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Interpolated Contractive Auto Encoder Sequential AI For Student Academic Performance Prediction

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ABSTRACT
Education is the foundation of individuals for encouragement intellectual development as well as determining prospect leaders. Student performance forecast an essential in edifying institutions, giving precious insights to student's academic results as well as assisting educators at executing adapted intercession. In preceding works, numerous variants of ML as well as AI methods have executed by increased accuracy. Student performance forecast espouse prognostic method to predict as well as compute student prospect educational result depend on historic information as well as pertinent features gathered over classes of syllabus. But, lack of clearness because of assorted nature of features which escort to biases, mandatory disparity or even demands at inferring method insinuation not mentioned. To mention above problems, novel method termed Interpolated Contractive Auto Encoder Sequential AI (ICAESqAI) Model is introduced. Major aim objective of ICAESqAI Model is to carry out effective predictive analytics on collected student data samples in educational institutions. ICAESqAI Model consists of four steps, namely data acquisition, preprocessing, FS as well as categorization to enhance student performance forecast. Initially, the student data samples are gathered as of database in data acquisition phase. Followed by, the data pre-processing is carried out using Nevanlinna–Pick interpolation estimator for handling the missing data and Berk-Jones test for outlier data removal from the input dataset. After data pre-processing, FS is performed using Contractive Auto Encoder to choose pertinent features as of the input dataset based on Marczewski-Steinhaus similarity index. After feature selection process, the classification process is carried out using sequential AI model with tamas correlation coefficient function. The fine tuning process is carried out for minimizing the error and enhancing the student performance prediction accuracy. Experimental assessment is conducted through dissimilar evaluation parameters. Outcome denote ICAESqAI attained higher accuracy in student performance prediction with lesser time consumption compared to existing deep learning methods.

Keywords: education, nevanlinna–pick interpolation estimator, contractive auto encoder, data pre-processing, tamas correlation coefficient, data acquisition

1. INTRODUCTION

Education is essential for providing the resources for student's career development. With development of artificial intelligence concepts, educational institutions can predict student academic performance at earlier stages. The academic success prediction has gained large interest in education for improving the university ranking and student employment opportunities. Modern education learning faces key challenges in examining the student performance for providing high-quality education and for identifying the future needs. An explainable artificial intelligence based approach was introduced in [1] for predicting undergraduate student performance in context of Bangladesh. The designed approach enhanced the transparency, fairness and reliability on student result forecast. However, it failed to address generalizability issues.

LSTM NN was designed [2] for student educational result prediction. But, the designed neural network attained less prediction accuracy. An integrated optimization method termed SailMutLoc algorithm was introduced in [3] depending on sailfish behavior. The designed method enhanced the precision performance through fine-tuning process. SailMutLoc algorithm improved the classification accuracy with minimum computing time. But, precision was not enhanced. Student performance prediction approach was presented [4] for student educational result forecast. However, time complexity was not minimized.

Novel model was designed [5] for forecasting the university student result. It computed the past educational grades between academy students. But, accuracy was not enhanced. FAMD and MLR was designed [6] to recognize factors manipulating student result. However, the true positive of student data classification was not improved by FAMD and MLR. A sparse attention mechanism was introduced in [7] to identify the relevant features. The extracted learning features were processed by deep neural network with Cost-Sensitive Combined Loss function. But, the prediction time was not minimized by sparse attention mechanism.

A soft voting ensemble termed Hybrid Productivity Prediction (HPrEd) was introduced in [8] with multiple machine learning. LIME and SHAP were employed to examine the connection between social media engagement and academic productivity. But, computational complexity was not minimized. EDM system was designed [9] for combining machine learning for categorizing the student academic performance with XAI methods. XAI technique was employed for global and local explainability. However, accuracy was not better. Multimodal data fusion algorithm was introduced in [10] to predict academic performance of college students accurately. It improved the model ability to understand learning behavior. However, accuracy was not enhanced through multimodal data fusion algorithm.

A comprehensive and high-performance prediction framework was designed in [11] with SAP characteristics on educational data. The designed framework addressed the imbalanced data problems for improving the academic prediction performance. But, the false negative was not reduced. Radial Basis Function NN was designed [12] for student performance prediction with past academic records and cognitive abilities. However, the computational cost was not reduced by Radial Basis Function Neural Network.

The machine learning approach was introduced in [13] to forecast the vocational undergraduate students for computing the academic performance. But, the recall performance was not improved by designed approach. Probit Generative Restricted Deep Boltzmann Machine (PGRDBM) method was introduced in [14] with deep boltzmann machine classification process for accurate and space-efficient student academic performance prediction. However, the prediction error was not reduced by PGRDBM method. Student Academic Performance Predicting (SAPP) system was introduced in [15] to categorize the data samples into pass or fail outcomes with high prediction accuracy. But, the true positive was not enhanced by SAPP system.

The issues identified from the above literature includes lower student academic performance prediction accuracy, minimum precision, higher computational complexity, lesser mathews correlation coefficient, lesser coefficient of determination etc. To mention existing problems, Interpolated Contractive Auto Encoder Sequential AI (ICAESyAI) Model is introduced.

1.1 Key Contribution

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

- To improve student educational result forecast accuracy, ICAESqAI Model is introduced with data pre-processing, feature selection, data classification and fine-tuning process.
- To improve the coefficient of determination result through student educational result forecast, the missing information points as well as outlier information are detected using Nevanlinna–Pick interpolation estimator and Berk-Jones test correspondingly
- To choose the relevant features for minimizing the student academic performance prediction time, Contractive Auto Encoder is utilized with Marczewski-Steinhaus similarity index
- To enhance student educational result forecast accuracy with selected features, a sequential AI model is used in ICAESqAI Model with the tamas correlation coefficient function for efficient data classification

- To reduce the false negatives during student academic performance prediction, modified rat swarm optimization is carried out in ICAESqAI Model for efficient fine tuning.
- Lastly, comprehensive experimental analysis across different metrics shows ICAESqAI achieves enhanced performance than conventional deep learning methods

1.2 Structure of Article

Rest of manuscript is arranged as: Section 2 evaluates literature of student educational result forecast. Section 3 describes explanation of proposed ICAESqAI Model with neat architecture diagram and detailed explanation. Section 4 demonstrates experimental outcomes as well as implementation results. In Section 5, comparative result study is carried out with dissimilar performance metrics. Lastly, Section 6 concludes the research article.

2. RELATED WORKS

Education is essential for the development of life skills. A student performance-based temporal dynamic approach was introduced in [16] to forecast the semester-wise performance. The dynamic experimental framework was employed to forecast the student performance in semester-wise. Machine Learning-Based Academic Result Prediction System was introduced in [17] to forecast semester GPA of students depending on traits. The designed system considered the past academic performance and personal habits through machine learning concepts. The feature-ranking mechanism was introduced in [18] for identifying the relevant features and their correlation values for student academic performance prediction. An optimization strategy was used to configure the deep neural network.

The educational data mining approach was introduced in [19] for categorizing the student data into multiple performance level. ML technique was introduced in [20] for student result prediction. It was used through computing the correlation between behavioral indicators. The different regression methods were designed [21] to predict student academic result with higher accuracy.A DL method was introduced [22] with Bi-LSTM network to predict academic performance prediction.

A fit candidate method was designed in [23] based on similarity measurement and roulette wheel selection with synthetic data samples. High-Performance Intelligent Framework was introduced in [24] for forecasting student educational result with binarized CNN in EDM. ML was presented [25] to forecast student educational result. The student academic data was employed for examining the relationship between different factors and academic performance.

An ensemble model was introduced in [26] with voting method for student academic performance prediction. The student behavior trajectory was introduced in [27] for academic performance prediction. The tri-branch convolutional neural network (CNN) architecture was used with convolution and attention operation. Student result forecast approach was introduced [28] for addressing student educational result problems. Educators present individualized support and assistance for every student samples. A conceptual model was introduced in [29] with PSO and DNN. SHAP and LIME method compute different feature contribution for efficient prediction. A multi-graph spatial-temporal synchronous network (MGSTSN) was introduced in [30] for improving the precision performance improvement.

3. METHODOLOGY

Student performance prediction is essential in education. The successful prediction of student performance positively influences the student achievement goals, enhances student personal expectancy value and encourages the student efficiency. The student performance prediction creates the positive driving forces for student futures from multiple viewpoints. With artificial intelligence concepts in education field, it provides the opportunities for student academic performance prediction and grade improvement. Student result forecast helps teachers to understand student learning patterns and address the problems at earlier stage. In order to predict the student performance, new method called Interpolated Contractive Auto Encoder Sequential AI (ICAESqAI) Model is introduced. Major aim of ICAESqAI method is to carry out effective student performance predictive analytics on collected data samples in educational institutions with high accuracy and lesser time consumption.

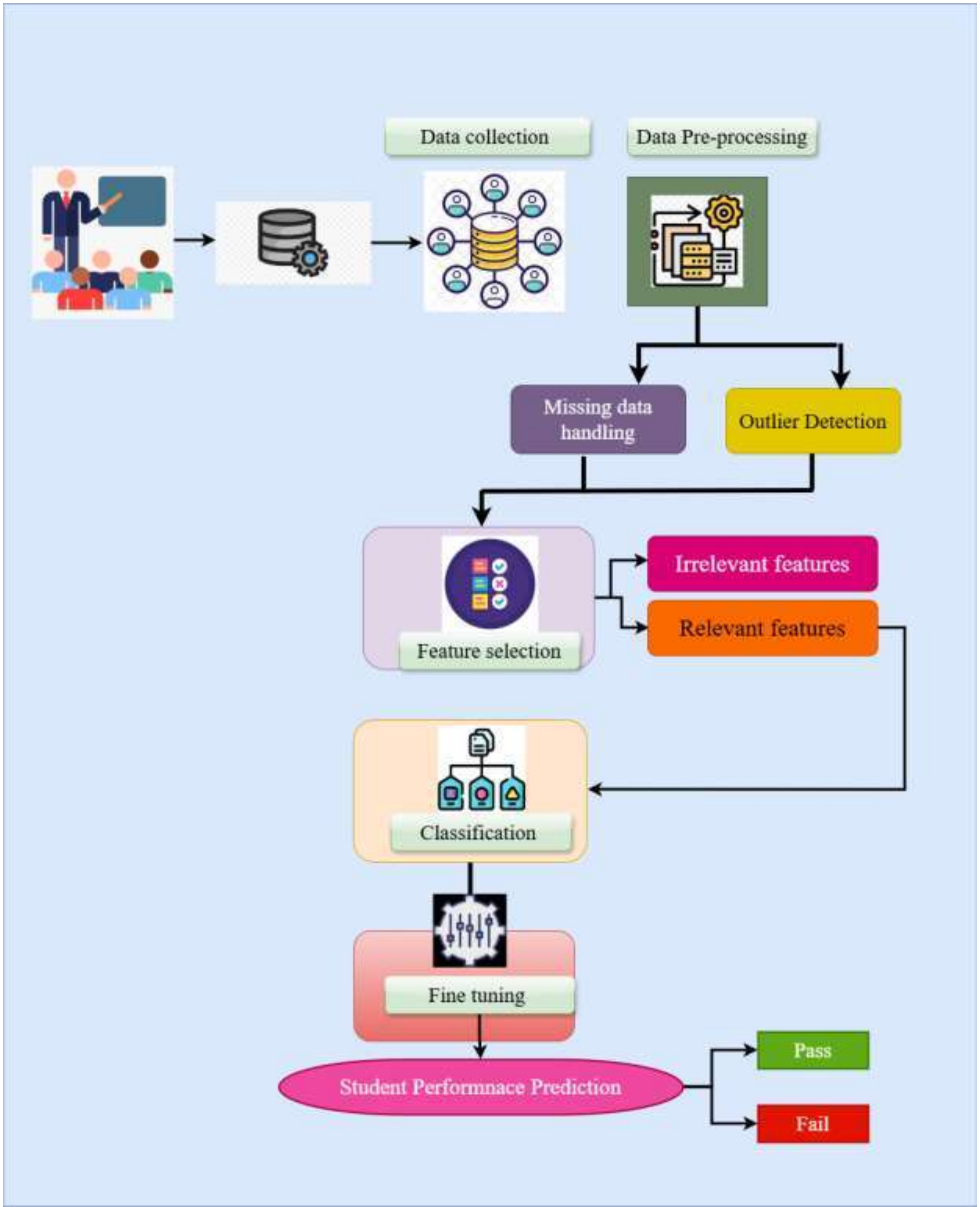


Figure 1 Architecture Diagram of ICAESqAI method

Figure 1 shows structural design diagram of ICAESqAI, performing efficient student performance prediction. The proposed ICAESqAI Model carried out five different processes. The student data pre-processing is vital for performance prediction through missing data handling and outlier detection. The feature selection process helps in choosing the relevant features from pre-processed student performance dataset. After that, the data classification is carried out to classify the student data points into two different classes (i.e., pass or fail) for enhancing the student performance. The below mentioned sub-section describes the proposed ICAESqAI Model in detail for improving student result prediction by minimum time consumption.

3.1 Dataset Description

In the proposed ICAESqAI Model, data collection is the first process for student performance prediction. The proposed ICAESqAI Model collects student data points as of Student Performance Prediction database. The URL of input dataset is given as https://www.kaggle.com/datasets/souradippal/student-performance-prediction. Student performance forecast method is employed to forecast student educational result depending on historical information as well as pertinent features gathered during curriculum course. Student performance prediction database is employed with 40,000 student data points. Dataset is employed for efficient student data classification task. Dataset comprised of features namely attendance rate, etc. Dataset handles missing data points, incorrect data, and noise through data cleaning process, exploratory data analysis and feature engineering.

Table 1 attribute information

S. No	Features	Description
1	Student ID	An identifier for each student
2	Study Hours per Week	Average number of hours that student studies per week
3	Attendance Rate	Number of classes student attended to the total number of classes
4	Previous Grades	Average grade that the student received in previous course
5	Participation in Extracurricular Activities	The student participation in extracurricular activities (Yes/No)
6	Parent Education Level	Student's parent highest education
7	Passed	The student passed course (Yes/No)

3.2 Data Pre-processing

It is considered as second process of proposed ICAESqAI model. Preprocessing is carried out to convert the raw student data points into meaningful data points for accurate student performance prediction. Preprocessing task is employed to enhance effectiveness as well as to minimize forecast time. Pre-processing in proposed ICAESqAI Model handled the missing data points and detected the outliers for student performance prediction with higher accuracy and minimum time consumption. ICAESqAI Model uses Nevanlinna–Pick interpolation estimator for performing missing data handling and Berk-Jones test for performing outlier detection. A missing value is a data point where no value is assigned to a specific feature in the dataset. The student dataset is constructed in input matrix 'IM' with number of features and data points. The student data points are organized in the form of 'n' rows and 'm' columns. It is formulated as,

$$IM = \begin{bmatrix} Fa_1 & Fa_2 & \dots & Fa_m \\ StD_{11} & StD_{12} & \dots & StD_{1n} \\ StD_{21} & StD_{22} & \dots & StD_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ StD_{m1} & StD_{m2} & \dots & StD_{mn} \end{bmatrix} \quad (1)$$

From (1), 'IM' symbolizes the input matrix. After that, the missing data point is filled through choosing the nearest data points with in specific column. Consequently, proposed ICAESqAI Model employs Nevanlinna–Pick interpolation estimator process for handling the missing data values before performing effective student performance prediction. Nevanlinna–Pick interpolation estimator uses the nearest neighboring ideas to pick and fill the optimal values in missing places. Nevanlinna–Pick interpolation estimator uses pick theorem for filling the missing data points.

Let us consider input student data points 'StD_1, StD_2, ... , StD_n' for every features in input pre-processed dataset. Nevanlinna–Pick interpolation estimator computed the missing data points using bounded analytic function. It is expressed as follows,

$$PM_{mn} = \frac{1-np_i\bar{\bar{n}}\bar{\bar{p}}_{\bar{y}}}{1-StD_i\bar{\bar{S}}\bar{t}\bar{\bar{D}}_{\bar{y}}} \quad (2)$$

From (2), 'PM_{mn} ' symbolizes the pick matrix. 'np_i' denotes the neighboring data points. 'StD_i' represent the student data points. Consequently, Berk-Jones test is used in proposed ICAESqAI Model to recognize the outlier data samples in input dataset. Berk–Jones test computes whether the set of observed student data point values deviates from the reference distribution with particular sensitivity to small clusters of extreme values. Berk-Jones test is used to separate the outliers from normal data points. Afterward, the Berk-Jones test is formulated as,

$$BJ(StD_i) = StD_i \log\left(\frac{StD_i}{np(StD_i)}\right) + (n - StD_i)\log\left(\frac{n-StD_i}{n(1-p(StD_i))}\right) \quad (3)$$

$$BJ = \max_{StD_i} BJ(StD_i) \quad (4)$$

From (3) and (4), '$BJ(StD_i)$' symbolizes the Berk-Jones test of student data points. The Berk-Jones test output ranges from '0 to ∞'. It is given by,

$$PR = \begin{cases} BJ > T, \text{ Outliers} \\ BJ < T, \text{ Normal data} \end{cases} \quad (5)$$

From (5), 'PR' denotes the data pre-processing results. When the statistic test results 'BJ' value is superior than 'T', exacting student data point indicated as outlier. When the statistic test results 'BJ' value is lesser than threshold 'T', the particular student data point is denoted as normal data points. Thus, the outlier data points are identified and removed from the input dataset for accurate student performance prediction.

3.3 Feature Selection

The feature selection is the third process in proposed ICAESqAI model. After preprocessing task, FS is employed for selecting relevant features from input pre-processed dataset for precise student result prediction. FS process in proposed ICAESqAI model reduces time utilization of student result forecast. Proposed ICAESqAI model uses contractive autoencoder for performing efficient feature selection. The contractive autoencoder is a kind of deep neural network with encoder function and decoder function. The encoder function is employed in proposed ICAESqAI model to convert the input pre-processed student data samples into a lower-dimensional representation. The decoder function is employed to reconstruct original input dataset as of encoded version. Contractive autoencoder (CAE) in proposed ICAESqAI model improves the performance over conventional autoencoder by adding regularization penalty. CAE is used in proposed ICAESqAI model to achieve the robust and generalized results. The contractive autoencoder provides the high stability and enhanced feature selection results for student performance prediction. CAE in proposed ICAESqAI model identifies the relevant features for improving the student performance prediction results.

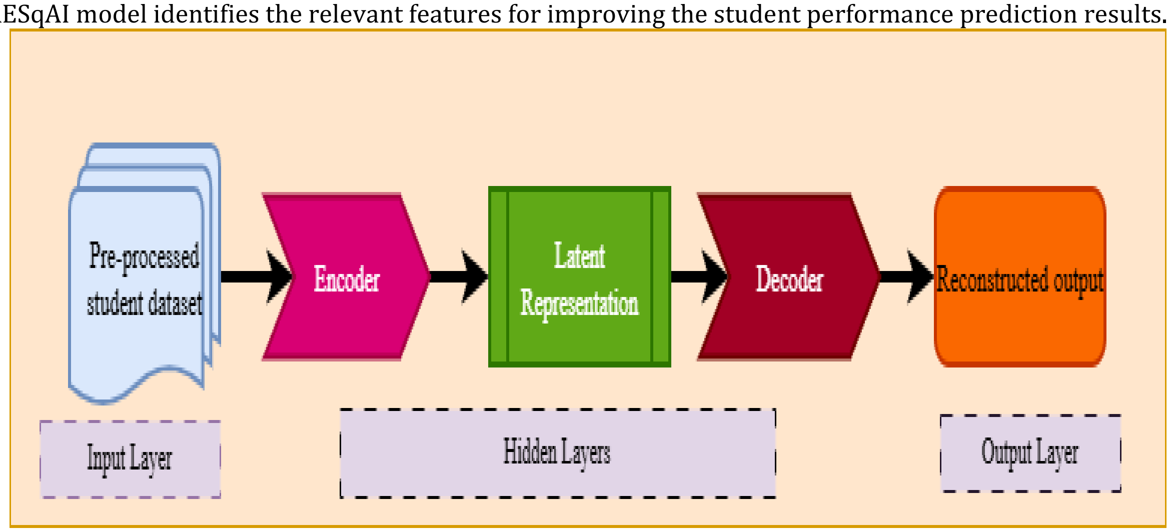


Figure 2 Network structure of Contractive Autoencoder

Figure 2 shows the structure of contractive autoencoder with two major functions such as encoder and decoder. The preprocessed student dataset is transmitted to input layer of contractive autoencoder. After that, input preprocessed dataset is sent to the hidden layers. Encoder as well as decoder employed for relevant feature selection in student performance prediction. In encoder layer, ICAESqAI model uses Marczewski-Steinhaus similarity index to identify pertinent features as well as eliminate irrelevant features.

Let us consider input features '$\{Fa_1, Fa_2, \ldots, Fa_m\}$' in high-dimensional student database. After that, the Marczewski-Steinhaus similarity index is used to calculate similarity among the feature as well as objective for efficient feature selection. Marczewski-Steinhaus similarity index is computed as,

$$MSSI = \frac{|Fa_p \cap objective|}{max(|Fa_p|, |objective|)} \quad (6)$$

From (6), '$MSSI$' represent the Marczewski-Steinhaus similarity index. The similarity value ranges as of '0 to '1'. Then, T value is predefined as 0.5 for performing efficient student performance prediction. The output of the similarity in

$$MSSI = \begin{cases} 1, & Relevant\ features \\ 0, & Irrelevant features \end{cases} \quad (7)$$

From (7), the feature similarity is computed. When the Marczewski-Steinhaus similarity is close to 1, the feature is pertinent feature. When Marczewski-Steinhaus similarity is close to 0, the feature is said to be irrelevant features. The latent space of an autoencoder is a reduced through lower-dimensional representation in encoder part. In autoencoder, encoder gathers relevant patterns and eliminates the irrelevant data patterns. The latent representation is formulated as,

$$lr = af_{en}(we_{en}Fa_j + b_{en}) \quad (8)$$

From (8), 'lr' symbolizes the latent representation of input dataset. 'Fa_j' indicates the input features to the encoder. 'we_{en}' represent the weight matrix of encoder level. Weight matrix converts feature vector into latent space. 'b_{en}' symbolizes bias vector of encoder level. 'af_{en}' represent activation function of encoder to identify the irrelevant patterns. Consequently, the decoder maps the latent vector to the input space. It is formulated as,

$$do = af_{de}(we_{de}lr + b_{de}) \quad (9)$$

From (9), 'do' represent the decoded output. 'lr' symbolizes the latent space representation. Aim of contractive autoencoder is to minimize the reconstruction loss within low-dimensional representation of data points. The objective of contractive autoencoder is formulated ally as follows,

$$arg\,min|Fa_j - do| + \lambda|K| \quad (10)$$

From (10), 'Fa_j' represent the input data matrix. 'do' symbolizes the reconstructed output of autoencoder. 'λ' indicate the regularization parameter. '$arg\ min$' denotes the argument of minimal function. Depending on autoencoder analysis, relevant features are selected and irrelevant aspects are removed to enhance student performance forecast accuracy. By this way, the proposed ICAESqAI model selects the relevant feature to reduce the time consumption. The algorithmic steps of contractive autoencoder feature selection is given as,

//Algorithm 1: Contractive Autoencoder Feature Selection

Input: Datasets 'DS', pre-processed student data points $StD_i = \{StD_1, StD_2, \ldots, StD_m\}$
Output: Selects the relevant features

Begin
Step 1: Collect the pre-processed student data points
Step 2: Input the features given to encoder
Step 3: Encoder maps the features into latent space
Step 4: For each feature in latent space
Step 5: Compute Marczewski-Steinhaus similarity value
Step 6: End for
Step 7: Reconstruct the features at decoder from the latent vector
Step 8: Return (Obtain relevant features)
End

Algorithm 2 shows the feature selection process using contractive autoencoder. The feature selection process initiates with input features and given to the encoder layer. The features map them into latent space for attaining lower-dimensional representation in selecting relevant features. In latent space, the feature similarity is computed for efficient feature selection. The decoder reconstructs the original features from the latent vector. Finally, the relevant features are selected for performing data classification in student performance prediction. The relevant features are used in the classification process to reduce time utilization for student performance forecast.

3.4 Data Classification

The fourth process of proposed ICAESqAI model is data classification. The student performance prediction is carried out using Liquid Time-Constant Networks (LTCN) with the selected features. LTCN is a type of Sequential AI used to perform data classification process by using the neurons capable of different input student data samples. In the proposed ICAESqAI model, the sequential AI architecture used LTCN to recognize the pass and fail class of the student data samples. With selected features of student performance dataset, the data classification is performed using sequential AI architecture to compute the relationship among selected features and student performance classes, namely pass or fail.

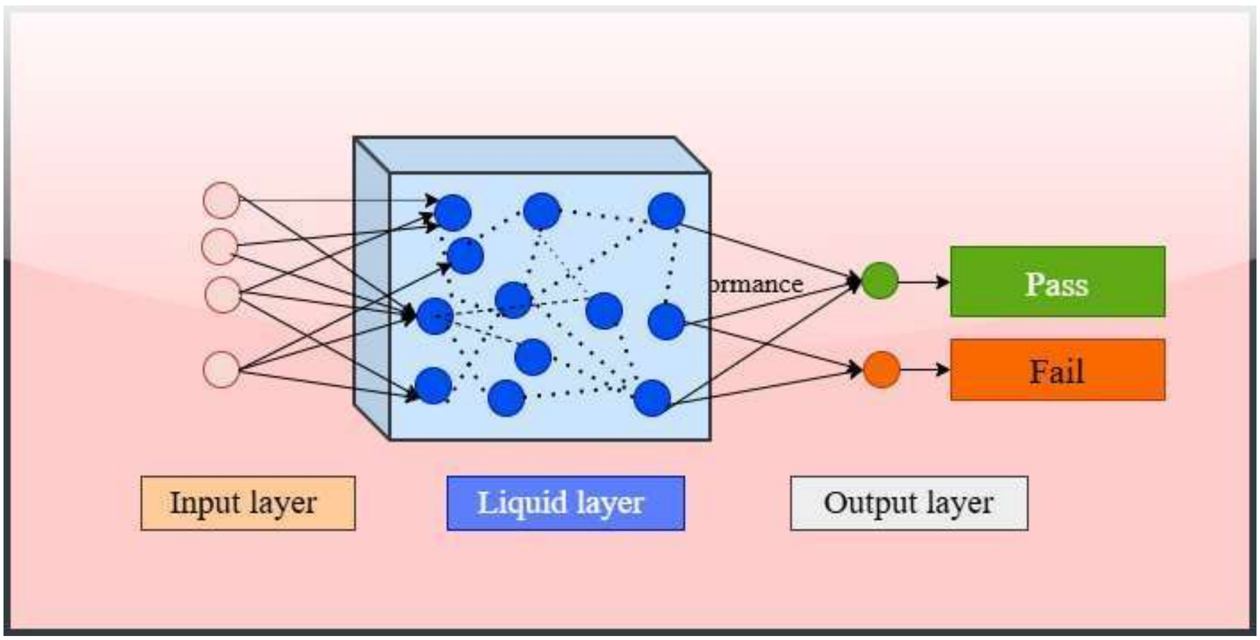


Figure 3 Structure of Liquid Time-Constant Networks

Figure 3 illustrates the structure of LTCN. LTCN contain three layers. Each layer comprised computational units termed as nodes that imitate the adaptive behavior observed in neural systems. Liquid Time-Constant Networks enable continuous, time-dependent communication between neurons for processing sequential student data samples. The input layer collects the selected features and transmitted to the network. The input layer transmits the selected features to the liquid layer through the neurons for performing data classification. The circular nodes denote individual neurons for transmitting and processing the student information throughout the liquid time-constant networks.

In input layer, every neuron applies weights as well as biases to selected input features of student data samples. The input layer at time instant allowed the LTCNs to capture and learn relationship for effective student performance prediction. It is formulated as,

$$IL(t) = \sum_{j=1}^{r} SFa_j * we_{IL} + b_{IL} \qquad (11)$$

From (11), '$IL(t)$' denotes the input layer result at the time instant. ' we_{IL} ' represent the weights between input as well as liquid layer. ' SFa_j' indicates number of selected relevant features.In liquid layer, spiking neurons form dynamic connections for creating the network liquid behaviour. The liquid layer processes the student information through computing different possible interpretations of input student data samples at the same time. The liquid layer allows LTCNs to effectively compute the dependencies between the selected features of training data samples and selected features of testing data samples using tamas correlation function. Tamas CC is a statistical method employed to compute relationship among featured for data classification. Tamas CC calculates proportion of student data samples which are equally there in together sets to whole number of student data samples. Association among the features of training and testing student samples is formulated as,

$$TMC = \frac{[StD_{tr} \cap StD_{te}]}{n} \quad (12)$$

From (12), 'TMC' denotes the tamas matching coefficient. 'StD_{tr}' indicates the training data samples. 'StD_{te}' represent the testing student data samples. '$StD_{tr} \cap StD_{te}$' symbolizes the mutual dependence among two student data samples. 'n' represents total number of student data samples. Tamas matching coefficient 'TMC' presents output value as of 0 to 1. Depending on correlation outcomes, output value of '1' denotes the pass class and output '0' indicates fail class. It is formulated as,

$$TMC = \begin{cases} 1\ ; & Pass \\ 0\ ; & Fail \end{cases} \quad (13)$$

From (13), TMC is computed. Output results of 'TMC' denotes the binary classification results for student performance prediction. The binary classification results categorize the student data samples into either pass or fail classes for efficient student performance prediction. The spiking neuron in the liquid layer at time period 't' is formulated as follows,

$$LL(t) = L_{af}\left(\sum_{j=1}^{r} SFa_j * we_{IL} + we_L\, LL_{t-1} + b_L\right) \quad (14)$$

From (14), '$LL(t)$' represent the liquid layer results at the time period. 'L_{af}' indicate the liquid activation function to compute spiking neuron output in liquid layer. 'LL_{t-1}' represent the previous liquid layer. 'we_{IL}' symbolizes the weights between input layer to liquid layer. 'we_L' symbolizes the recurrent weights in the liquid layer. 'b_L' represent the bias term in liquid layer.

3.5 Fine-tuning

In proposed ICAESqAI model, the fine-tuning is considered as fifth process for tuning the classification results to attain enhanced student performance prediction results with minimum classification error. For minimizing the classification error, the hyper parameter tuning is carried out in proposed ICAESqAI model. The list of hyper-parameters in liquid time constant network is bias, activation function and weights. Among the list of hyper-parameters, the weight value is considered for performing the fine-tuning process. The classification error is determined as follows,

$$SPCE = [AV - OV] \quad (15)$$

From (15), '$SPCE$' symbolizes the student performance classification error. The fine tuning process is performed in proposed ICAESqAI model for varying the weights between layers of liquid time constant network architecture. The weight adjustment is performed through Nadam method

$$we_{new} = we_t - \eta\, B_t \quad (16)$$

$$B_t = \gamma\, B_{t-1} + (1-\gamma)\left(\frac{\partial SPCE}{\partial we_t}\right) \quad (17)$$

From (16) and (17), 'we_{new}' represent the updated new weights between layers. 'we_t' denotes the previous weight. 'η' symbolizes the learning rate. '$\frac{\partial SPCE}{\partial we_t}$' indicates the partial derivative of student performance classification error '$SPCE$' with respect to the current weight 'we_t'. 'ρ' represent the constant value (i.e, 0.9). The different weight values are attained after weight update. Among the different weight values, optimal weight value is identified with MRSO algorithm with minimum classification error rate. In proposed ICAESqAI model, MRSO enthused by rat activities in groups. In proposed ICAESqAI model, MRSO is to simulate behavior of rats such as chasing, and fighting the prey. MRSO operates with fast convergence to balance the exploration and exploitation phases. The rat populations (i.e., weights) are initialized in search space. After performing the weight initialization '$we_1, we_2, we_3 \dots . we_b$', the fitness of weight is formulated as,

$$Fitness(we) = arg\,min\,SPCE \quad (18)$$

From (18), '$Fitness(we)$' represent the fitness of weight value. '$arg\ min\ SPCE$' denotes the argument minimum of student performance classification error.

Chasing and Fighting through Prey

Rats use agnostic behaviour for chasing the prey in group. Rats sense the smell and find the food. When rats search for prey, the sense of smell is an important factor. Though the rats depend on additional senses smell acts important part at investigate for food as well as detecting hazard. Following identifying the quarry, rats communicate information through specific behavioral patterns. With help of these behavior, the rats identify the prey location to chase as well as brawl. MRSO algorithm uses present best solution as prey position.

$$D = R - t * \left(\frac{R}{I_{max}}\right). X(t) + 2. rand \,.\, (X^*(t) - X(t)) \qquad (19)$$

From (19), 'D'denotes position update. '$X^*(t)$' represent greatest ideal location. '$X(t)$' denotes position of rats. 'I_{max}' symbolizes maximum number of iteration. 'R' and '$rand$' indicates the random number in the intervals [1,5] and [0,2] respectively. During prey hunting process, rats consumes large amount of time searching for prey. The prey hunting process forces exploration to perform the global search. It is carried out by,

$$X(t+1) = |X_{rand}(t) - D| \qquad (20)$$

From (20), '$X_{rand}(t)$' denotes the arbitrarily chosen rats from the population.

Attacking Prey (Exploitation Phase):

The rats uses the containment strategy to capture prey. When rats discover prey, they collect around it to guarantee triumphant detain. In the prey hunting process, every rat performs arbitrary bound at semi-circular form. The attacking prey formulated as,

$$X(t+1) = X^*(t) - D \ sin\frac{\pi l}{4} \qquad (21)$$

From (21), 'r' denotes the parameter to regulate distance among semi-circular as well as prey. MRSO execute switching operation between jumping at semi-circular movement approximately prey as well as assaulting and fighting through prey. Process gets repeated till satisfying the termination condition. Therefore, the final student performance prediction outcomes are attained with tangent activation function. It is given as,

$$OR = O_{af}\ (LL\ (t) * we_{LO}) \qquad (22)$$

From (22), 'OR' represent the output classification results. 'O_{af} ' symbolizes the output activation function. '$LL(t)$' denotes the liquid layer results. ' we_{LO} ' indicates the weight between liquid layer and output layer. This in turn, accurate student performance forecast outcomes are attained at output level. Algorithmic description of student performance prediction is given below,

Algorithm 2: Sequential AI Student Performance Prediction
Input: Number of selected features '$SFa_j = \{SFa_1, SFa_2, \dots, SFa_p\}$'
Output: Enhanced student performance classification accuracy
Begin Step 1: Collect selected features 'SFa_j' of testing student samples at input layer Step 2: Transmit selected features to the liquid layer Step 3: For every selected features do ------ liquid layer Step 4: Measure the tamas correlation coefficient (TMC) 93, 971592 Step 5: if($TMC = 1$) then Step 6: Student data samples is classified into pass class Step 7: else if ($TMC = 0$) then Step 8: Student data samples is classified into fail class Step 9: End if Step 10: End for Step 11: For each student performance data classification result Step 12: Compute student performance classification error for Step 13: Initialize the weight population Step 14: Compute the fitness Step 15: Select current best rat position Step 16: Update the position of rat Step 17: Identify the global best position of rat Step 18: End for Step 19: Return (pass or fail classification output) Step 20: Obtain the student performance prediction results with minimum error at output layer End

Algorithm 2 illustrates algorithmic procedure for increasing the student performance prediction accuracy by using Sequential AI algorithm. The algorithm initiates with selected features into input layer of the LTCN. In the liquid layer, TMC is used to discover relationship among training data points as well as testing information points. Depending on coefficient value, each student data sample is categorized to two different classes. After classification task, the error rate is computed and their weight values are initialized. Then, the weight values are optimized with helps of modified rat swarm optimization. The fitness is calculated for every student data. Then, the current best solution is identified for position update of the weights. The process gets repeated until maximum iteration count is attained. Lastly, the final classification result is attained at the output layer to guarantee accurate student performance classification results with lesser time consumption.

4. EXPERIMENTAL SETTINGS

Experimental valuation of three different methods, namely proposed ICAESqAI model and existing explainable AI-based approach (XAI) [1] and Long Short-Term Memory (LSTM) [2] are executed by Python. To perform the experiment, Student result Prediction dataset employed in this research article. The student dataset comprises 7 attributes and 40,000 data instances for carry out student academic performance forecast. For experimental consideration, the number of student data considered with different numbers ranging as of 4,000, to 40,000 instances.

3.1 Implementation Results

The proposed ICAESqAI model uses sequential AI to evaluate student academic performance prediction efficiency. The proposed model performed includes data collection, data preprocessing, feature selection and classification with student performance prediction dataset taken from Kaggle repository. The 40000 student data sample are collected from input dataset as illustrated in the figure 4 for evaluating the performance of proposed ICAESqAI model.

Student Performance Data Acquisition

Student ID	Study Hours per Week	Attendance Rate	Previous Grades	Participation in Extracurricular Activities	Parent Education Level	Passed
S00001	12.5		75.0	Yes	Master	Yes
S00002	9.3	95.3	60.6	No	High School	No
S00003	13.2		64.0	No	Associate	No
S00004	17.6	76.8	62.4	Yes	Bachelor	No
S00005	8.8	89.3	72.7	No	Master	No
S00006	8.8	73.8	69.3	Yes	High School	Yes
S00007	17.9	38.6	93.6	No	Doctorate	Yes
S00008	13.8	95.8	59.2	Yes	Doctorate	No
S00009	7.7	100.1	91.9	No	Bachelor	Yes
S00010	12.7	38.4	37.8	Yes	High School	nan
S00011	7.7	54.1	72.3	No	Master	No
S00012	7.7	115.5	41.2	Yes	Master	No
S00013	11.2	79.6	49.6	Yes	Bachelor	nan
S00014	0.4	75.1	50.4	nan	nan	Yes
S00015	1.4	66.5	49.2	No	Associate	Yes
S00016	7.2	54.4	55.9	Yes	High School	No
S00017	4.9	71.1	98.0	Yes	High School	No
S00018	11.6	94.5	51.8	No	Bachelor	Yes
S00019	5.5	74.7	40.8	No	Doctorate	No
S00020	2.9	87.2	72.4	No	Associate	Yes
S00021	17.3	110.3	68.6	No	Bachelor	Yes
S00022	8.9	63.4	98.2	No	Doctorate	No
S00023	10.3	81.1	64.4	No	High School	No
S00024	2.9	95.1	30.7	No	Bachelor	Yes
S00025	7.3	56.3	58.6	Yes	High School	Yes
S00026	10.6		68.3	No	Doctorate	Yes
S00027	4.2	112.4	46.5	nan	High School	Yes
S00028	11.9	68.2	56.6	Yes	High School	No
S00029	7.0	96.4	62.8	Yes	Associate	No
S00030	8.5	72.2	64.1	No	Doctorate	Yes
S00031	7.0	111.0	44.3	No	Doctorate	Yes

Figure 4 Data acquisition results

After performing the data acquisition, data preprocessing is carried out by Nevanlinna–Pick interpolation estimator for performing missing data handling and Berk-Jones test for performing outlier detection. The size of 40000 sample is 1,464KB that gets reduced to 1,323KB after performing data preprocessing. The data preprocessing results are depicted in figure 5.

Nevanlinna–Pick interpolation based Missing Data Handling

Student ID	Study Hours per Week	Attendance Rate	Previous Grades	Participation in Extracurricular Activities	Parent Education Level	Passed
S00001	12.5	95.3	75.0	Yes	Master	Yes
S00002	9.3	95.3	60.6	No	High School	No
S00003	13.2	86.05	64.0	No	Associate	No
S00004	17.6	76.8	62.4	Yes	Bachelor	No
S00005	8.8	89.3	72.7	No	Master	No
S00006	8.8	73.8	69.3	Yes	High School	Yes
S00007	17.9	38.6	93.6	No	Doctorate	Yes
S00008	13.8	95.8	59.2	Yes	Doctorate	No
S00009	7.7	100.1	91.9	No	Bachelor	Yes
S00010	12.7	38.4	37.8	Yes	High School	No
S00011	7.7	54.1	72.3	No	Master	No
S00012	7.7	115.5	41.2	Yes	Master	No
S00013	11.2	79.6	49.6	Yes	Bachelor	Yes
S00014	0.4	75.1	50.4	No	Associate	Yes
S00015	1.4	66.5	49.2	No	Associate	Yes
S00016	7.2	54.4	55.9	Yes	High School	No
S00017	4.9	71.1	98.0	Yes	High School	No
S00018	11.6	94.5	51.8	No	Bachelor	Yes
S00019	5.5	74.7	40.8	No	Doctorate	No
S00020	2.9	87.2	72.4	No	Associate	Yes
S00021	17.3	110.3	68.6	No	Bachelor	Yes
S00022	8.9	63.4	98.2	No	Doctorate	No
S00023	10.3	81.1	64.4	No	High School	No
S00024	2.9	95.1	30.7	No	Bachelor	Yes
S00025	7.3	56.3	58.6	Yes	High School	Yes
S00026	10.6	84.35	58.3	No	Doctorate	Yes
S00027	4.2	112.4	46.5	Yes	High School	Yes
S00028	11.9	68.2	56.6	Yes	High School	No
S00029	7.0	96.4	62.8	Yes	Associate	No
S00030	8.5	72.2	64.1	No	Doctorate	Yes

5(a)

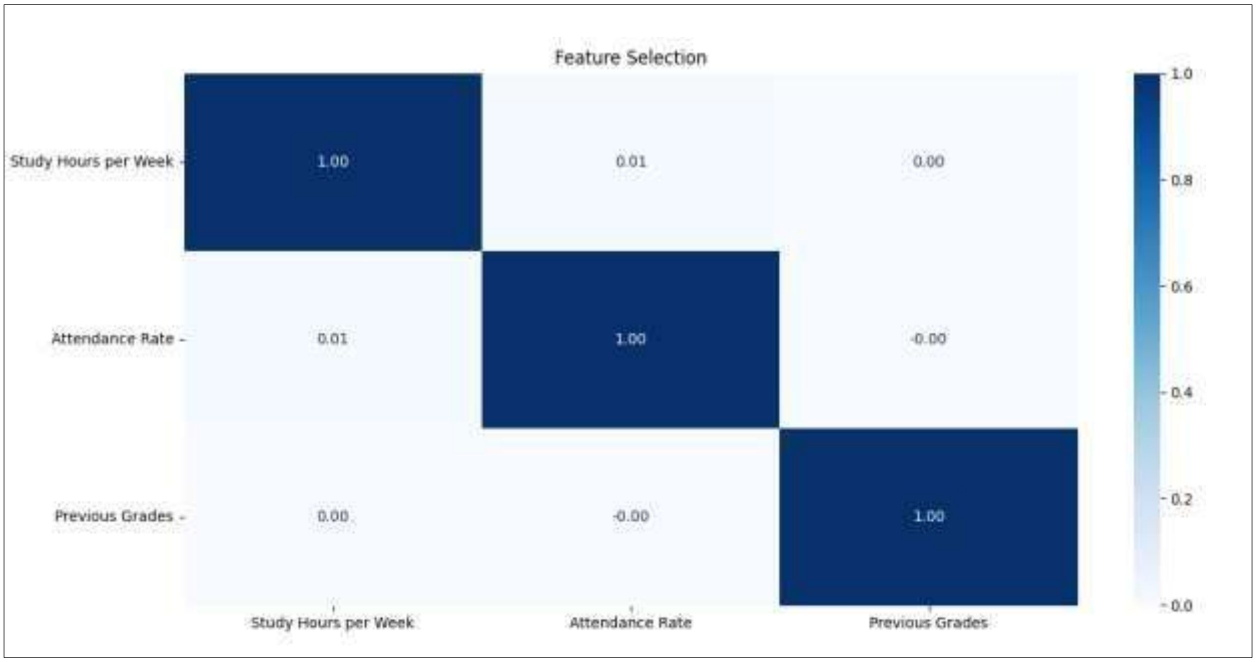
Berk-Jones Test Based Outlier Detection

Student ID	Study Hours per Week	Attendance Rate	Previous Grades	Participation in Extracurricular Activities	Parent Education Level	Passed
S00001	12.5	95.3	75.0	Yes	Master	Yes
S00002	9.3	95.3	60.6	No	High School	No
S00003	13.2	86.05	64.0	No	Associate	No
S00004	17.6	76.8	62.4	Yes	Bachelor	No
S00005	8.8	89.3	72.7	No	Master	No
S00006	8.8	73.8	69.3	Yes	High School	Yes
S00007	17.9	38.6	93.6	No	Doctorate	Yes
S00008	13.8	95.8	59.2	Yes	Doctorate	No
S00009	7.7	100.1	91.9	No	Bachelor	Yes
S00010	12.7	38.4	37.8	Yes	High School	No
S00011	7.7	54.1	72.3	No	Master	No
S00012	7.7	115.5	41.2	Yes	Master	No
S00013	11.2	79.6	49.6	Yes	Bachelor	Yes
S00014	0.4	75.1	50.4	No	Associate	Yes
S00015	1.4	66.5	49.2	No	Associate	Yes
S00016	7.2	54.4	55.9	Yes	High School	No
S00017	4.9	71.1	98.0	Yes	High School	No
S00018	11.6	94.5	51.8	No	Bachelor	Yes
S00019	5.5	74.7	40.8	No	Doctorate	No
S00020	2.9	87.2	72.4	No	Associate	Yes
S00021	17.3	110.3	68.6	No	Bachelor	Yes
S00022	8.9	63.4	98.2	No	Doctorate	No
S00023	10.3	81.1	64.4	No	High School	No
S00024	2.9	95.1	30.7	No	Bachelor	Yes
S00025	7.3	56.3	58.6	Yes	High School	Yes
S00026	10.6	84.35	58.3	No	Doctorate	Yes
S00027	4.2	112.4	46.5	Yes	High School	Yes
S00028	11.9	68.2	56.6	Yes	High School	No
S00029	7.0	96.4	62.8	Yes	Associate	No
S00030	8.5	72.2	64.1	No	Doctorate	Yes

5(b)

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

After data pre-processing, the proposed ICAESqAI model identifies pertinent features for effective student academic result forecast. Relevant feature selection is carried out through Marczewski-Steinhaus similarity index.



6(a)

Contractive Auto Encoder Based Feature Selection

Study Hours per Week	Attendance Rate	Previous Grades	Passed
12.5	95.3	75.0	1
9.3	95.3	60.6	0
13.2	86.05	64.0	0
17.6	76.8	62.4	0
8.8	89.3	72.7	0
8.8	73.8	69.3	1
17.9	38.6	93.6	1
13.8	95.8	69.2	0
7.7	100.1	91.9	1
12.7	38.4	37.8	0
7.7	54.1	72.3	0
7.7	115.5	41.2	0
11.2	79.6	49.6	1
0.4	75.1	50.4	1
1.4	66.5	49.2	1
7.2	54.4	55.9	0
4.9	71.1	98.0	0
11.6	94.5	51.8	1
5.5	74.7	40.8	0
2.9	87.2	72.4	1
17.3	110.3	68.6	1
8.9	63.4	98.2	0
10.3	81.1	64.4	0
2.9	95.1	30.7	1
7.3	56.3	58.6	1
10.6	84.35	58.3	1
4.2	112.4	46.5	1
11.9	68.2	56.6	0
7.0	96.4	62.8	0
8.5	72.2	64.1	1
7.0	111.0	44.3	1
19.3	42.1	74.1	1
9.9	76.3	89.5	0

6(b)

Figure 6(a) and 6 (b) Feature Selection Results

The above figure 6 illustrates the feature selection results. The regression analysis chooses 4 features from the 7 features to reduce the student educational result forecast. Selected feature illustrated below figure 7.

```
-----Marczewski Steinhaus Similarity Index------
Student ID      0.4915722518238981

Study Hours per Week    0.9864061877002647

Attendance Rate 0.7377147712170522

Previous Grades 0.8840212369451281

Participation in Extracurricular Activities     0.2059628873236755

Parent Education Level  0.310774934084242

Passed  0.9896253939074085
-----Relevant Features------
Study Hours per Week

Attendance Rate

Previous Grades

Passed
```

Figure 7 List of Selected Features

Based on the selected features, student academic performance classification is carried out using sequential AI model with tamas correlation coefficient function. The proposed ICAESqAI model is trained with the selected features to categorize the data samples into pass and fail classes with lesser error rate. The classification outcomes are depicted in the figure 8.

Student Performance Prediction

Student Passed Data

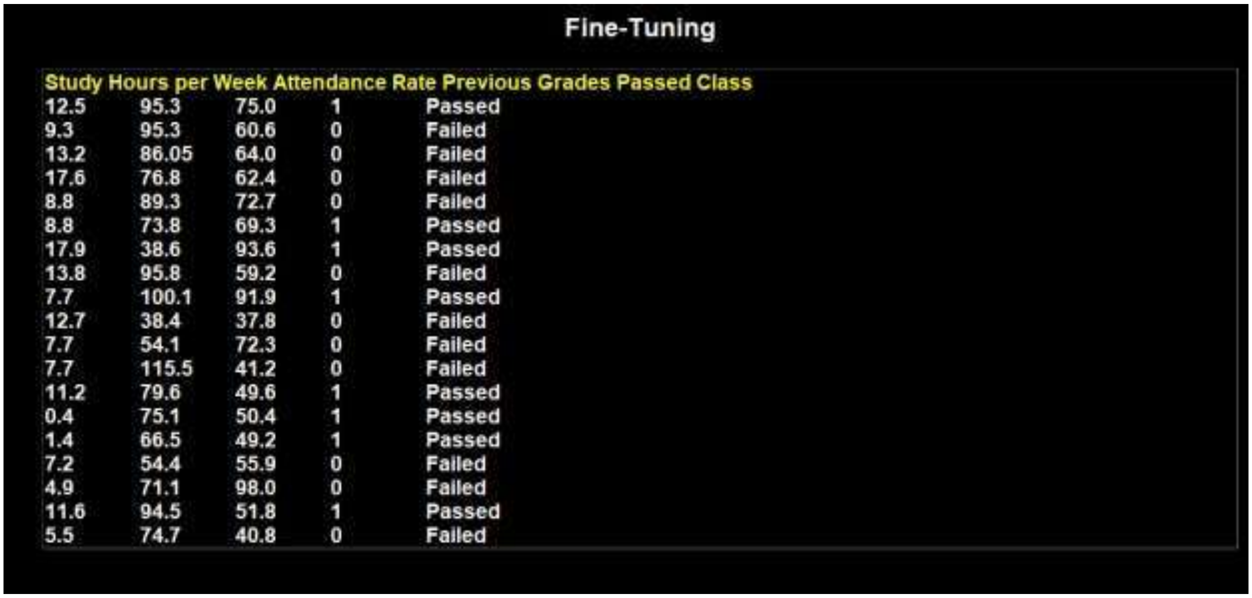
12.5, 95.3, 75.0 - Passed: 1
8.8, 73.8, 69.3 - Passed: 1
17.9, 38.6, 93.6 - Passed: 1
7.7, 100.1, 91.9 - Passed: 1
11.2, 79.6, 49.6 - Passed: 1
0.4, 75.1, 50.4 - Passed: 1
1.4, 66.5, 49.2 - Passed: 1
11.6, 94.5, 51.8 - Passed: 1
2.9, 87.2, 72.4 - Passed: 1
17.3, 110.3, 68.6 - Passed: 1

Student Failed Data

9.3, 95.3, 60.6 - Passed: 0
13.2, 86.05, 64.0 - Passed: 0
17.6, 76.8, 62.4 - Passed: 0
8.8, 89.3, 72.7 - Passed: 0
13.8, 95.8, 59.2 - Passed: 0
12.7, 38.4, 37.8 - Passed: 0
7.7, 54.1, 72.3 - Passed: 0
7.7, 115.5, 41.2 - Passed: 0
7.2, 54.4, 55.9 - Passed: 0
4.9, 71.1, 98.0 - Passed: 0

Figure 8 Data Classification Results

The proposed ICAESqAI model employs similarity measure for accurate student academic performance prediction. With the classification results, fine-tuning process is performed using modified rat swarm optimization process. The fine-tuning results are illustrated in figure 9.


Fine-Tuning

Study Hours per Week	Attendance Rate	Previous Grades	Passed	Class
12.5	95.3	75.0	1	Passed
9.3	95.3	60.6	0	Failed
13.2	86.05	64.0	0	Failed
17.6	76.8	62.4	0	Failed
8.8	89.3	72.7	0	Failed
8.8	73.8	69.3	1	Passed
17.9	38.6	93.6	1	Passed
13.8	95.8	59.2	0	Failed
7.7	100.1	91.9	1	Passed
12.7	38.4	37.8	0	Failed
7.7	54.1	72.3	0	Failed
7.7	115.5	41.2	0	Failed
11.2	79.6	49.6	1	Passed
0.4	75.1	50.4	1	Passed
1.4	66.5	49.2	1	Passed
7.2	54.4	55.9	0	Failed
4.9	71.1	98.0	0	Failed
11.6	94.5	51.8	1	Passed
5.5	74.7	40.8	0	Failed

Figure 9 Fine-tuning Process Outcomes

Figure 9 shows the fine-tuning results of student academic performance prediction. The fine-tuning process used modified rat swarm optimization performance to reduce the classification error with higher true positive and true negative rate for accurate student academic performance prediction.

5. RESULTS

Result evaluation of ICAESqAI model, existing XAI [1] and LSTM [2] is carried out using different metrics through dissimilar number of student data samples.

5.1 Impact on Student academic performance prediction accuracy:

It is ratio of number of data samples which are accurately predicting student educational result as pass or fail. It is formulated as,

$$SAPPA = \left(\frac{tp+tn}{tp+tn+fp+fn}\right) * 100 \qquad (23)$$

From (23), '$SAPPA$' represent student academic performance forecast accuracy. 'tp' symbolizes true positive. 'tn' denotes true negative. 'fp' represent false positive. 'fn' represents false negative. It is computed in terms of percentage (%). Table 2 illustrates the comparison of $SAPPA$.

Table 2 Comparison of $SAPPA$

Number of student data	$SAPPA$ (%)		
	Proposed ICAESqAI model	XAI [1]	LSTM [2]
4000	97	92	91
8000	96.85	93.22	91.86
12000	97.65	94.38	92.33
16000	97.32	93.69	91.33
20000	96.03	93.93	92.06
24000	97.91	93.51	92.65
28000	97.26	94.80	92.05
32000	97.38	94.76	91.36
36000	97.74	93.98	92.89
40000	97.15	94.11	92.11

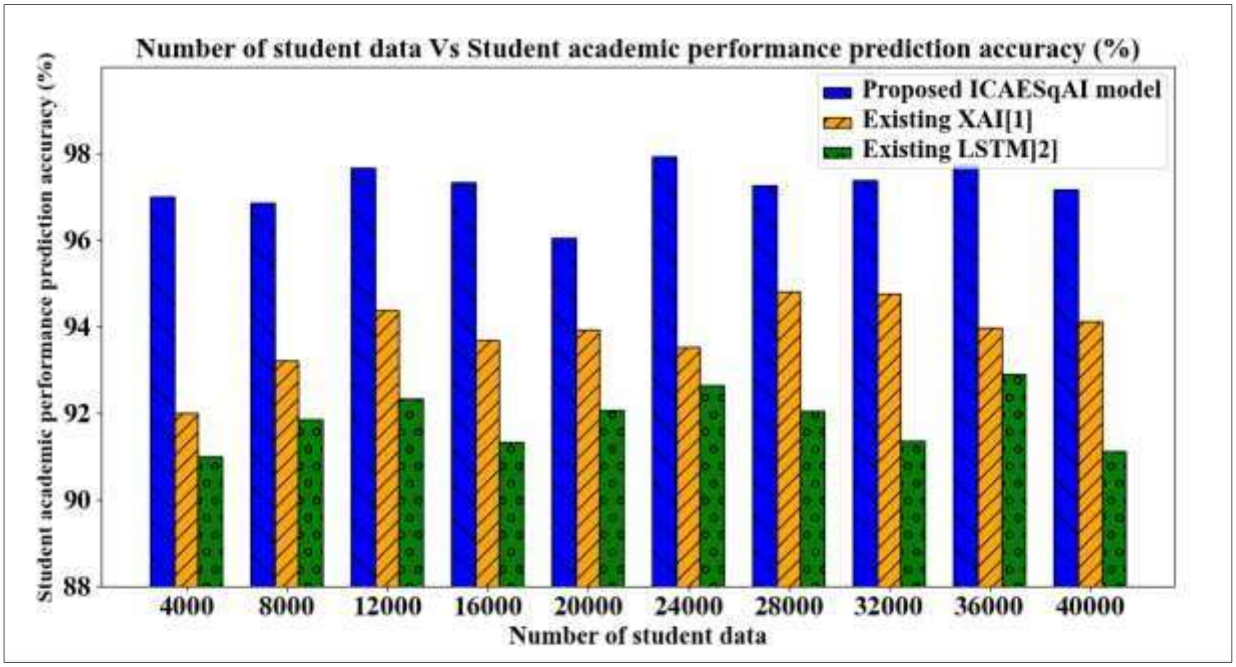


Figure 9 Measurement Analysis of *SAPPA*

Figure 9 illustrates *SAPPA* results using three methods namely proposed ICAESqAI model, existing XAI [1] and LSTM [2]. Let us consider the input student data samples as 4000 in the first run, the proposed ICAESqAI model achieved student academic performance prediction accuracy of 97% whereas two existing techniques [1] and [2] obtained 92% and 92% respectively. Among three different methods, the proposed ICAESqAI model achieves the better student academic performance prediction results when compared to the conventional methods. The improvement is because of using Nevanlinna–Pick interpolation estimator for handling the missing data and Berk-Jones test for outlier detection from input dataset. In addition, Contractive Auto Encoder chooses the relevant features depending on the Marczewski-Steinhaus similarity index. The data classification process is performed using sequential AI model with tamas correlation coefficient function to categorize the data samples into pass and fail classes. In addition, the fine-tuning process uses the modified rat swarm optimization to reduce classification error by improving the tp as well as true negative for accurate student educational result forecast. Similarly, ten different student educational performance forecast results are computed for every method through dissimilar number of student information samples. Proposed ICAESqAI model enhanced the student academic performance prediction accuracy by 4% and 6% over [1] and [2].

5.2 SAPPT:

Student academic performance prediction time is referred as time required to forecast academic performance as of total number of student information samples. It is formulated as,

$$SAPPT = \sum_{i=1}^{n} StD_i * Time(PP) \quad (24)$$

From (24), '$SAPPT$' represent student academic performance prediction time. '$Time(SAPP)$' indicates the amount of time consumed for predicting the academic result forecast. It is calculated in ms. Table 3 illustrates the comparison of $SAPPT$.

Table 3 Comparison of *SAPPT*

Number of student data	*SAPPT* (ms)		
	Proposed ICAESqAI model	XAI [1]	LSTM [2]
4000	20.8	23.3	24.8
8000	23.2	25.6	28.9
12000	26.1	29.7	33.5

16000	30.4	32.2	38.5
20000	33.7	35.4	42.7
24000	36.6	39.1	46.5
28000	38.3	42.6	50.7
32000	40.8	46.8	53.6
36000	43.7	50.5	58.9
40000	46.2	52.8	64.5

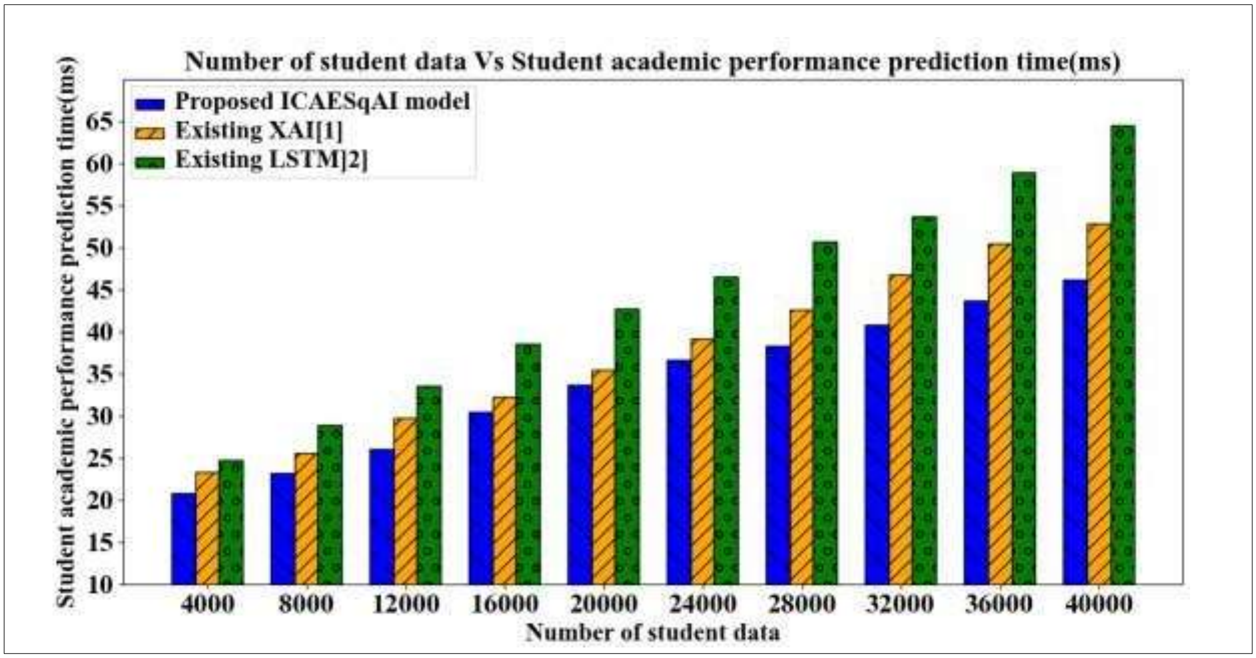


Figure 10 Measurement Analysis of $SAPPT$

Figure 10 illustrates overall result of student academic performance prediction time. Student academic performance prediction time gets increased with number of student data samples for all proposed and existing methods. However, proposed ICAESqAI model reduces the $SAPPT$ when compared to the existing techniques. For instance with 4000 student data, $SAPPT$ for proposed ICAESqAI model is 20.8ms while existing method [1] consumed 23.3ms and existing method [2] consumed 24.8ms. The performance enhancement is attained because of data pre-processing and feature selection process in proposed ICAESqAI model. Nevanlinna–Pick interpolation estimator in proposed ICAESqAI model is employed for handling the missing data points and Berk-Jones test is used for outlier data removal from input dataset. After data pre-processing task, the feature selection process chooses the relevant features from input database depending on Marczewski-Steinhaus similarity index. This in turn helps to reduce student academic performance prediction time. Outcomes demonstrate ICAESqAI minimizes $SAPPT$ by 10% when compared to [1] and 22% when compared to [2].

5.3 Impact on Coefficient of Determination:

Coefficient of determination is a performance metric used to evalulate student academic performance prediction outcomes. Coefficient of determination is defined as the residual sum of square between actual and predicted student academic prediction class to the total sum of squares. It is defined as,

$$CoD = 1 - \frac{(OR_{Act} - OR_{pre})^2}{(\bar{Y} - Y_{Act})^2} \qquad (25)$$

From (25), '$\boldsymbol{CoD}$' symbolizes the coefficient of determination. '$\boldsymbol{OR_{Act}}$' denotes the actual student academic performance prediction results. '$\boldsymbol{OR_{pre}}$' denotes the predicted results of student samples. '$\boldsymbol{\bar{O}R}$' indicates the mean of actual prediction value of student performance prediction. Table 4 shows the coefficient of determination result using three different methods.

Table 4 Comparison of Coefficient of Determination

Number of student data	Coefficient of Determination		
	Proposed ICAESqAI model	XAI [1]	LSTM [2]
4000	0.966	0.926	0.919
8000	0.965	0.927	0.916
12000	0.969	0.939	0.915
16000	0.967	0.935	0.912
20000	0.963	0.933	0.906
24000	0.962	0.937	0.917
28000	0.977	0.934	0.908
32000	0.966	0.938	0.919
36000	0.975	0.944	0.916
40000	0.971	0.945	0.913

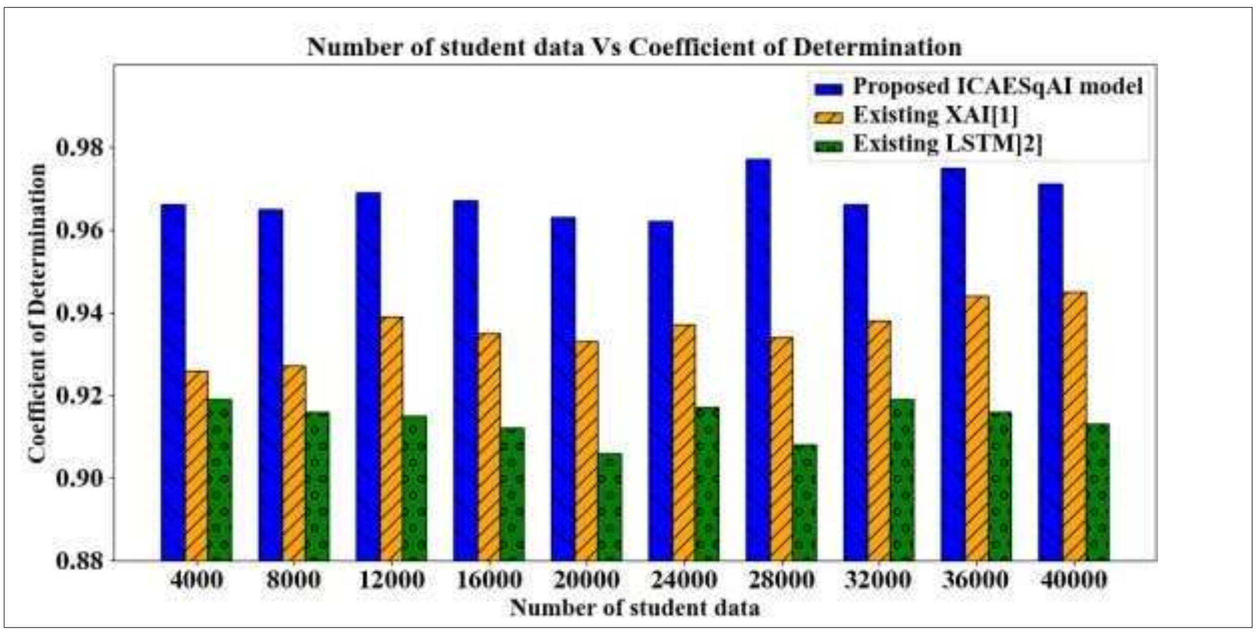


Figure 11 Measurement Analysis of Coefficient of Determination

Figure 11 shows the coefficient of determination results for different number of student data samples ranging from 4000 to 40000. The proposed ICAESqAI model attains higher coefficient of determination performance in student academic performance prediction for two different existing methods [1] and [2]. With 4000 student data samples, the proposed ICAESqAI model attained the coefficient of determination of 0.966 whereas the existing methods [1] and [2] achieved the coefficient of determination of 0.926 and 0.919. The proposed ICAESqAI model improved coefficient of determination performance than the conventional techniques. This is owing to Nevanlinna–Pick interpolation estimator for missing data handling and Berk-Jones test for outlier data detection from input dataset. The feature selection process uses the Contractive Auto Encoder to choose the relevant features using Marczewski-Steinhaus similarity index. After feature selection process, the data classification process is carried out using sequential AI model with tamas correlation coefficient. The fine tuning process is performed in proposed ICAESqAI model for minimizing the error and increasing the coefficient of determination performance. Similarly, results are obtained for ten different dataset sizes using the proposed ICAESqAI model. The result analysis shows that the proposed ICAESqAI model increases the coefficient of determination performance by 3% and 6% than the[1], [2].

5.4 Matthews Correlation Coefficient(MCC):

It is computed with the tp, tn, fp and fn in student academic performance prediction. It is computed as,

$$MCC = \frac{(tp*tn)-(fp*fn)}{\sqrt{(tp+fp)(tp+fn)\,(tn+fp)(tn+fn)}} \quad (26)$$

From (26), matthew's correlation coefficient is computed. The method is more effective when the mathews correlation is high. Table 5 shows the matthews correlation measure result using three methods.

Table 5 Tabulation of Matthews Correlation Coefficient

Number of student data	Matthews Correlation Coefficient		
	Proposed ICAESqAI model	XAI [1]	LSTM [2]
4000	0.952	0.904	0.892
8000	0.965	0.907	0.898
12000	0.951	0.909	0.895
16000	0.958	0.905	0.894
20000	0.956	0.901	0.896
24000	0.952	0.903	0.893
28000	0.956	0.905	0.894
32000	0.957	0.906	0.895
36000	0.953	0.907	0.899
40000	0.959	0.908	0.897

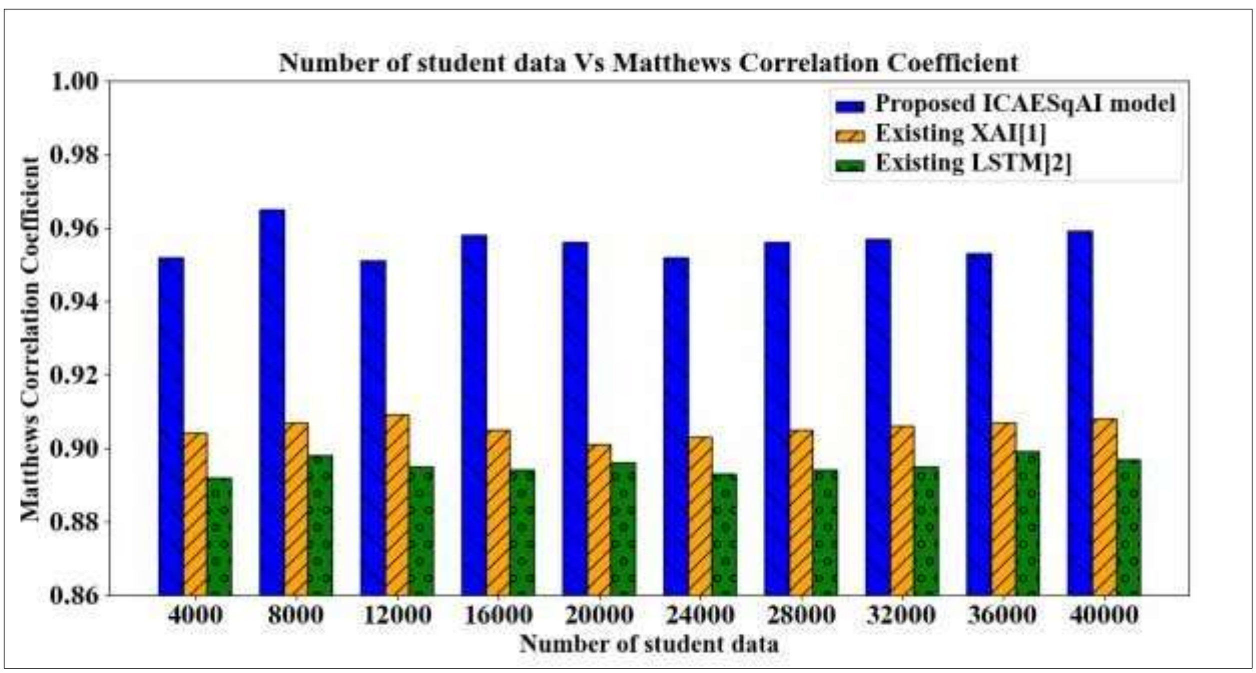


Figure 12 Measurement Analysis of Matthews Correlation Coefficient

Figure 12 displays the matthews correlation coefficient performance for different number of student data samples varying from 4000 to 40000. The proposed ICAESqAI model achieved higher matthews correlation coefficient performance in student academic performance prediction for two different existing methods [1] and [2]. With 4000 student data samples, proposed ICAESqAI model achieved matthews correlation coefficient of 0.952 while existing methods [1] and [2] achieved 0.904 and 0.892 correspondingly. The proposed ICAESqAI model improved matthews correlation coefficient performance than the conventional techniques. This is owing to using Nevanlinna–Pick interpolation estimator for data pre-processing. In addition, Contractive Auto Encoder selects the relevant features with help of Marczewski-Steinhaus similarity index. The student data classification is carried out using sequential AI model with tamas correlation coefficient function to categorize the student data samples into pass and fail classes. In addition, the fine-tuning process employs the modified rat swarm optimization to reduce the classification error through increasing tp and tn for accurate student educational result forecast. Likewise, ten different student educational performance forecast outcomes are determined for every technique through different number of student data samples. Result analysis illustrates that proposed ICAESqAI model improves the matthews correlation coefficient by 6% when compared to [1] and 7% when compared to [2] respectively.

5.5 Performance analysis of ROC-AUC

ROC-AUC curve is parameter metric employed to estimate result of ICAESqAI model, existing XAI [1] and LSTM [2] in student academic performance prediction. ROC-AUC curve computes trade-off among tp and fp across dissimilar categorization thresholds. AUC presents single value to accurately differentiate among pass as well as fail cases in student academic performance prediction.

Table 6 Comparison of ROC-AUC

False positive rate	True positive rate		
	Proposed ICAESqAI model	XAI [1]	LSTM [2]
0	0	0	0
0.1	0.465	0.431	0.371
0.2	0.589	0.514	0.414
0.3	0.615	0.595	0.525
0.4	0.735	0.658	0.649
0.5	0.858	0.795	0.725
0.6	0.924	0.828	0.808
0.7	0.939	0.859	0.832
0.8	0.958	0.914	0.859
0.9	0.969	0.935	0.879
1	0.985	0.948	0.905

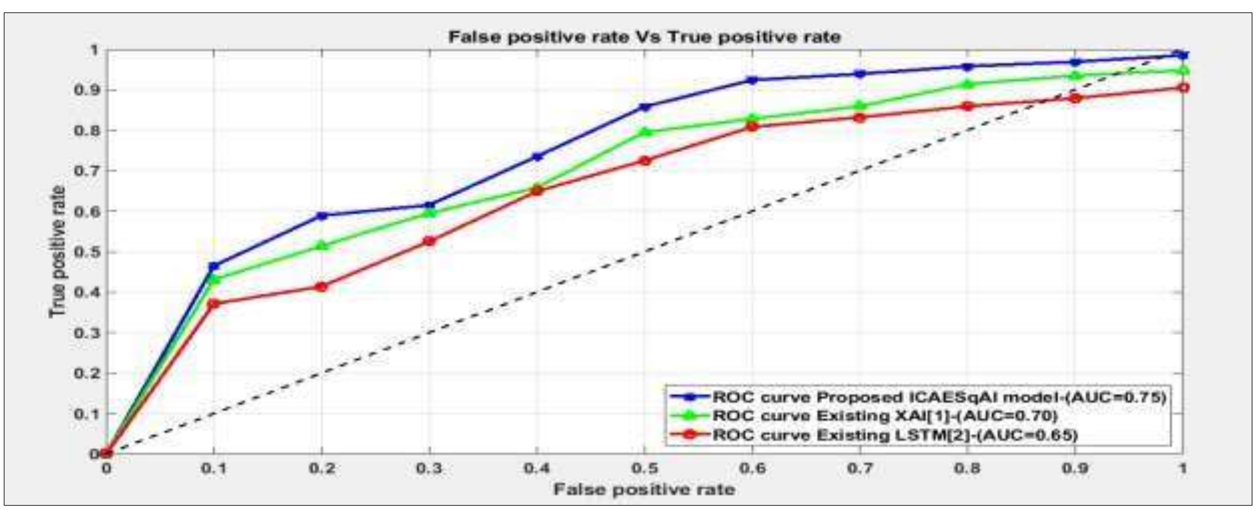


Figure 13 ROC-AUC Performance

Table 6 and Figure 13 demonstrates ROC-AUC performance of ICAESqAI model, existing XAI [1] and LSTM [2]. AUC determines capability of each method to correctly categorize student data samples into pass and fail classes by computing the total area below ROC curve. AUC values ranges from 0 to 1. AUC score above 0.5 represents that the proposed ICAESqAI model distinguishes the student data samples into two classes. In contrast, AUC below 0.5 achieves poor student academic performance. In above figure, the dashed diagonal line denotes the baseline representing the classifier performance. Among different methods, the ICAESqAI model obtained better student academic performance when compared to the other approaches [1], [2].

5.6 Impact on Confusion matrix

It is used for computing result of different classification methods in student academic performance prediction. The confusion matrix evaluates student educational class result against actual outcomes. In the confusion matrix analysis, a dataset comprised 40000 student data samples to carry out student academic result forecast. Confusion matrix is employed to compare result of three different classification models, namely proposed ICAESqAI model, existing XAI [1] and LSTM [2].

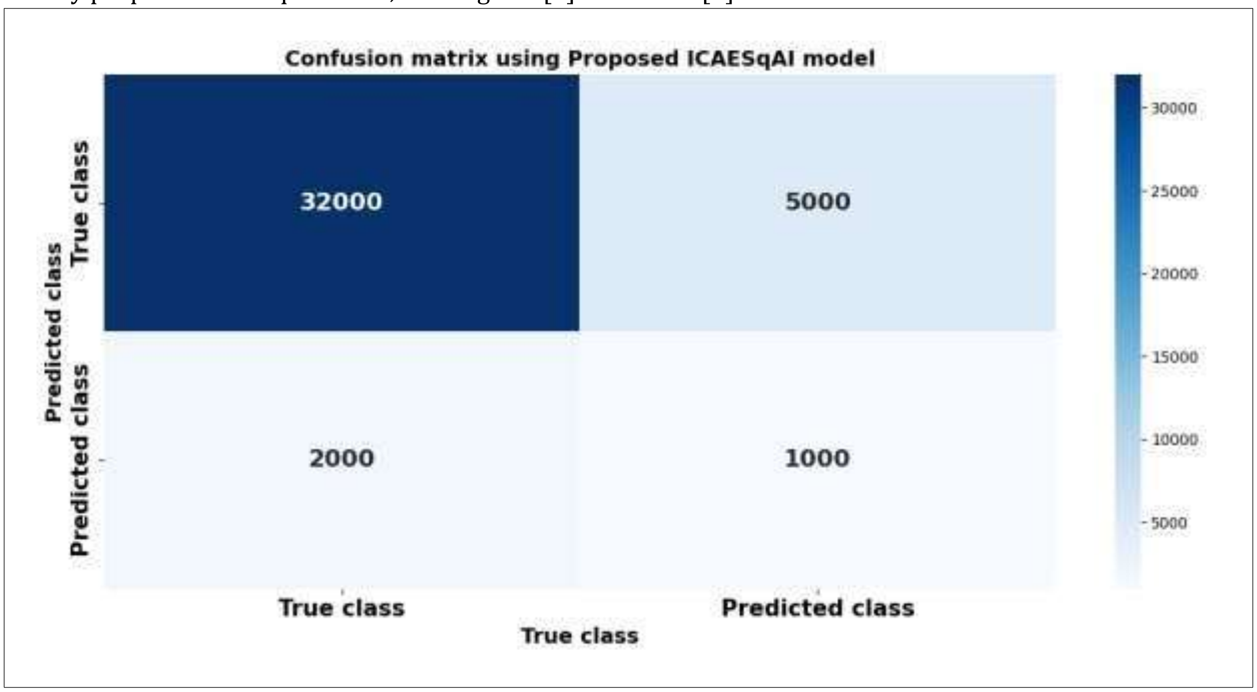


Figure 14 Confusion Matrix results

Figure 14 presents the confusion matrix of ICAESqAI model. It presents the visual representation of proposed ICAESqAI model in forecasting student educational result prediction through 40000 student data. Each confusion matrix emphasizes the classification performance by showing four essential metrics, namely tp, fp, fn and tn. ICAESqAI model achieves improved performance through attaining higher tp, and tn with lesser fp and fn.

6. CONCLUSION

In this research article, a novel ICAESqAI Model is introduced for efficient and accurate student academic performance prediction. The proposed ICAESqAI Model helps the educational institutions to recognize student academic performance at earlier stage. The proposed ICAESqAI Model introduces sequential AI learning approach to carry out precise student academic result forecast. Proposed ICAESqAI Model performed efficient data pre-processing and selects relevant features to enhance the student academic result forecast performance with lesser time consumption. Then, the classification process is carried out by proposed ICAESqAI Model to examine the training and testing student samples based on similarity measure and classify them into pass or fail classes. Finally, the ICAESqAI Model performs efficient fine-tuning process to reduce prediction error during student academic performance prediction with high accuracy. A comprehensive evaluation of proposed ICAESqAI Model is carried out using several performance metrics such as student academic performance prediction accuracy, ROC-AUC, Matthews Correlation Coefficient, Coefficient of Determination and SAPPT. The performance results demonstrates that the proposed ICAESqAI Model outperforms conventional deep learning methods with higher accuracy in student academic performance prediction.

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