental health indicators with academic and behavioral features to accurately predict student performance. PLRExGAN Model uses one input layer, three hidden layers and one output layer for student performance analysis. PLRExGAN Model uses deep learning concepts for performing four processes, namely data pre-processing, feature selection, classification and fine-tuning. Hybrid Graph Attention Network uses the attention mechanism for finding the student academic performance prediction. PLRExGAN Model considers the number of student data points as input at input layer. Probabilistic Local Outlier Factor Data Handling Process is employed in hidden layer 1 for identifying the outlier data points through evaluating the density of data points in their local neighborhoods. Then, Robust Expectile Regressive Feature Selection process is employed in hidden layer 2 to select the relevant features based on mental health. With the selected features, an Extended Jaro–Winkler Similarity Classification is carried out in the hidden layer 3 based on mental health (i.e., memory capability) for performing student academic performance analysis. Then, meta-heuristic elephant herd optimization is carried out for performing hyperparameter fine-tuning to attain the accurate student academic performance results with minimum error.

Finally, output layer displays the student academic performance results. Experimental analysis of PLRExGAN Model is carried out with the performance metrics, namely student academic performance prediction accuracy, student academic performance prediction time, precision, recall, f1-score, specificity, confusion matrix and ROC-AUC with respect to number of student data points.

Keywords: Student academic performance prediction, extended jaro–winkler similarity classification, robust expectile regression, mental health indicators, psychological indicators.

I. Introduction

Student academic performance prediction has received large attention in the research community because of its importance in understanding student progress and assisting in achieving success. Student academic performance is influenced by different factors like socio-economic status, past academic history, academic practices and personal behaviors. Different traditional methods are used for predicting the academic performance of students. A student academic performance prediction model was introduced in [1] with the hypergraphs and TabNet. The designed model extracted behavior features with embedding representations. However, the prediction accuracy was not enhanced.

Multi-dimensional Student Performance Prediction Model (MSPP) was introduced in [2] with data preprocessing and feature selection process. MSPP enhanced the accuracy and precision during academic performance prediction. But, the time consumption remained unaddressed. A multi-factor machine learning framework was introduced in [3] to predict the student academic performance with behavioral data. But, the prediction performance was not improved by designed framework. An explainable AI-based approach was designed in [4] for forecasting the student academic performance. However, the prediction accuracy level was not improved by designed approach.

A fully embedded bi-order network (FE-BiON) model was designed in [5] for mental health prediction of college students. The fully embedded feature processing method computed relationship between features for prediction performance enhancement. Machine learning model was introduced in [6] for student academic performance prediction. The designed model examined the student data through computing relationship between factors and academic performance. However, the prediction accuracy was not improved by designed model.

A variable reduction with an optimal deep recurrent neural network (VR-ODRNN) approach was introduced in [7] for student performance analysis. However, the computational overhead was not minimized by VR-ODRNN approach. An efficient prediction model was designed in [8] for elementary school children academic performance with individuality in analytical framework. Large Language Model Empowered Early Prediction of Student Performance (LLM-EPSP) was introduced in [9] to make academic performance prediction with student data points. But, the recall was not improved by LLM-EPSP. Optuna-Optimized Meta-Learner and Ensemble Learning Model were introduced in [10] for student performance prediction for guaranteeing the transparency. But, the accuracy level was not improved by designed model.

Bay-DeepMIL framework was introduced in [11] with technical capabilities of predictive model for enhancing educational decision-making. But, the time consumption for student academic performance was not reduced by Bay-DeepMIL framework. A Back Propagation neural network–based early warning system was introduced in [12] for student academic performance. But, the computational cost was not reduced by designed system. Random forest using genetic algorithm was designed in [13] for feature selection. Sequential Forward Selection mechanism was employed for identifying the most relevant indicators. However, the academic performance precision was not enhanced by designed algorithm.

A multi-graph spatial-temporal synchronous network (MGSTSN) was introduced in [14] for performance prediction precision enhancement. MGSTSN performed spatial-temporal dynamic representation through spatial trend and pattern graphs. However, the prediction accuracy was not improved by MGSTSN. Principal Component Analysis (PCA) was introduced in [15] for reducing dataset dimensionality with improved visualization. K-Means clustering partitioned the students into different groups. But, the prediction precision level was not improved by PCA.

The existing problems identified from reviews are lesser accuracy, high prediction time, lesser precision, lesser specificity, lesser prediction performance, higher computational cost and so on. In order to address the conventional method problems, Probabilistic Local Robust Expectile Graph Attention Network (PLRExGAN) Model is introduced in this manuscript.

A. ***Key Contribution***

The key contribution of the proposed PLRExGAN Model is given as,

- To improve the accuracy of student academic performance prediction, PLRExGAN Model is introduced with four processes, namely data pre-processing, feature selection, data classification and fine-tuning process.
- To improve the specificity level of student academic performance prediction, the data filtering and outlier data removal is carried out using Gaussian moving average and probabilistic local outlier factor concepts correspondingly
- To reduce the dimensionality of the datasets for improving the student academic performance prediction performance, robust expectile regression analysis is used in proposed PLRExGAN Model

- To increase the student academic performance prediction accuracy with selected features, an extended Jaro-Wrinkle similarity is used in PLRExGAN Model for efficient data classification
- To reduce the false negative during student academic performance prediction, meta-heuristic elephant herd optimization is carried out in PLRExGAN Model for fine tuning process.
- Lastly, the experimental evaluation across different metrics shows that the proposed PLRExGAN Model attains improved prediction results than conventional methods

B. *Article Organization*

The structure of the paper is given as the follows: Section 2 discusses the literature of student academic performance prediction. Section 3 describes the explanation of proposed PLRExGAN Model with neat architecture diagram and brief explanation. Section 4 illustrates the experimental results and implementation results with brief dataset description. In Section 5, the result analysis of proposed methods and existing methods is carried out with different performance metrics. Lastly, Section 6 concludes the research article.

II. Related Works

The student performance prediction is an essential one in higher education for development of future study plans. The multifaceted approach was designed in [16] for educational institution to address the education system issues. The designed approach performed continuous improvement in educational excellence. Predictive Analytics and Decision-Making Using Recurrent Autoencoder with Dimensionality Reduction (PADM-RAEDR) approach was designed in [17] to improve predictive analytics through decision-making in education domain. But, the f1-score was not enhanced by PADM-RAEDR approach.

The multisource-domain transfer learning regression framework was introduced in [18] with domain selection, feature extraction and joint distribution adaptation. But, the time consumption was not reduced by designed framework. A generative artificial intelligence (AI) technology was designed in [19] to improve classroom learning and support student success. Student Academic Performance Predicting (SAPP) system was designed in [20] to predict student pass or fail outcomes with high prediction accuracy.

Learning Ability Self-Adaptive Algorithm (LASA) was introduced in [21] with feature space and distribution in long-term data. LASA employed the features with meaningful semantics. A student performance prediction model was designed in [22] with random forest attribute selection. The designed model combined the knowledge with the feature information for performance prediction. Academic Multi-Factor Prediction Net (AMP-Net) framework was introduced in [23] to forecast student academic performance through combining multiple data dimensions. Hybrid AI-based model was introduced in [24] for academic performance monitoring and intervention. The hybrid learning framework termed chaotic Niche alpha evolution-long short-term memory (CNAE-LSTM) was introduced in [25] with Chaotic initialization for student academic performance.

The deep learning (DL) framework was introduced in [26] for student grades and marks prediction with intermediate and secondary education. A data-driven approach was designed in [27] for finding student at risk for early interventions. The data-driven approach improved the retention rate with labor market demands for decision-making. An error complementarity-based iterative learning approach was introduced in [28] for student performance prediction. A comprehensive behavioral modeling framework was introduced in [29] with sleep disruption to academic outcomes. The psychometric assessment was employed to identify students at academic risk. A multimodal data fusion algorithm was introduced in [30] to forecast college student academic performance. The multimodal data fusion algorithm improved the model ability with learning behaviors.

III. Methodology

Student academic performance prediction is considered as the significant research area in educational data mining and learning analytics. Accurate student performance prediction is carried out by educational institutions to identify the risk students at earlier stage to improve the learning outcomes. Academic performance is assessed based on cognitive factors like grades, attendance and examination scores. In addition, mental health conditions plays essential role in identifying the student academic success. Mental health issues like stress, anxiety, depression, and poor sleep quality affect student concentration and decision-making abilities. The integration of mental health indicators into predictive models enhanced the student performance and increased the reliability of prediction system. Many existing student academic performance prediction methods failed to incorporate domain knowledge in relation to mental health factors. To deal with this need, a novel PLRExGAN Model is introduced to improve the accuracy of student academic performance prediction. The architecture diagram includes four processes, namely data acquisition, preprocessing, feature selection and classification. The different phases combined to categorize the students into multiple classes.

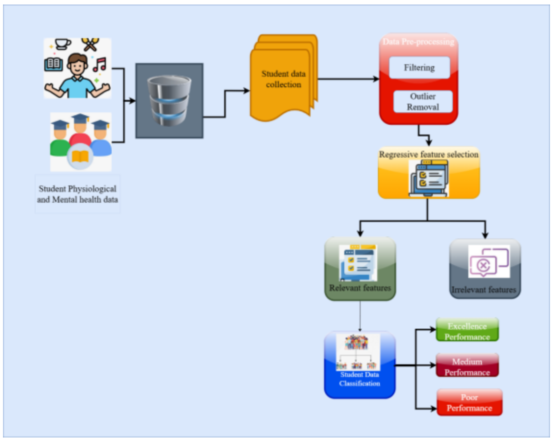


Figure 1 Architecture Diagram of PLRExGAN Model

Figure 1 illustrates the overall structural design of the proposed PLRExGAN Model for student academic performance prediction. PLRExGAN Model comprises four processes namely data acquisition, pre-processing, feature selection, and classification to enhance the accuracy of student academic performance prediction. At first, the student data samples are collected from input dataset for accurate student academic performance prediction. The important process of proposed PLRExGAN Model is data pre-processing. The data pre-processing task is to clean the unprocessed dataset into suitable structure through outlier data removal. After that, the relevant feature selection is carried out for accurate student academic performance prediction with minimal time consumption. To end with, the proposed PLRExGAN Model executes the student academic performance through classification process based on mental health with lesser error rate. The detailed explanation of proposed PLRExGAN Model is explained in brief manner.

A. Probabilistic Local Robust Expectile Graph Attention Network

Probabilistic Local Robust Expectile Graph Attention Network is a hybrid deep learning framework used for improving the prediction accuracy and robustness of student academic performance prediction. In proposed PLRExGAN Model, Graph Attention Networks (GATs) are the neural architecture for graph-structured data. GATs employ the masked self-attention layers to weight the neighboring nodes. The proposed PLRExGAN Model combines the probabilistic learning, local neighborhood representation, expectile regression and similarity concepts to efficiently improve prediction accuracy of student academic performance analysis. The structure of probabilistic local robust expectile graph attention network is illustrated in the figure 2.

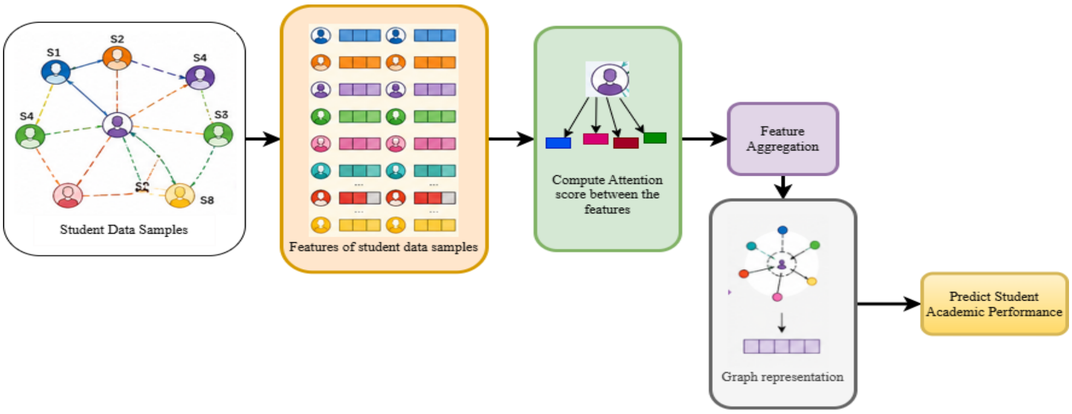


Figure 2 Structure of Graph Attention Network

Figure 2 illustrates the structure of graph attention network. Graph Attention Network (GAT) architecture comprises the student data samples as nodes in a graph and their features as the edges for performing the student academic performance prediction. Initially, student data points with their features are collected as an input. Then, the features are sent to the GAT layers for performing feature transformation process. The feature transformation process converts the raw input into higher-dimensional representations. The attention mechanism determines the attention coefficients between features of student data samples for predicting the academic performance. With attention coefficients, the neighborhood aggregation of student features is carried out for performing student academic performance prediction. Finally, the academic performance of the student data samples is predicted based on mental health with higher accuracy and lesser time consumption.

B. Dataset Acquisition:

The first process of proposed PLRExGAN Model is data acquisition. The data acquisition process gathers the student raw data samples from the dataset. For conducting the experiments, student placement data is taken from the Kaggle. The URL of the dataset is given as https://www.kaggle.com/datasets/koshikasaiprasad/student-placement-data/data. The dataset comprised multi-dimensional student information like academic performance, skill-based attributes, behavioral characteristics, personal characteristics and placement outcomes. The dataset comprised approximately 20,000 student records with academic, technical, and behavioral attributes. The attribute list are given as,

Table I. List of Features

S. No	Attributes Name
1.	• Academic percentage in Operating Systems
2.	• Percentage in Algorithms
3.	• Percentage in Programming Concepts
4.	• Percentage in Software Engineering
5.	• Percentage in Computer Networks
6.	• Percentage in Electronics Subjects
7.	• Percentage in Computer Architecture
8.	• Percentage in Mathematics
9.	• Percentage in Communication skills
10.	• Hours working per day

11.	• Logical quotient rating
12.	• Hackathons
13.	• Coding skills rating
14.	• Public speaking points
15.	• Can work long time before system?
16.	• Self-learning capability?
17.	• Extra-courses did
18.	• Certifications
19.	• Workshops
20.	• Talent tests taken?
21.	• Olympiads
22.	• Reading and writing skills
23.	• Memory capability score
24.	• Interested subjects
25.	• Interested career area
26.	• Job/Higher Studies?
27.	• Type of company wants to settle in?
28.	• Taken inputs from seniors or elders
29.	• Interested in games
30.	• Interested Type of Books
31.	• Salary Range Expected
32.	• In a Relationship?
33.	• Gentle or Tuff behavior?
34.	• Management or Technical
35.	• Salary/work
36.	• Hard/smart worker
37.	• Worked in teams ever?
38.	• Introvert
39.	Suggested Job Role

C. Data preprocessing

The second process of proposed PLRExGAN Model is the data preprocessing for accurate student academic performance prediction. The raw student data point collected from the input database with noisy data filtering and outlier data point detection. Therefore, the PLRExGAN Model performs the data preprocessing task through

Indian Engineering Journal
ISSN: 2984-9047
Vol 4 Issue 2 (2026)

filtering and outlier detection for performing student academic performance prediction. Let us consider that the student placement dataset 'DS' with number of features '$\{F_1, F_2, \dots, F_m\}$' are arranged in matrix format. Therefore, the input matrix is formulated as given below,

$$IM = \begin{bmatrix} F_1 & F_2 & \dots & F_m \\ SD_{11} & SD_{12} & \dots & SD_{1n} \\ SD_{21} & SD_{22} & \dots & SD_{2n} \\ \vdots & \vdots & \dots & \vdots \\ SD_{m1} & SD_{m2} & \dots & SD_{mn} \end{bmatrix} \quad n = rows, m = column \quad (1)$$

From (1), 'IM' comprised the input data matrix with number of rows and columns. Every column represents the number of features. Every row symbolizes the number of data samples '$SD = \{SD_1, SD_2, \dots, SD_n\}$' correspondingly. At first, noise data filtering process is carried out through gaussian moving average data filtering process. The data filtering eliminates the unwanted, noisy, irrelevant and abnormal data points from input datasets before student academic performance prediction. The data filtering process improved the data quality and prediction accuracy. Gaussian moving average data filtering process is a smoothing technique used to eliminate the noisy data points and fluctuations in input database through averaging neighboring data values. Gaussian moving average filter uses the gaussian weighting function with neighboring data points. The Gaussian moving average filter in proposed PLRExGAN Model is formulated as,

$$GMAF = \frac{\sum_{i=-k}^{k} we_i SD_{t+i}}{\sum_{i=-k}^{k} we_i} \quad (2)$$

From (2), '$GMAF$' represent the gaussian moving average filter. 'we_i' symbolizes the gaussian weights. 'k' denotes the window size. 'SD_{t+i}' indicates neighboring data values. After filtering the noisy data points, the outliers are identified using probabilistic local outlier factor data handling process in proposed PLRExGAN Model. Probabilistic Local Outlier Factor is an advanced outlier detection process used to identify unusual data points through evaluating local density of data points with neighboring data point density. The probabilistic local outlier factor for performing the outlier detection is formulated as,

$$PLOF = \frac{ALDN}{SDLD} - 1 \quad (3)$$

From (3), '$ALDN$' symbolizes average local density of neighbor of student data samples. '$SDLD$' represent the student data samples local density. The local density of the target student data point is compared with average density of its neighbors. Therefore, the probabilistic score is used to identify the outlier. The higher scores denote the stronger outliers. Consequently, the outliers are removed from input dataset. The hidden layer 1 helps in reducing the dataset dimensionality for eliminating the outlier samples. After that, the preprocessed dataset results are sent to the next hidden layer.

D. Feature Selection

After pre-processing task, feature selection process is performed in the proposed PLRExGAN Model. The preprocessed student samples are sent to the hidden layer 2 for relevant feature selection. The feature selection process minimizes the dimensionality of the input dataset. The feature selection process is performed using Robust Expectile Regression analysis with attention score for accurate student academic performance with minimal time consumption. Robust Expectile regression is the statistical method employed with the conditional expectiles of student data samples. Robust Expectile Regression Analysis is a machine learning technique used for determining the relationship between feature and objective with attention score. The attention score is computed by,

$$ASF = ReLU\left(a^T \left| h_i' \parallel h_j' \right|\right) \quad (4)$$

From (4), 'a^T' represent the learnable attention vector. 'h_i'' symbolizes the transformed feature. '‖' denotes the concatenation operation. Robust Expectile Regression analysis helps in identifying the relevant features for accurate student academic performance prediction. The expectile regression analysis is expressed as follows,

$$Ob_k = {ASF_m}^T \, \widehat{Pr} + E \quad (5)$$

$$ASF_m = \begin{bmatrix} ASF_1 \\ ASF_2 \\ \vdots \\ ASF_m \end{bmatrix} \quad (6)$$

$$\widehat{Pr} = \arg\min \sum we_\varepsilon\,(Ob_k)\,\left(Ob_k - ASF_m{}^T\ Pr\right)^2 \quad (7)$$

$$we_\varepsilon\,(Ob_k) = \begin{cases} \varepsilon\ ; & Ob_k \geq ASF_k{}^T\ \widehat{Pr} \\ 1-\varepsilon\ ; & Ob_k < ASF_k{}^T\ \widehat{Pr} \end{cases} \quad (8)$$

From (5), (6), (7) and (8), 'Ob_k' symbolizes the observed response of feature and objective (i.e., student academic performance). 'ASF_m' symbolizes the attention score of features. '$ASF_m{}^T$' symbolizes transpose of 'ASF_m'. The attention score is employed to measure the difference between observed responses 'Ob_k' and the predicted classification results 'Pr'. '$we_\varepsilon\,(Ob_k)$' symbolizes the asymmetric weights. 'ε' represent expectile parameter varied in the range 0 to 1. The lower values of expectile parameter 'ε' symbolizes the irrelevant features for student academic performance. The higher values of expectile parameter denote the relevant features for performing the student academic performance. The output value '1' symbolizes that the feature is relevant features and the value '0' represents the irrelevant feature. This in turn, the robust expectile regression analysis in proposed PLRExGAN model chooses the relevant features for performing student academic performance. Finally, data classification is carried out in the next hidden layer 3.

E. Data Classification

The third step of proposed PLRExGAN model is student data classification. The data classification is carried out in hidden layer 3 for categorizing the student samples based on selected features through feature aggregation and graph representation. In the data classification process, similarity concepts are employed for measuring the relationship between the aggregated features of student data sample and testing features. In proposed PLRExGAN model, Extended Jaro–Winkler similarity data classification process is carried out for efficient student academic performance prediction. In proposed PLRExGAN model, Extended Jaro–Winkler similarity is used to determine the similarity between features of training student data and testing student data.

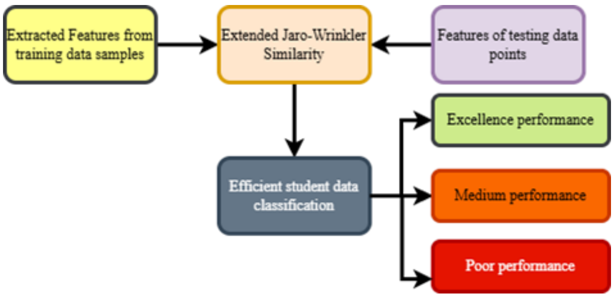


Figure 3 Extended Jaro-Wrinkler Similarity Data Classification

Figure 3 describes the structural diagram of Extended Jaro–Winkler Similarity Data Classification. Extended Jaro–Winkler similarity is determined depending on selected features in training student data samples and testing student data samples for student academic performance prediction. It is given as,

$$JS\,(Tr_F, Te_F) = \frac{1}{3}\left(\frac{M(Tr_F,Te_F)}{|C_1|} + \frac{M(Tr_F,Te_F)}{|C_2|} + \frac{Tr_F - Te_F}{M}\right) \quad (9)$$

From (9), '$JS\,(Tr_F, Te_F)$' symbolize the Jaro–Winkler similarity between extracted features of training data and testing data points. '$M(Tr_F, Te_F)$' denotes the number of matching features of training data and testing data points. 'C_1' indicates first class and 'C_2' symbolizes the second class. As a result, the Jaro–Winkler Similarity value varies from value '0' to '1'. The similarity value '0' denotes the training data not belongs to that particular class. The similarity value '1' symbolizes the training data belongs to that particular class. When the training data features have high similarity with testing data features of excellent performance class, the student data point is categorized as excellent performance student data. Or else, the student data point is categorized remaining class. The student data classification for academic performance prediction are given as,

$$Co = JS\,(Tr_F, Te_F) = \begin{cases} 1\ ; & Excellent\ Performance \\ 0.5\ ; & Medium\ Performance \\ 0\ ; & Poor\ Performance \end{cases} \qquad (10)$$

From (10), the academic performance prediction results are achieved. This in turn, accurate student academic performance based on mental health is carried out with higher accuracy and minimum time consumption. For each student academic performance result, the error rate is evaluated as follows,

$$PE = [Co - Pr]^2 \qquad (11)$$

From (11), 'PE' denotes the prediction error. 'Co' represent the classification output results. 'Pr' symbolizes the prediction results. In fine-tuning process of proposed PLRExGAN model, the hyperparameters of generative attention network is adjusted through adaptive momentum algorithm. The weight hyperparameter helps in minimizing the academic performance prediction error with higher accuracy. The fine tuning process helps in varying the weight between layers for effective student academic performance prediction. The weight update is carried out by,

$$we_{new} = we_t - \eta\, \frac{\delta_1\, A_{t-1} + (1-\delta_1)\left[\frac{\partial PE}{\partial we_t}\right]}{\sqrt{\delta_2\, B_{t-1} + (1-\delta_2)\left[\frac{\partial PE}{\partial we_t}\right]^2 + pc}} \qquad (12)$$

From (12), 'we_{new}' represent the updated weights. 'we_t' symbolizes current weight. 'η' denotes the learning rate. '$\frac{\partial PE}{\partial we_t}$' indicates the partial derivative of prediction error 'PE' with respect to the current weight 'we_t'. The momentum parameters is represented as 'δ'. 'A_t' denotes the first moment. The mean value is termed as the first moment. 'B_t' symbolizes the second moment. 'pc' denotes the positive constant. Consequently, an optimal weight is chosen by meta-heuristic elephant herd optimization in student academic performance prediction. In proposed PLRExGAN model, an Elephant herd optimization is a nature-inspired meta-heuristic algorithm. Elephant is considered as the weights. The minimum error is considered as the food source. Based on the error value, an optimal weight is selected among the elephant population. The number of elephants is initialized randomly in the search space '$we_b = we_1, we_2, we_3, \ldots, we_b$'. The fitness of the weight value is computed as,

$$Fit(we) = \arg\min PE \qquad (13)$$

From (13), '$Fit(we)$' represent the fitness function. '$\arg\min PE$' denotes the argument of minimum prediction error. The current best weight is selected among population. When the fitness of one weight is higher than previous one, then current position is identified as the best one. After that, clan updating operator and separating operator are carried out in the elephant herding optimization process.

- **Clan-Updating Operator**

The elephant herding optimization process carried out the chase-updating process to shift the current best position to the global best position. The single matriarch goes behind the elephants in every clan. Accordingly, the new position of each elephant is computed through matriarch operation. It is given by,

$$A_{i+1} = A_i + sf * 0.5|A_{best} - A_i| * RN \qquad (14)$$

From (14), 'A_{i+1}' represent the updated position. 'A' denotes the old position for elephant in clan. 'A_{best}' indicate the best elephant position in clan. The best position is determined through product of influenced factor and center elephant position of clan. '$sf \in [0,1]$' symbolizes the scale factor. 'RN' denotes the random number. The best position of elephant is computed by,

$$A_c = \frac{1}{b} * \sum_{RN=1}^{b} A_{RN} \qquad (15)$$

From (15), 'b' symbolizes the number of elephants in clan, 'A_{RN}' denotes rn^th^ dimension of elephant individual. In clan updating operator, elephant position gets updated through performing the attraction mechanism.

- **Separating Operator**

The separating process mimics the male elephants leaving from herd. The separating operator is executed through replacing elephant with worst fitness in each generation.

$$A_{worst} = A_{min} + (A_{max} - A_{min} + 1) * R \quad (16)$$

From (16), 'A_{worst}' symbolizes the worst individual in clan. 'A_{min}' denotes the lower bound of individual elephant. 'A_{max}' denotes the upper bound of individual elephant. 'R' symbolizes the random number between '0 and 1'. The worst position and best position of elephant population are identified. The position updating process gets repeated till termination criteria are met. Finally, the optimal weight is chosen with lesser error value. At last, accurate student performance prediction results with minimal error are attained at the output layer. This in turn, accurate student academic performance prediction is carried out with higher accuracy and minimum time consumption. The algorithmic process of proposed PLRExGAN model is given as,

//**Algorithm 1:** Probabilistic Local Robust Expectile Graph Attention Network
Input: Dataset 'DS', features '$F_1, F_2, \dots, F_m$' and student samples '$SD_1, SD_2, \dots, SD_n$' **Output:** Improve student academic performance prediction accuracy
Begin **Step 1: Collect** number of student samples '$SD_1, SD_2, \dots, SD_n$' and their features '$F_1, F_2, \dots, F_m$' from input dataset **// Student Data Acquisition** **Step 2**: Input features and student data samples is given to input layer **Step 3:** Transmit the input samples to hidden layer 1 **// Data Pre-processing** ------Hidden layer 1 **Step 4: For each** student data samples **do** **Step 5:** Perform data filtering process **Step 6:** **Compute** Probabilistic Local Outlier Factor for outlier detection **Step 7: End for** **// Feature selection** **------** Hidden layer 2 **Step 8: For each preprocessed** data samples do **Step 9**: Perform Robust Expectile Regression Analysis **Step 10**: $\boldsymbol{if}$ $(Ob_k \geq ASF_k{}^T \, \widehat{Pr} = \varepsilon)$ **then** **Step 11:** Features is said to be relevant **Step 12:** **else**

Step 13: Features is said to be irrelevant

Step 14: **End if**

Step 15: End for

// Classification------ Hidden layer 3

Step 16: For each selected feature with training student data samples

Step 17: **For each testing** data samples

Step 18: Measure Extended Jaro–Winkler similarity

Step 19: $\boldsymbol{if}$ $(JS = 1)$**then**

Step 20: Student samples classified into excellent performance

Step 21: $\boldsymbol{elseif}$ $(JS = 0.5)$ **then**

Step 22: Student samples classified into medium performance

Step 23: $\boldsymbol{else}$

Step 24: Student samples classified into poor performance

Step 25: **End if**

Step 26: **End for**

Step 27: End for

// Fine tuning

Step 28: For each classification result

Step 29: Compute the prediction error 'E_{pre}'

Step 30: Update the weight

Step 31: **Initialize the weight population**

Step 32: **For** each weight 'we_b'

Step 33: Compute the fitness

Step 34: Perform clan updating operator and separating operator

Step 35: Identify global best solution

Step 36: Return (optimal weight)

Step 37: Accurate student performance prediction results at the **output layer**

End

Algorithm 1 describes the different process of student performance prediction using PLRExGAN model. The number of student data samples is gathered from the input dataset. Then, the input student data samples are sent to the input layer of proposed PLRExGAN model. For every student data sample, activation probability is determined with the weight and bias value in hidden layer 1. Then, the data preprocessing is carried out through data filtering and outlier detection. In hidden layer 2, the relevant features are selected through robust expectile regression analysis for reducing the dimensionality. After that, data classification is carried out in hidden layer 3 with selected relevant features using extended jaro-winkler similarity to compute similarity between the training and testing student samples to enhance student performance prediction accuracy. The excellent performance memory capability student has the higher chance of getting placement and poor performance memory capability student has the lesser chance of getting placement. The fine-tuning process is performed through meta-heuristic elephant herd optimization algorithm. The weight population is initialized and fitness is computed. Based on the fitness value, global optimal position is identified. Finally, the accurate student academic performance prediction results based on mental health are obtained at the output layer with higher accuracy.

IV. Experimental Setup

The experimental setup of the proposed PLRExGAN model and existing student academic performance prediction model [1] and Multi-dimensional Student Performance Prediction Model (MSPP) [2] are implemented using Python high level programming language. In order to conduct experiments, student placement data is taken from https://www.kaggle.com/datasets/koshikasaiprasad/student-placement-data/data for performing efficient student academic performance prediction. The primary objective of the dataset is to categorize the student data points into high performance data points and low performance data points based on features from input dataset. The dataset includes 39 features with number of data points. For experimental consideration, the number of student data samples considered with different numbers ranging from 1500, 3000, 4500, 6000, 7500, 9000, 10500, 12000, 13500 and 15000 instances.

A. Implementation Results

The proposed PLRExGAN model uses graph attention network for improving the efficiency of student academic performance prediction. The PLRExGAN model performed comprises the data collection, data preprocessing, feature selection and classification with student placement data taken from Kaggle repository. The number of student data samples is gathered from input dataset as shown in figure 4 for performance evaluation of proposed PLRExGAN model.

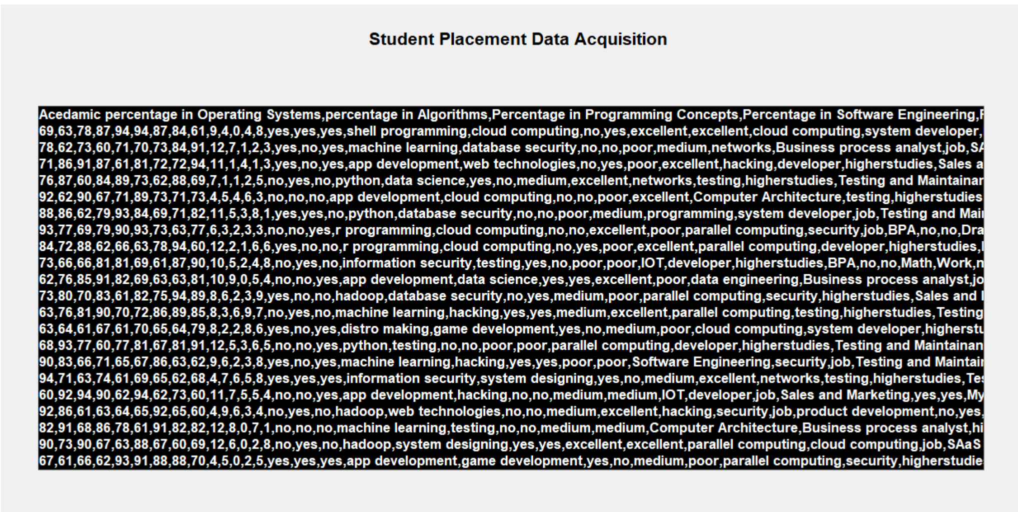
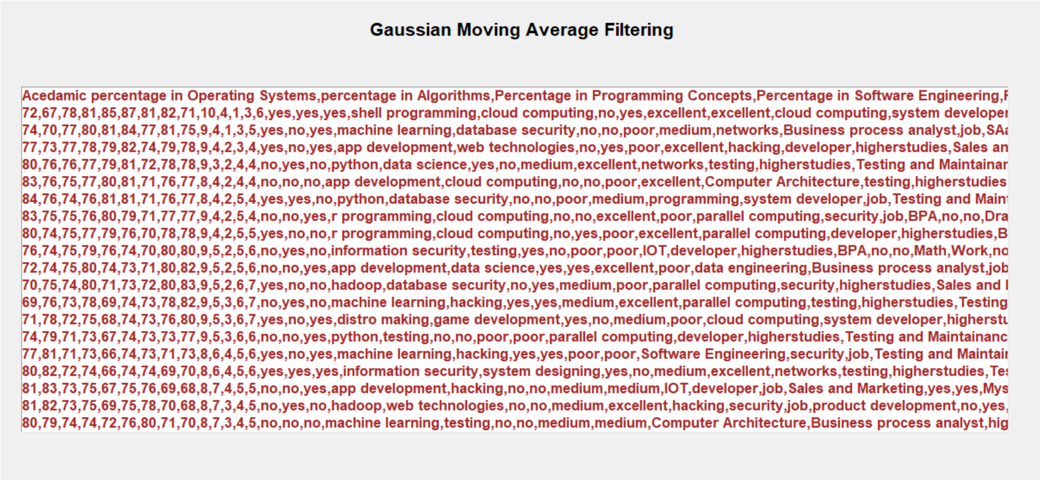


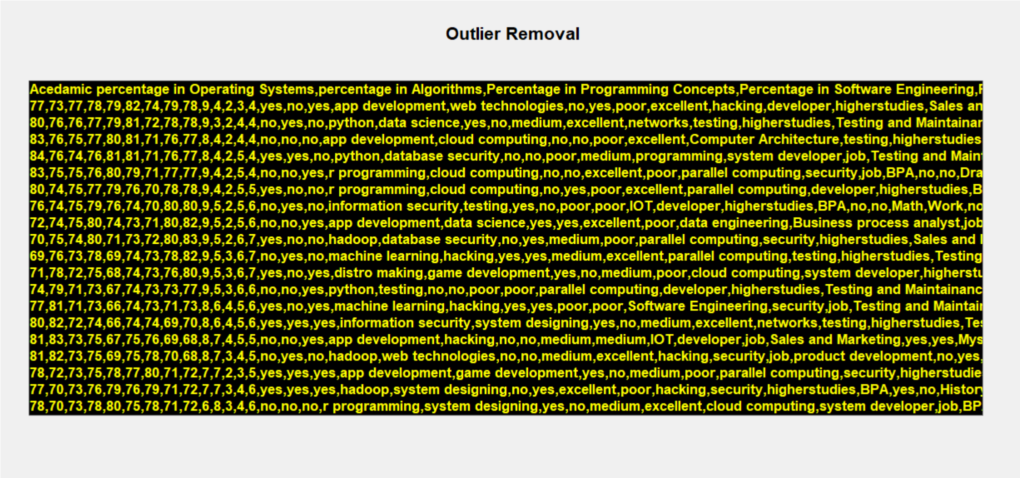
Figure 4 Data acquisition results

After data acquisition process, data preprocessing is carried out by Gaussian moving average filtering for data filtering and probabilistic local outlier factor for outlier detection. The size of 20000 student data samples is 4,758KB. The dataset size gets reduced to 4,296KB after data preprocessing with 18000 student data samples. The data preprocessing results are shown in the figure 5.

Indian Engineering Journal
ISSN: 2984-9047
Vol 4 Issue 2 (2026)



5(a) Gaussian Moving Average Filtering



5(b) Outlier Removal

Figure 5(a) and 5(b) Data preprocessing results

After data pre-processing task, the proposed PLRExGAN model identifies the relevant features for student academic performance prediction. The relevant feature selection is carried out through robust expectile regression analysis. The regression analysis chooses 18 features from the 39 features to minimize the student academic performance prediction time consumption. The selected feature is shown in below figure 6.

```
-----Relevant Features------
Acedamic percentage in Operating Systems

percentage in Algorithms

Percentage in Programming Concepts

Percentage in Software Engineering

Percentage in Computer Networks

Percentage in Computer Architecture

Percentage in Mathematics

Logical quotient rating

hackathons

coding skills rating

self-learning capability?

Extra-courses did

certifications

workshops

olympiads

reading and writing skills

memory capability score

Interested subjects
```

Figure 6 List of Selected Features

Based on the selected features, the student academic performance data classification is carried out with extended jaro-wrinkle similarity. The proposed PLRExGAN

model used selected features to categorize the data samples into excellent, medium and poor classes with lesser error rate. The student data classification results are illustrated in the figure 7.

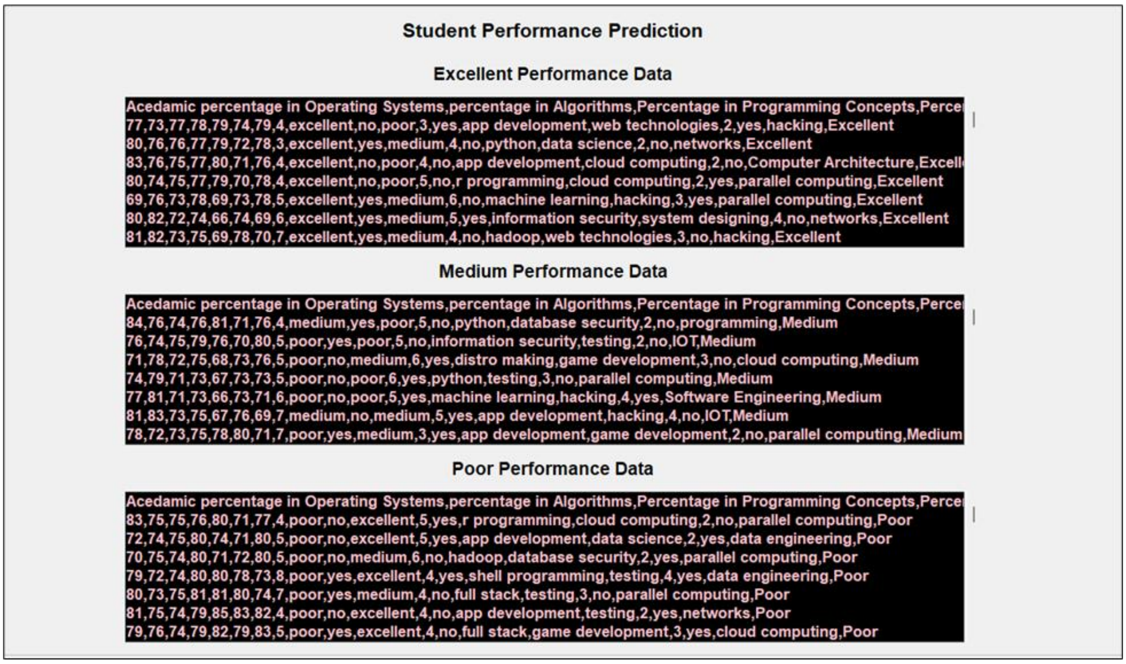


Figure 7 Data Classification Results

The proposed PLRExGAN model uses similarity measure for accurate student academic performance prediction. Based on the classification results, fine-tuning process is performed using meta-heuristic elephant herd optimization process. The fine-tuning results are illustrated in the figure 8.

Figure 8 Fine-tuning Process Results

Figure 8 illustrates the fine-tuning results of student academic performance prediction. The fine-tuning process employed meta-heuristic elephant herd optimization process to minimize the error with during student academic performance prediction.

V. Result and Discussion

The performance evaluation of three different methods, namely proposed PLRExGAN model, existing student academic performance prediction model [1] and existing Multi-dimensional Student Performance Prediction Model (MSPP) [2] are evaluated for different performance parameters such as student academic performance prediction accuracy, precision, recall, F1 score, specificity, student academic performance prediction time, confusion matrix and ROC-AUC with across different number of student data samples.

A. ***Impact on Student Academic Performance Prediction Accuracy:***

Student academic performance prediction accuracy is defined as the ratio of total number of student data samples that correctly detects the academic performance to the total number of student data samples. The student academic performance prediction accuracy is calculated as, $SAAPA = \frac{TP+TN}{TP+TN+FP+FN} * 100$ (17)

From (17), '$SAAPA$' represent the student academic performance prediction accuracy. 'TP' denotes the true positives. 'TN' indicate the true negatives. 'FP' symbolize the false positive. 'FN' denotes the false negatives. When student academic performance prediction accuracy level is high, the method is more efficient. Table 2 illustrates the student academic performance prediction accuracy result using three methods for different number of student data samples.

Table 2 Tabulation of Student Academic Performance Prediction Accuracy

Number of Student Data Points (Number)	**Student Academic Performance Prediction Accuracy**		
	Proposed PLRExGAN model	**Existing Student academic performance prediction model [1]**	**Existing MSPP [2]**
1500	97.24	93.92	91.42
3000	97.83	93.43	92.85
4500	96.76	92.29	90.47
6000	95.37	93.85	92.86
7500	96.42	93.44	91.77
9000	97.57	92.52	90.79
10500	97.68	91.18	90.52
12000	97.15	93.84	90.78
13500	94.88	92.45	91.39
15000	97.76	94.58	91.46

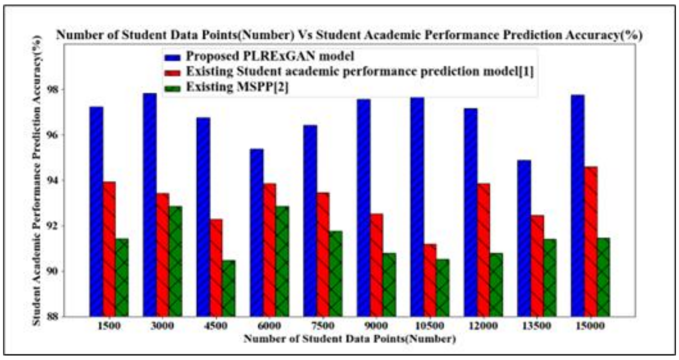


Figure 9 Graphical Representation of Student Academic Performance Prediction Accuracy

Figure 9 shows the student academic performance prediction accuracy results using three methods namely proposed PLRExGAN model, existing student academic performance prediction model [1] and existing MSPP [2]. As illustrated in figure 10, the horizontal axis represents the number of student data samples ranging from 1500 to 15000. The vertical axis denotes the student academic performance prediction accuracy. Let us consider the input student data as 1500 in first iteration, the proposed PLRExGAN model attained student academic performance prediction accuracy of 97.24% whereas two existing techniques [1] and [2] attained 93.92% and 91.42% respectively. Among three different methods, the proposed PLRExGAN model attained improved student academic performance prediction results when compared to conventional methods. The improvement is due to application of Hybrid Graph Attention Network for identifying the student academic performance prediction. Gaussian moving average function is used to perform data filtering process and probabilistic local outlier factor identifies the outlier data points through computing the density of data points in local neighborhoods. Robust Expectile Regressive process chooses the relevant features depending on mental health. Extended Jaro–Winkler Similarity Classification categorizes the student data samples into different classes. Meta-heuristic elephant herd optimization performed fine-tuning process to decrease classification error with true positive rate and true negative rate for accurate student academic performance prediction. Likewise, ten different student academic performance prediction results are determined with different number of student data samples. The proposed PLRExGAN model improved the student academic performance prediction accuracy by 4% and 6% over [1] and [2] respectively.

B. ***Impact on Precision:***

Precision is defined as the metric to determine the student academic performance prediction in accurate manner. Precision is described as the ratio of the true positives to the total number of positives (i.e., true positives and false positives). Precision is defined as,

$$Pr = \frac{TP}{TP+FP} \tag{18}$$

From (18), 'Pr' represent the precision. When the precision is high, the method is said to be more effective. Table 3 illustrates the precision result using three methods for different number of student data samples.

Table 3 Tabulation of Precision

Number of Student Data Points (Number)	**Precision**		
	Proposed PLRExGAN model	**Existing Student academic performance prediction model [1]**	**Existing MSPP [2]**
1500	0.978	0.945	0.922
3000	0.969	0.954	0.938
4500	0.971	0.944	0.927
6000	0.973	0.959	0.939
7500	0.965	0.942	0.936
9000	0.977	0.958	0.923
10500	0.974	0.947	0.926
12000	0.979	0.958	0.935
13500	0.962	0.943	0.928
15000	0.978	0.954	0.939

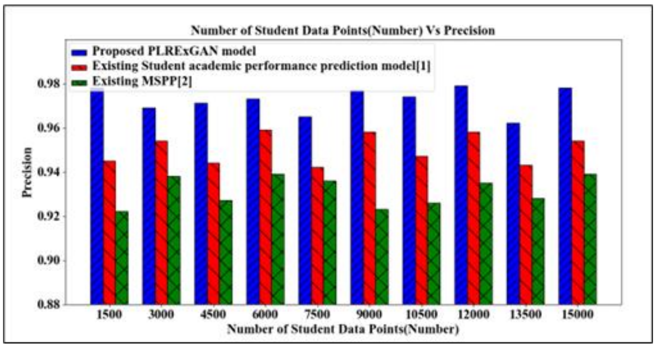


Figure 10 Graphical Representation of Precision

Figure 10 illustrates the precision performance for number of student samples varying from 1500 to 15000 student data samples respectively. The precision performance in student academic performance prediction is computed using different methods namely proposed PLRExGAN model, existing student academic performance prediction model [1] and existing MSPP [2]. The horizontal axis represents the number of student samples and horizontal axis denotes the precision. Let us consider that 1500 student data samples. The proposed PLRExGAN model achieved the precision of 0.978 whereas the existing methods [1] and [2] achieved precision of 0.945 and 0.922 correspondingly. Likewise, ten different iterations are carried out for achieving ten different precision results. It is observed that proposed PLRExGAN model attained higher precision performance when compared to existing methods [1] and [2]. This is because of using graph attention network for student academic performance prediction analysis with selected features. In addition, the fine-tuning process is carried out using meta-heuristic elephant herd optimization for improving the true positives and minimizing the false positives in student academic performance prediction. Therefore, the proposed PLRExGAN model achieves the precision improvement by 2% when compared to method [1] and 4% when compared to method [2].

C. *Impact on Recall:*

Recall is the metric employed to correctly identify the actual positive cases of student data samples. It is described as the ratio of true positives to the sum of true positives and false negatives. The recall is given as,

$$Re = \frac{TP}{TP+FN} \quad (19)$$

From (19) 'Re' represent the recall. When recall measure is high, the method is more efficient. Table 4 shows the recall performance using three methods for different number of student data samples.

Table 4 Tabulation of Recall

Number of Student Data Points (Number)	**Recall**		
	Proposed PLRExGAN model	**Existing Student academic performance prediction model [1]**	**Existing MSPP [2]**
1500	0.961	0.930	0.911
3000	0.966	0.948	0.928
4500	0.968	0.951	0.927
6000	0.962	0.956	0.929
7500	0.967	0.947	0.926
9000	0.968	0.943	0.923
10500	0.965	0.952	0.926

12000	0.966	0.948	0.925
13500	0.963	0.949	0.928
15000	0.967	0.950	0.929

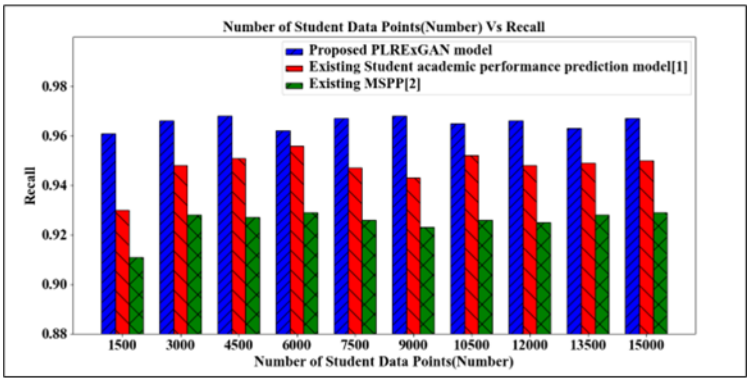


Figure 11 Graphical Representation of Recall

Figure 11 illustrates the recall performance for different number of student samples gathered from the input dataset. The proposed PLRExGAN model attained higher recall performance in student academic performance prediction when compared to existing methods [1] and [2]. Let us consider the number of student data sample as 1500, proposed PLRExGAN model attained the recall of 0.961 while existing methods [1] and [2] achieved 0.930 and 0.911 correspondingly. The proposed PLRExGAN model enhanced the recall performance when compared to existing methods. The performance improvement is due to application of fine-tuning process in graph attention network. In the hybrid network, the proposed PLRExGAN model reduces the prediction error between obtained results and actual results in student academic performance prediction using meta-heuristic elephant herd optimization. Likewise, ten different recall results are obtained for different number of input student samples. Therefore, the result analysis illustrates that recall of proposed PLRExGAN model improved by approximately 2% compared to [1] and 4% compared to [2].

D. ***Impact on F1 score:***

F1-score is described as the harmonic mean of both precision and recall. It is given as,

$$F1 - score = 2 * \left[\frac{Pr * Re}{Pr + Re}\right] \qquad (20)$$

From (20), f1–score is calculated. When f1-score is high, the method is more efficient. Table 5 shows the f1-score performance of proposed model and existing methods for different number of student data samples.

Table 5 Tabulation of F1-Score

Number of Student Data Points (Number)	F1-Score		
	Proposed PLRExGAN model	Existing Student academic performance prediction model [1]	Existing MSPP [2]
1500	0.978	0.944	0.935
3000	0.967	0.941	0.928
4500	0.974	0.955	0.935
6000	0.965	0.948	0.931

7500	0.972	0.949	0.938
9000	0.976	0.951	0.939
10500	0.971	0.947	0.941
12000	0.976	0.948	0.932
13500	0.973	0.954	0.943
15000	0.986	0.953	0.948

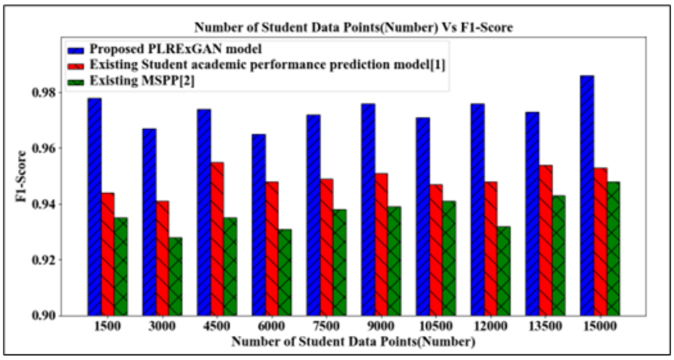


Figure 12 Graphical Representation of F1-Score

Figure 12 illustrates the f1-score results of different number of student data samples ranging from 1500 to 15000. The proposed PLRExGAN model achieved higher f1-score performance results in student academic performance prediction for two different existing methods [1] and [2]. With 1500 student data samples, proposed PLRExGAN model achieved f1-score of 0.978 while existing methods [1] and [2] achieved 0.944 and 0.935 respectively. The proposed PLRExGAN model increased the f1-score performance results than conventional methods. The improvement in the f1-score performance is due to application of graph attention network to enhance the student academic performance prediction accuracy. The comparative analysis reveals that the PLRExGAN model increases the F1-score by 3% compared to [1] and 4% compared to [2].

E. Impact on Student Academic Performance Prediction Time:

Student academic performance prediction time is described as the amount of time consumed to predict the student academic performance. It is given as,

$$SAPPT = \sum_{i=1}^{n} SD_i * Time[APP] \quad (21)$$

From (21), '$SAPPT$' denotes the student academic performance prediction time. '$Time[APP]$' indicates the time consumed for student academic performance prediction. The student academic performance prediction time is computed in terms of milliseconds (ms). Table 6 illustrates the student academic performance prediction time for different number of student data samples.

Table 6 Tabulation of Student Academic Performance Prediction Time

Number of Student Data Points (Number)	**Student Academic Performance Prediction Time (ms)**		
	Proposed PLRExGAN model	**Existing Student academic performance prediction model [1]**	**Existing MSPP [2]**
1500	19.1	25.9	31.9

3000	22.3	28.5	34.5
4500	24.7	30.2	37.1
6000	27.8	33.6	42.6
7500	30.6	36.1	45.2
9000	32.4	38.7	47.4
10500	35.8	41.9	50.2
12000	38.6	44.2	53.8
13500	42.7	48.7	56.2
15000	44.8	52.3	59.3

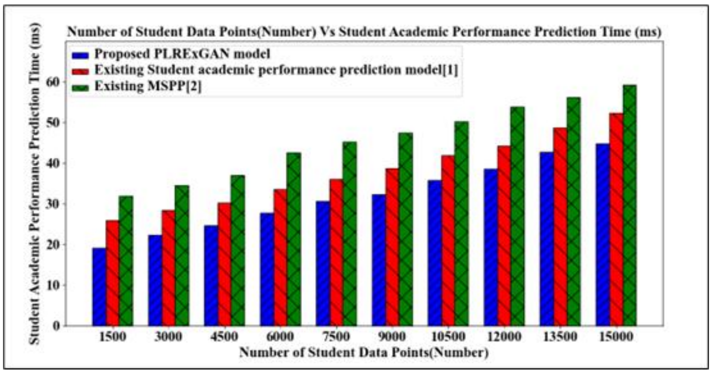


Figure 13 Graphical Representation of Student Academic Performance Prediction Time

Figure 13 shows the overall performance of student academic performance prediction time for diverse number of student data samples collected from input dataset. From the above figure, student academic performance time consumption gets increased with number of student data samples for all methods. But, proposed PLRExGAN model minimizes the student academic performance prediction time when compared to existing techniques. Let us consider that 1500 student data samples, the student academic performance prediction time for proposed PLRExGAN model is 19.1ms while existing method [1] consumed 25.9ms and existing method [2] consumed 31.9ms. The student academic performance prediction time gets reduced because of data pre-processing and feature selection process. Gaussian moving average function and probabilistic local outlier factor performed efficient data filtering and outlier detection. After that, robust expectile regressive process in PLRExGAN model selects the relevant features depending on mental health. This in turn helps to reduce student academic performance prediction time. The proposed PLRExGAN model reduces the student academic performance prediction time by 17% when compared to [1] and 31% when compared to [2].

F. ***Impact on Specificity:***

Specificity is described as the ability to differentiate between high performance and less performance student data samples. The specificity is defined as,

$$S = \frac{TN}{TN+FP} \qquad (22)$$

From (22), the specificity is determined. When specificity level is high, the method is more efficient. Table 7 illustrates specificity result using three methods for different number of student data samples.

Table 7 Tabulation of Specificity

Number of Student Data Points (Number)	**Specificity**		
	Proposed PLRExGAN model	**Existing Student academic performance prediction model [1]**	**Existing MSPP [2]**
1500	0.921	0.878	0.725
3000	0.916	0.885	0.754
4500	0.934	0.892	0.765
6000	0.948	0.827	0.739
7500	0.922	0.881	0.795
9000	0.911	0.813	0.772
10500	0.937	0.852	0.771
12000	0.929	0.842	0.759
13500	0.913	0.884	0.768
15000	0.938	0.847	0.787

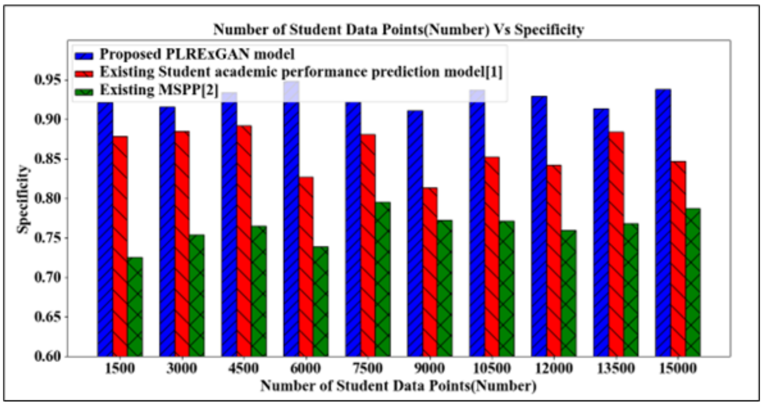


Figure 14 Graphical Representation of Specificity

Figure 14 illustrates the specificity performance for different number of student data samples varying from 1500 to 15000. The proposed PLRExGAN model attained higher specificity performance in student academic performance prediction for two different existing methods [1] and [2]. With 1500 student data samples, proposed PLRExGAN model attained the specificity of 0.921 while existing methods [1] and [2] achieved 0.878 and 0.625 respectively. The proposed PLRExGAN model achieved improved specificity performance when compared to conventional methods. This is due to the application of graph attention network for diverse number of student samples. The meta-heuristic elephant herd optimization is used for fine-tuning to increase the true positives and reduce the false positives in student academic performance prediction. Normally, the comparative analysis reveals that proposed PLRExGAN model increases the specificity by 8% compared to [1] and 21% compared to [2].

*G. **Performance analysis of ROC-AUC***

ROC-AUC curve is employed to compute the performance of three different classification models, namely proposed PLRExGAN model, existing student academic performance prediction model [1] and existing MSPP [2] in student academic performance prediction. ROC-AUC curve is used to determine the substitution between true positive rate and false positive rate. Area under Curve (AUC) provides the single value to differentiate between higher performance and lesser performance student data samples in student academic performance prediction.

Table 8 Comparison of ROC-AUC

False positive rate	**True positive rate**		
	Proposed PLRExGAN model	**Existing Student academic performance prediction model [1]**	**Existing MSPP [2]**
0	0	0	0
0.1	0.474	0.424	0.397
0.2	0.594	0.539	0.465
0.3	0.625	0.601	0.559
0.4	0.749	0.698	0.620
0.5	0.867	0.780	0.718
0.6	0.918	0.855	0.820
0.7	0.927	0.891	0.877
0.8	0.936	0.909	0.890
0.9	0.948	0.925	0.912
1	0.979	0.952	0.935

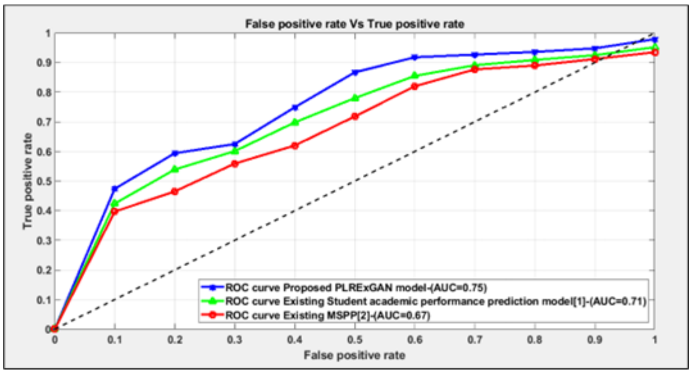


Figure 15 ROC-AUC Result

Table 8 and Figure 15 illustrates the ROC-AUC performance of three different methods namely proposed PLRExGAN model, existing student academic performance prediction model [1] and existing MSPP [2]. Area Under the Curve (AUC) computes the ability of every model to correctly classify the student data samples into excellent performance, medium performance and poor performance classes by calculating the total area below ROC curve. An AUC value varies from 0 to 1. AUC score above 0.5 denotes that the proposed PLRExGAN model distinguishes the student data samples into three classes. In contrast, AUC below 0.5 attained the poor student academic performance. In figure 13, the dashed diagonal line represents the baseline of classifier performance. Among three different methods, the PLRExGAN model attained better student academic performance prediction performance when compared to the other approaches [1], [2].

H. *Impact on Confusion matrix*

The confusion matrix is employed for performance evaluation of different student academic performance prediction methods. The confusion matrix used to determine the student academic class performance, namely high or less performance. In confusion matrix analysis, a dataset comprised 15000 student data samples for student academic performance prediction. The confusion matrix helps in evaluating the performance of three models, namely proposed PLRExGAN model, existing student academic performance prediction model [1] and existing MSPP [2].

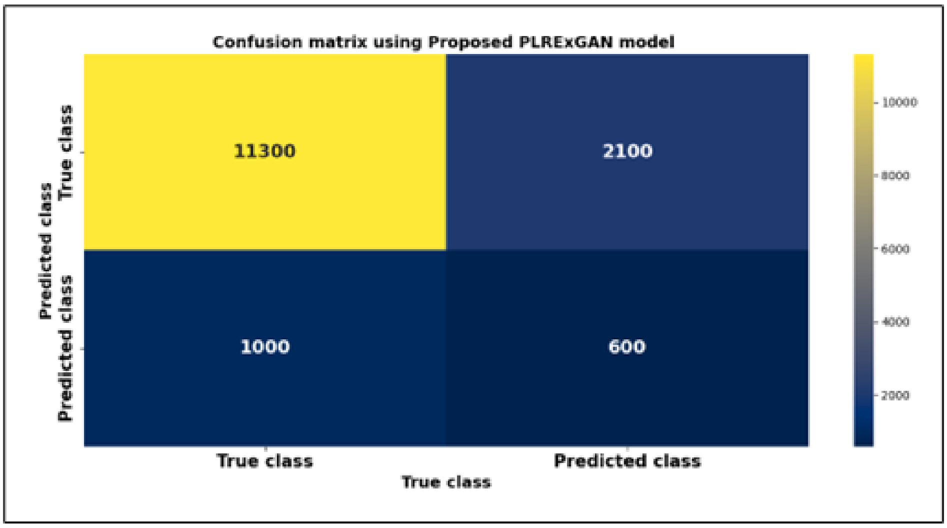


Figure 16 Confusion Matrix results

Figure 16 illustrates the confusion matrix of proposed PLRExGAN model. The confusion matrix provides the visual representation for predicting the student academic performance prediction with 15000 student data. Each confusion matrix discusses classification performance based on the positive and negatives obtained. The proposed PLRExGAN model improved the student academic performance prediction when compared to existing methods.

VI. Conclusion

In this research article, a novel PLRExGAN model is introduced for performing accurate student academic performance prediction. The proposed PLRExGAN model helps the educational institutions to predict the student academic performance based on the mental health indicators. The proposed PLRExGAN model uses graph attention network for performing accurate student academic performance prediction. The proposed PLRExGAN model performed efficient data filtering with outlier detection. After that, the proposed PLRExGAN model selects the relevant features for student academic performance prediction enhancement with minimum time consumption. Then, the classification process is carried out proposed PLRExGAN model to analyze the training and testing student samples based on similarity measure for categorizing into excellent, medium or poor classes. Finally, the PLRExGAN model performs efficient fine-tuning process to minimize the prediction error during student academic performance prediction. A comprehensive evaluation of proposed PLRExGAN model is carried out with several performance metrics like student academic performance prediction accuracy, ROC-AUC, precision, recall, f1-score, specificity and student academic performance prediction time across different number of student data samples. The performance results demonstrate that the proposed PLRExGAN model attains improved the performance results than conventional methods with higher accuracy and minimum time consumption during student academic performance prediction.

References

[1] Yisheng Yang, Shiyu Zhao, Sufang An, Xiaoyong Li and Yong Zhang, "Student academic performance prediction via hypergraph and TabNet", Journal of Big Data, Springer, Volume 12, Issue 119, 2025, Pages 1-15

[2] V. Balachandar and K. Venkatesh, "A multi-dimensional student performance prediction model (MSPP): An advanced framework for accurate academic classification and analysis", MethodsX, Elsevier, Volume 14, June 2025, Pages 1-15

[3] A L Akash Devaraje Urs and Akshay Sudharshan P K, "A multi-factor machine learning framework for predicting and profiling student academic performance using behavioral, financial, and wearable data", MethodsX, Elsevier, Volume 15, December 2025, Pages 1-15

[4] Fatema Tuz Johora, Md Nahid Hasan, Aditya Rajbongshi, Md Ashrafuzzaman and Farzana Akter, "An explainable AI-based approach for predicting undergraduate students academic performance", Array, Elsevier, Volume 26, July 2025, Pages 1-15

[5] Tao Yang, Wendong Xu, Lingbo Wang and Morozova Olga Petrovna, "A Deep Learning Model for Psychological Support in Student Entrepreneurship", IEEE Access, Volume 13, March 2025, Pages 40931 – 40942

[6] Najah Al-Shanableh, Mazen S. Alzyoud, Ahmed Khalil, Mohamed Benlamine, Insaf Kraidia, Sadeq Damrah and Atena M. Tabakhi, "Forecasting Students' Academic Performance in Educational Data Using Machine Learning Techniques", International Journal of Information and Communication Technology Education, Elsevier, Volume 22, Issue 1, 22 January 2026, Pages 1-15

[7] Iyad Katib and Mahmoud Ragab, "Harnessing variable reduction approach with deep recurrent neural network for student's academic performance analysis", Alexandria Engineering Journal, Elsevier, Volume 118, April 2025, Pages 393-405

[8] Jielin Deng, Xiaohua Huang and Xiaopeng Ren, "A multidimensional analysis of self-esteem and individualism: A deep learning-based model for predicting elementary school students' academic performance", Measurement: Sensors, Elsevier, Volume 33, June 2024, Pages 1-16

[9] Huawei Zhou, Shuanghong Shen, Yu Su, Yongchun Miao, Qi Liu, Linbo Zhu, Junyu Lu and Zhenya Huang, "LLM-EPSP: Large language model empowered early prediction of student performance", Information Processing & Management, Elsevier, Volume 63, Issue 1, January 2026, Pages 1-15

[10] Amani Khalifa, Fatma Ben Said and Yessine Hadj Kacem, "Optuna-Optimized Meta-Learner and Ensemble Learning Models for Student Performance Prediction", Procedia Computer Science, Elsevier, Volume 270, 2025, Pages 1826-1835

[11] Jiayang Huang, Keyi Yang, Quan Wang, Pengfei Yang, Ziling Ruan, Jiaxi Wang and Zhi-Qiang Zhang, "Bayesian deep multi-instance learning for student performance prediction based on campus big data", Neurocomputing, Elsevier, Volume 647, 28 September 2025, Pages 1-18

[12] Benli Shi, "An Exploration of the Early Warning System for College Students' Academic Performance Based on BP Neural Network Driven by Multidimensional Data", International Journal of Web-Based Learning and Teaching Technologies, Elsevier, Volume 20, Issue 1, May 2025, Pages 1-15

[13] Mengyao Chen and Zhengqi Liu, "Predicting performance of students by optimizing tree components of random forest using genetic algorithm", Heliyon, Elsevier, Volume 10, Issue 12, 30 June 2024, Pages 1-15

[14] Yifen Zhou and Xian Yu, "Multi-Graph Spatial–Temporal Synchronous Network for Student Performance Prediction", IEEE Access, Volume 12, October 2024, Pages 142306 – 142319

[15] Ghaith Al-Tameemi, James Xue, Israa Hadi Ali and Suraj Ajit, "A Hybrid Machine Learning Approach for Predicting Student Performance using Multi-class Educational Datasets", Procedia Computer Science, Elsevier, Volume 238, 2024, Pages 888-895

[16] Biqian Cheng, Yuping Liu and Yunjian Jia, "Evaluation of students' performance during the academic period using the XG-Boost Classifier-Enhanced AEO hybrid model", Expert Systems with Applications, Elsevier, Volume 238, 15 March 2024, Pages 1-15

[17] Abdulrahman H. Altalhi and Mahmoud Ragab, "Modelling of enhanced predictive analytics and decision-making approach using recurrent autoencoder with attribute subset reduction for students' academic performance", Ain Shams Engineering Journal, Elsevier, Volume 17, Issue 3, March 2026, Pages 1-18

[18] Li Wang, Lucong Zhang, Haotian Wu, Teng Zhang, Ke Qiu, Tianyu Chen and Hongwu Qin, "Multisource-domain regression transfer learning framework for predicting student academic performance considering balanced similarity", Engineering Applications of Artificial Intelligence, Elsevier, Volume 156, Part A, 15 September 2025, Pages 1-15

[19] Asma Abdulmana Alhamadi, "Predicting the Academic Performance of the Students: Machine Learning Algorithms", SN Computer Science, Springer, Volume 6, Issue 1016, 2025, Pages 1-15

[20] Ashima Kukkar, Rajni Mohana, Aman Sharma and Anand Nayyar, "Prediction of student academic performance based on their emotional wellbeing and interaction on various e-learning platforms", Education and Information Technologies, Springer, Volume 28, 2023, Pages 9655–9684

[21] Yi Ren and Xinjie Yu, "Long-term student performance prediction using learning ability self-adaptive algorithm", Complex & Intelligent Systems, Springer, Volume 10, 2024, Pages 6379 - 6408

[22] Wenkai Zhou, Yunsong Li, Jiaxing Li, Tianhao Zhang, Xiping Duan, Ning Ma and Yuhe Wang, "A student academic performance prediction model based on the interval belief rule base", Scientific Reports, Springer, Volume 15, Issue 30607, 2025, Pages 1-15

[23] Ying Qi, "A multi-dimensional prediction system for students academic performance driven by deep learning", Discover Artificial Intelligence, Volume 6, Issue 69, 2026, Pages 1-15

[24] Yueying Wang, "Artificial intelligence in student management systems to enhance academic performance monitoring and intervention", Scientific Reports, Springer, Volume 15, article number 35122, 2025, Pages 1-14

[25] Claudia Diamantini, Laura Genga, Alessandro Mele, Alex Mircoli and Domenico Potena, "Predicting students' academic performance based on early career behaviors: a process-aware approach", Process Science, Springer, Volume 2, Issue 17, 2025, Pages 1-15

[26] S. Selvi and M. Priya, "Enhanced academic performance prediction using ICNN and ISCO: a deep learning approach for intermediate and secondary education", OPSEARCH, Springer, 2026, Pages 1-16

[27] Mario B. Caday, Gleen A. Dalaorao and Cristopher C. Abalorio, "Academic Performance Analysis of Diploma Students using Predictive Analytics", Procedia Computer Science, Elsevier, Volume 257, 2025, Pages 913-920

[28] Zongwen Fan, Jin Gou and Cheng Wang, "An error complementarity-based iterative learning approach via categorical boosting for student performance prediction", Engineering Applications of Artificial Intelligence, Elsevier, Volume 161, Part B, 9 December 2025, Pages 1-15

[29] Shireen Fathima and Maaz Ahmed, "A Psychometric Framework for modeling the impact of Insomnia on Academic Performance", Sleep Epidemiology, Elsevier, Volume 6, December 2026, Pages 1-15

[30] Yan Wu, "Research on prediction algorithm of college students' academic performance based on Bert-GCN multi-modal data fusion", Systems and Soft Computing, Elsevier, Volume 7, December 2025, Pages 1-15