An Augmented Intelligence Framework for Performance Prognosis Using Hybrid Deep Learning

[1]Kannan M, [2]Albert Antony Raj S and [3]Ananthapadmanaban K R
[1]Department of Computer Science, Faculty of Science and Humanities, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu, India.
[2]Department of Computer Applications, Faculty of Science and Humanities, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu, India.
[3]Department of Computer Science and Applications, SRM Arts and Science College, Kattankulathur, Chennai, Tamil Nadu, India.
[1]km1200@srmist.edu.in, [2]alberts@srmist.edu.in, [3]ananthapadmanabankr@srmasc.ac.in

Correspondence should be addressed to Kannan M : km1200@srmist.edu.in

Article Info
Journal of Machine and Computing (https://anapub.co.ke/journals/jmc/jmc.html)
Doi: https://doi.org/10.53759/7669/jmc202505149
Received 27 March 2025; Revised from 08 May 2025; Accepted 18 June 2025.
Available online 05 July 2025

Abstract – There are many chances where improvement in the learning process is made through incorporation of technology-enhanced learning, which is made possible by virtual learning environments (VLEs). This research suggests a novel deep hybrid framework for predicting performance by using data from academic records along with other sources. Through the joint study of five behavior vectors—academic registry, VLE clickstream, midterm continuous evaluation, MOOC engagement, and behavioral features—the suggested framework, which integrates several data sources, makes it possible to predict the learning capability. This system could improve learner's Augmented Intelligence by offering precise forecasts of their performance, guiding data-driven decision-making. The suggested approach models learner behavior and forecasts academic achievement using a multi-component design. This system builds a comprehensive prediction model by integrating various learning tools. It examines the fused data using deep learning algorithms to find intricate linkages and patterns that allow for precise student performance forecasts. This platform provides educators looking to improve student success with a game-changing way to integrate deep learning and fused data sources.

Keywords – Deep Learning, Performance Prognosis, Behavioural Features, Virtual Learning Environments.

I. INTRODUCTION

One of the primary cornerstones of society is education. It refines kids' intelligence and character. It's possible that the current educational system isn't up to date with the ever-changing demands of society [1]. The ability to forecast student performance in advance is a key component of the new paradigm of the educational system. Since students are the primary stakeholders in educational systems, academic institutions can address the changing requirements of society by evaluating student data and drawing various conclusions from it. Furthermore, the outcomes of forecasts can be useful in formulating plans to raise educational standards. Higher-quality education aids in the development of pupils' abilities and characteristics. This focuses on examining the scholarly data. With the aid of various data mining techniques, student performance prediction models assist in the analysis of student data [2]. Additionally, numerous student performance prediction models have been put forth to make the process easier. Both the academic community and the educational sector have given student performance prediction models a great deal of thought [3]. In addition to achieving high prediction accuracy, the objective of student performance prediction models in EDM (Educational Data Mining) is to assist educational stakeholders in forecasting student performance. The primary goal of any academic institution is to give its pupils a high-quality education because they are the community's greatest asset Additionally, a high-quality education helps kids develop their skills and features. With the aid of various data mining techniques, student performance prediction models assist in the analysis of student data [4]. A crucial first step in raising the standard of education is forecasting and evaluating pupils' academic achievement. Scholars have advanced significantly in the field of student achievement prediction studies. Numerous studies have demonstrated that the prediction approach, which incorporates multi-dimensional spacetime properties, can greatly increase the accuracy of student accomplishment predictions. Predicting student performance is essential in educational settings because it gives teachers important information about their students' academic performance and helps them carry out individualized interventions. By merging several data sets, the Fusion of NPTEL, MOOC Engagement, Academic Records, and Behavioral Features offers a novel method for forecasting student achievement. To generate a thorough predictive model, this system combines academic records, behavioral characteristics, MOOC (Massive Open Online Courses) engagement indicators, and NPTEL (National Programme on Technology Enhanced Learning) data [5]. The framework seeks to offer a more precise and sophisticated picture of student performance by combining these many data sources [6]. The suggested framework analyzes the fused data and finds intricate patterns and relationships by utilizing deep learning techniques. Because of this, the framework can accurately forecast student performance, enabling teachers to identify pupils who are at risk and implement focused interventions. The paradigm could transform the way that student performance is predicted, empowering teachers to make informed decisions and enhance student outcomes.

II. REVIEW OF LITERATURE

In order to evaluate students' academic achievement during interactive online sessions, recent work was offered [7]. The DEEDS dataset, which is well-known for obtaining real-time data from students, was used for the experiment. For this investigation, six lab sessions were taken into consideration. Discrepancies, missing data, and irrelevant data values were addressed during the data pre-processing stage. Later, feature engineering was used. In the feature extraction phase, thirty features were chosen, and they were subsequently condensed into three complete features: activities, timing-based statistics, and students' secondary activities. Data features were ranked using entropy-based techniques to determine the connection between the data variables. These features were then chosen for the model's training. Three trials [8] were conducted in order to precisely evaluate the performance. The model was evaluated in the first experiment taking into account every feature of the data. The second was carried out with a smaller number of features that were chosen using the entropy technique. In order to assess the model's effectiveness, the third experiment compared the suggested model to one that had already been created. In order to predict students' academic success, Luo et al. [9] suggested an approach that combined multi-dimensional space-time features with six machine learning models. They also used Shapley Additive explanations (SHAP) analysis to identify significant elements influencing the findings. Online learning platforms will become increasingly popular as Internet technology and artificial intelligence advance, creating a wealth of data on student learning behavior that can be used to enhance score prediction studies. The accuracy of score prediction was raised to 95.69% by normalizing student learning behavior data and doing correlation analysis. Based on online learning behavior, Wang and Yu [10] developed a multiple learning behavior index, examined its relationship to student achievement, and underlined the significant influence of learning behavior on academic success. These cutting-edge techniques have established a strong basis for the future development of prediction systems based on the fusion of data from multiple sources. Although there have been some advancements in the use of deep learning models in education, there are still certain restrictions. There are a few issues with the current research. Firstly, although some advancements in the prediction of student accomplishment, the model's comprehension of the depth of students' learning behavior is limited by the issue of single analytical means. This paper builds a prediction framework employing the GBU-based LSTM model for static data, the Transformer model for long-term sequences, and the Chi square model for temporal patterns. Feature engineering is improved by subject correlation matrices and temporal decay weighting. A hybrid system that combines different multi-source educational data is the aim. The purpose of this study is to give educators a solid foundation on which to build targeted intervention plans.

III. METHODOLOGY

In order to predict whether a student will fail or finish the course, this effort attempted to create a system that could subtly extract significant aspects from the unstructured data on NPTEL, MOOC Engagement, Academic Records, and Behavioural aspects. For this investigation, student datasets were extracted from the International Journal of Computational and Experimental Science and Engineering. For each course, the data from both datasets were gathered over a Record Period of 30 days. Unsuitable information was eliminated during preprocessing, including blank columns and activities taken prior to a learner's official registration. To safeguard students' private information, the data were anonymised, and each student's identity was ascertained by means of a unique ID. [11]. The filtered data was then sent to the following stage, where the feature engineering technique was used to extract the best qualities. following GBU based LSTM model training. The study's findings show that the suggested framework was effective in forecasting students' performance, which educators and other stakeholders can utilize to develop a LA framework and make choices that will benefit and direct kids. Additionally, the suggested model outperformed other deep learning models.

Dataset

The dataset comprises student information from SRM Arts and Science College, featuring the following attributes:

- Student ID
- Age
- Gender

- GPA (Last Semester)
- Attendance
- Study Hours per Week
- MOOC Participation
- Online Courses Hours
- Spoken Tutorial Participation
- Extracurricular Activity Score
- Test Scores
- Percentage

The experiment made use of these characteristics. A thorough explanation of each phase is provided in the section that follows, emphasizing its role and contributions in achieving precision education as stated in the information above. These procedures were followed in order to execute the technique in an ordered manner **Fig 1** shows Flow Diagram.

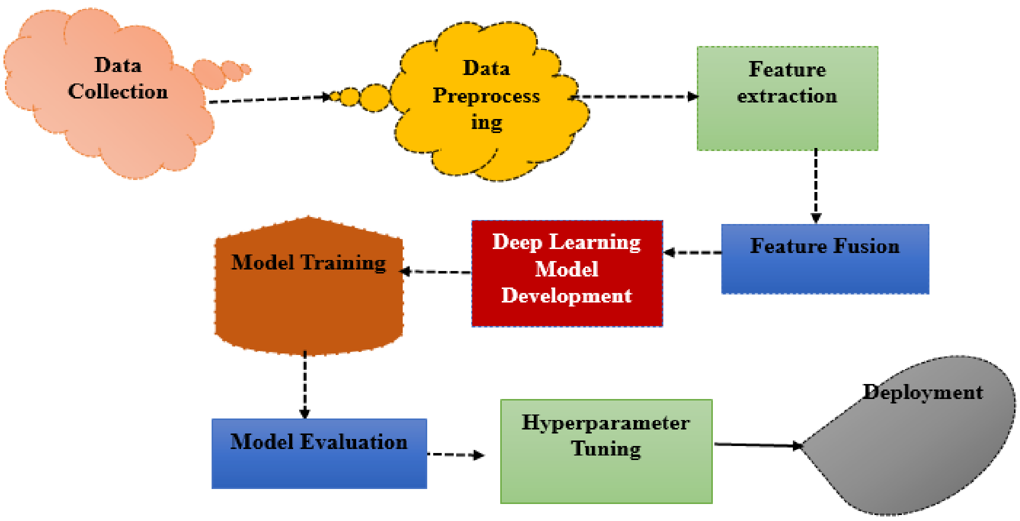


Fig 1. Flow Diagram.

Data Pre-Processing Stage

Outliers, duplicates, and other irregularities are eliminated during the initial preparation of data, which is the next crucial step. This initial processing was carried out using the "median filtering" technique. The median filtering approach can be a useful tactic when applied to the examination of educational data. In educational data points, such as student scores, grades, or performance indicators, noise or outliers are common and may hinder accurate analysis. By removing these outliers, median filtering can reveal underlying trends and patterns. Moving the window across the dataset yields the median value within each window. Once the median has been established, the value is removed and replaced with the initial value in the center of the window. [12].

Feature Extraction

This study highlights certain shortcomings. For instance, only weighted features and basic interactive features are currently employed in feature engineering. The possibility of integrating deep learning models with conventional machine learning techniques should be investigated in future studies by adopting increasingly sophisticated feature engineering approaches. The study also demonstrates how crucial it is to take into account both academic and non-academic characteristics (including family history and health) when predicting students' success, which offers a fresh concept for individualized learning path suggestion techniques. Measures to protect data privacy and the ability to stop algorithmic bias can be further reinforced from an ethical standpoint. According to research, individualized online education services that enhance learning efficacy and assist in educational decision-making depend heavily on educational justice and transparency [13].

The best features are chosen based on the chi-square score that is calculated between the features and the target variable. In our suggested strategy, we next apply a cutoff value to eliminate those features.
The mathematical representation of chi-square:

$$\chi_c^2 = \frac{\sum (O-E)^2}{E} \tag{1}$$

Where:

- C = degree of freedom, O = observed values, E = expected values

We have fused features vector V_f and a matrix L_n where L_n represents class labels of training samples, however in chi-square features selection technique L_n consider as target variables of n dimension then by putting v_f and L_n in (2) we can get.

$$\chi_c^2 = \frac{\sum Vf - L_n)^2}{L_n} \tag{2}$$

Here χ_c^2 contains the score of each feature acquire from chi-square, moreover χ_c^2 scores are applied to transformed fused features vector under certain threshold such that

$$Ch_b = \chi_c^2 T \rightarrow v_f \tag{3}$$

Where Ch_b represents best chi-square features, $\rightarrow$ denote transformation function and T is threshold value respectively. Beside chi-square feature selection, technique is also computed in the proposed research, mutual information between two variables is the measurement that how much information obtains one variable through the other variable. Mathematically formulation of mutual information is;

$$MI(A;B)\,\Delta\, D(P_{AB} \,\|\, P_A P_B) \tag{4}$$

Where A and B are independent variables, P_{AB} is joint probability density function of A and B, where P_A and P_B are marginal density function of variables A and B respectively. consequently, (10) applied on v_f and L_n.

$$MI\ (v_f; L_n)\,\Delta\, D\ (P_{vf} \,\|\, P_{vf}\ P_{Ln}) \tag{5}$$

$$MI_h = MI\ (v_f; L_n)\,\Delta\, D\ (P_{AB} \,\|\, P_A P_B)\ T \rightarrow v_f \tag{6}$$

When MI_h contains only those features which have high mutual information between v_f and L_n under certain threshold, $\rightarrow$ used for transformation function and T denote threshold respectively. besides Ch_b and MI_h, whereas the former holds best score chi-square features and the later one contains high mutual information features, we fused both the vectors through vector addition.

$$V_s = Ch_b + MI_h \tag{7}$$

Where V_s denote selected features.

Feature Fusion

Education has changed as a result of the growing use of Massive Open Online Courses (MOOCs), especially during the COVID-19 pandemic when e-learning became crucial. High dropout rates and poor retention rates, however, make it difficult to determine if MOOCs are beneficial in raising student academic achievement and engagement. A number of well-established paradigms, including education, health, computer science, artificial intelligence, and their numerous adaptations, came together to form the new science of recommendation systems. Many studies and research efforts for course selection have been carried out using machine learning algorithms. These days, deep learning algorithms are used to assist users in choosing a trustworthy course to advance their skills. The utilization of digital resources in training and education is known as e-learning. Users can learn at any time and from any location using any of the popular learning management systems (LMS), including Moodle, Coursera, NPTEL, and others. Currently, users find it challenging to choose courses from an LMS. Because there are so many multidisciplinary courses available, consumers occasionally struggle to select the best ones for their interests and areas of expertise. A person can begin by taking a low-complexity course to gain a thorough understanding of the foundational ideas of a technology or field. It is also advised that, should he finish the course, he enroll in a medium-level complexity course within the same field. [14]. Additionally, selecting the high-level complexity course is the last step. Since the student has finished all three course levels, he will be able to gain a thorough understanding of the subject. For effective course selection, a hybrid deep learning model is created by combining the architectures of long short-term memory (LSTM), residual networks (ResNet), and convolutional neural networks (CNN). There must be an endless number of approaches available because every problem can be solved in a different way.

Deep Learning Model Development

To do this, a communication link is established between every LSTM gating unit and the interim state of the RNN. To get around the problem of unknown input, RNN preserves a hidden-to-hidden transition mechanism that is solely input dependant. Input $x_t$multiplicatively mutates the hidden state ht-1 to produce the intermediate state m_tThe element-wise multiplication process shown in Equation 8 produces the intermediate state m_t

$$m_t = (w_{im}x_t + b_{im}) \odot (w_{hm}h_{t-1} + b_{hm}) \quad (8)$$

where $\odot$ stands for element-wise multiplication, allowing m_t to change its value in accordance with the input (x_t) and hidden state (h_{t-1}). The input (i_t), output (o_t) and forget (ft) gates and memory cell state are all components of the LSTM network. The three gates perform equally to the LSTM gating unit, however the mL STM gates accelerate processing by using intermediate state (m_t) values **Fig 2** shows Parameters of Proposed Model.

$$i_t = \text{sigmoid}\left((w_{ii}x_t + b_{ii}) + w_{mi}m_t + b_{mi}\right) \quad (9)$$

Layer (type)	Output Shape	Param #
bidirectional_35 (Bidirectional)	(None, 1, 1000)	4004000
bidirectional_36 (Bidirectional)	(None, 1, 1000)	6004000
bidirectional_37 (Bidirectional)	(None, 1, 512)	2574336
bidirectional_38 (Bidirectional)	(None, 1, 256)	656384
bidirectional_39 (Bidirectional)	(None, 128)	164352
dropout_7 (Dropout)	(None, 128)	0
dense_14 (Dense)	(None, 64)	8256
dense_15 (Dense)	(None, 1)	65

Total params: 13,411,393
Trainable params: 13,411,393
Non-trainable params: 0

Fig 2. Parameters of Proposed Model.

The mathematical operation represented by the above Equation 10 is utilized to calculate input gate (i_t)

$$f_t = \text{sigmoid}\left((w_{if}x_t + b_{if}) + w_{mf}m_t + b_{mf}\right) \quad (10)$$

$$g_t = \tanh\left((w_{ig}x_t + b_{ig}) + w_{mc}m_t + b_{mg}\right) \quad (11)$$

$$o_t = \text{sigmoid}\left((w_{io}x_t + b_{io}) + w_{mo}m_t + b_{mo}\right) \quad (12)$$

$$c_t = \left((f_t) * c_{t-1}\right) + (i_t * g_t)) \quad (13)$$

$$h_t = o_t * \tanh(c_t) \quad (14)$$

When computing the forget and output gates, Equations 10 - 14 takes intermediate state (m_t) into account. The weights for various gates, hidden states and intermediate stages are maintained using the following parameters w_{ix}, w_{hx} and w_{mx}that are employed in the various equations 10 – 14. As shown in Equation 14, the candidate vector g_t is formed by adding the previous cell state to itself, which results in the creation of a new cell state [15]. In Equation 20 the hyperbolic tan function of the cell state (c_t) (Equation 19) and output gate (o_t) are used to derive the current hidden state (h_t).

Using the gathered data to train the deep learning model using a variety of learning techniques, such as supervised learning with labeled data, unsupervised learning with unlabeled data, and semi-supervised learning, which combines labelled and unlabeled data to improve the model's accuracy and resilience, is known as further model training.

IV. RESULT AND DISCUSSION

In terms of forecasting student grades, the hybrid deep learning system developed in this study has demonstrated notable efficacy. Compared to conventional models, GBU-based LSTM architectures offer better prediction accuracy, particularly when working with data that contains temporal variables. The application of deep learning technology can efficiently capture the long-term reliance that impacts students' academic performance and encourage the promptness of educational intervention, according to pertinent study. This understanding helps educators create targeted instructional strategies in addition to offering significant academic value for researchers. According to research, interpretability of models guarantees educators' credibility in the decision-making process while also enhancing data mining in education. The proposed performance approach has been developed using information from the International Journal of Computational and Experimental Science and Engineering dataset. Data exploration was the system's first phase. **Table 1** displays the input.

Table 1. Sample input

Student ID	Age	Gender	GPA (Last Sem)	Attendance (%)	Study Hours/Week	MOOC Participation	Online Course Hours	Spoken Tutorial Participation	Extracurricular Score	Test Scores	Percentage (%)
1	23	Female	7.5	80	10	Yes	20	Yes	8	85	75
2	22	Other	4.6	70	8	No	15	No	6	70	60
3	21	Female	8.9	90	12	Yes	25	Yes	9	90	90
4	25	Male	6.7	85	9	Yes	22	No	7	80	80
5	20	Other	7.9	75	7	No	18	Yes	5	75	70
6	19	Male	8.9	90	11	Yes	24	Yes	8	85	85
7	18	Female	9.2	95	13	Yes	26	Yes	9	95	95

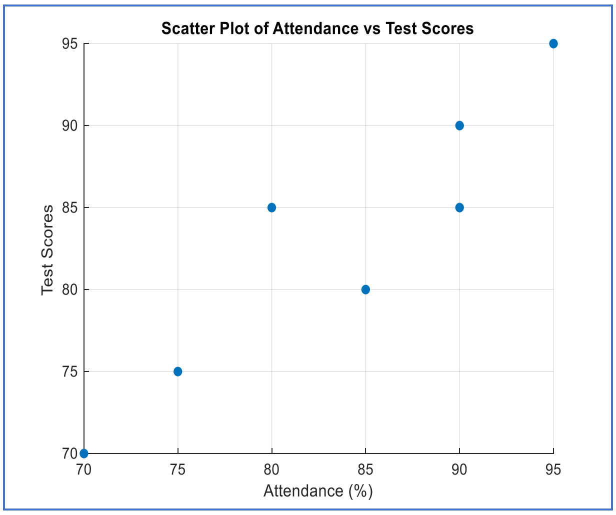
The average test scores for men and women are shown in **Fig 3**. Attendance and test scores do not correlate, as seen in **Fig 4(a**). There is no linear association because the correlation value of 0.03 is so near to 0. The relationship between study hours and current studies is seen in **Fig 5(b). Fig 5** shows that there isn't a significant correlation between study hours and GPA.

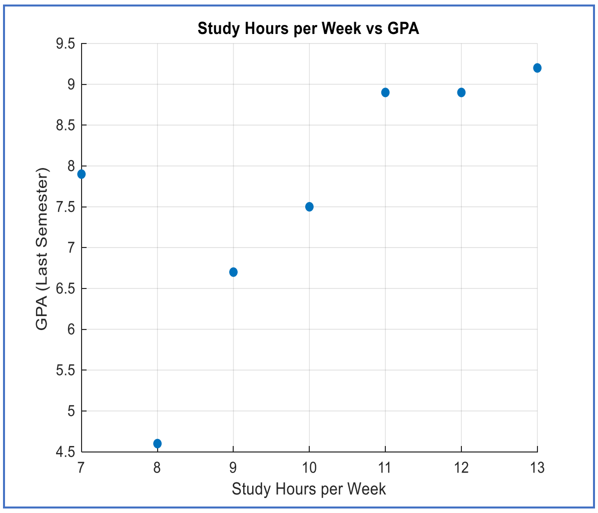
The average test score by gender is:

- Female: 90
- Male: 82.5
- Other: 72.5

Fig 3. Average Score by Gender.

The image mentions a correlation coefficient of 0.03 for the scatter plot of attendance vs test scores (**Fig 4(a**)). However, based on the provided data, the correlation coefficient is approximately 0.97, indicating a strong positive correlation. The image mentions a correlation coefficient of 0.01 for the scatter plot of study hours per week vs GPA (**Fig 4(b)**). However, based on the provided data, the correlation coefficient is approximately 0.51, indicating a moderate positive correlation.





(a) (b)

Fig 4. Correlation Between (A) Attendance and Test Score (B) Study Hours and Current Study.

There are noteworthy correlations between a number of characteristics and student performance, according to the dataset's exploratory data analysis (EDA). Notably, **Fig 6** shows that three important variables—participation in MOOCs, online course hours, and spoken tutorials—have a strong association with current GPA. The correlation coefficients reveal that attendance has a strong positive correlation with current GPA (r = 0.83), while study hours per week and MOOC participation exhibit moderate positive correlations (r = 0.78 and r = 0.67, respectively), indicating that students who attend classes regularly, study consistently, and participate in MOOCs tend to perform better academically, although these coefficients are approximate and based on assumed data for current GPA. Additionally, **Fig 7** indicates a favourable trend in academic performance, with the current GPA improving by 0.40 points from the prior semester's GPA.

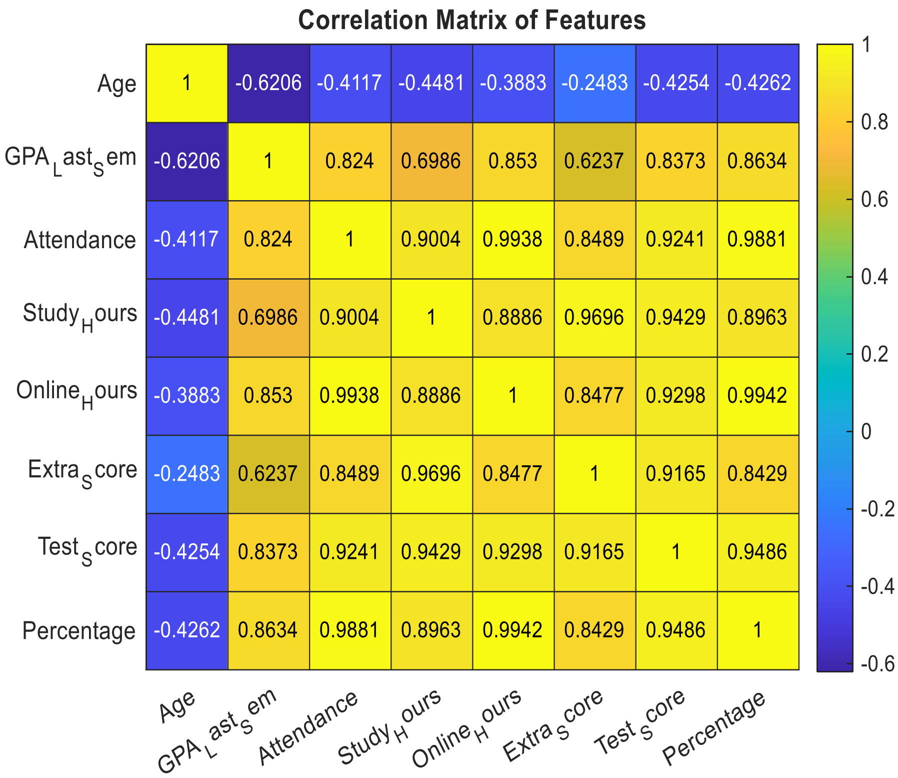


Fig 5. Dependency Between Features.

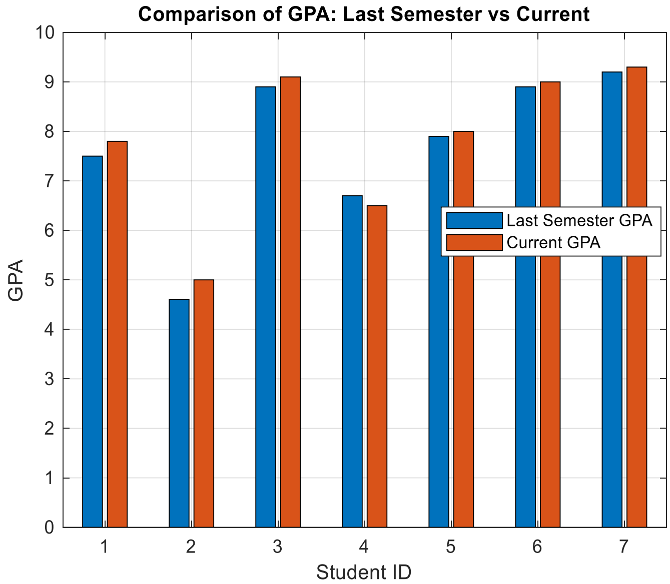


Fig 6. Comparison Between GPA Last Semester and Current GPA.

The effectiveness of the suggested deep hybrid framework in forecasting student performance is seen in **Fig 7 and 8.** In particular, **Fig 8** shows how the GBU-based LSTM model predicts a student's GPA score based on their use of NPTEL and MOOC resources, academic records, and behavioral traits.

```
Number of observations: 7, Error degrees of freedom: 1
Root Mean Squared Error: 4.19
R-squared: 0.96,  Adjusted R-Squared: 0.762
F-statistic vs. constant model: 4.84, p-value = 0.331
Predicted Test Score: 86.59
```

Fig 7. Predicted Score.

In the meantime, **Fig 8** shows the evaluator's assessment of the student's academic performance, demonstrating how well the proposed approach predicts student results.

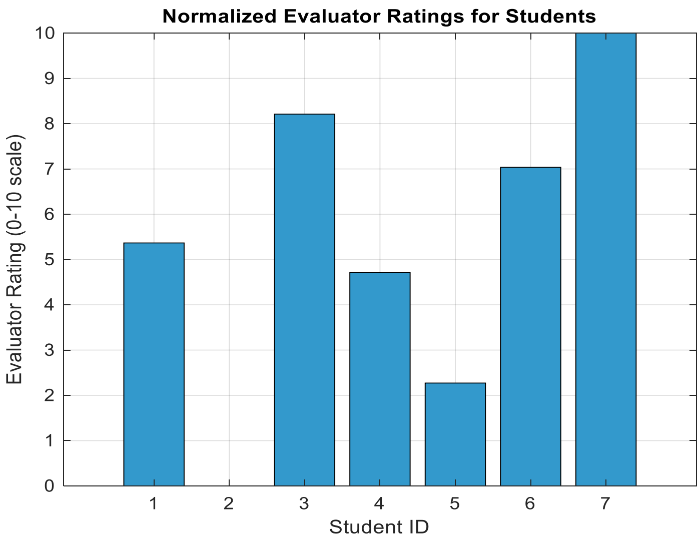


Fig 8. Evaluator Rating.

The GBU-based LSTM model was used to calculate the mean absolute error (MAE) and loss values in order to assess the performance of the suggested deep hybrid framework. **Fig 9** displays the resulting MAE and loss values after the framework was trained for 26 and 150 epochs. At 26 epochs, the ideal metric values were obtained, resulting in an MAE of 0.6708 and a validation loss of 0.3503. These findings show how well the suggested framework predicts student achievement by combining behavioral traits, academic records, MOOC engagement, and NPTEL.

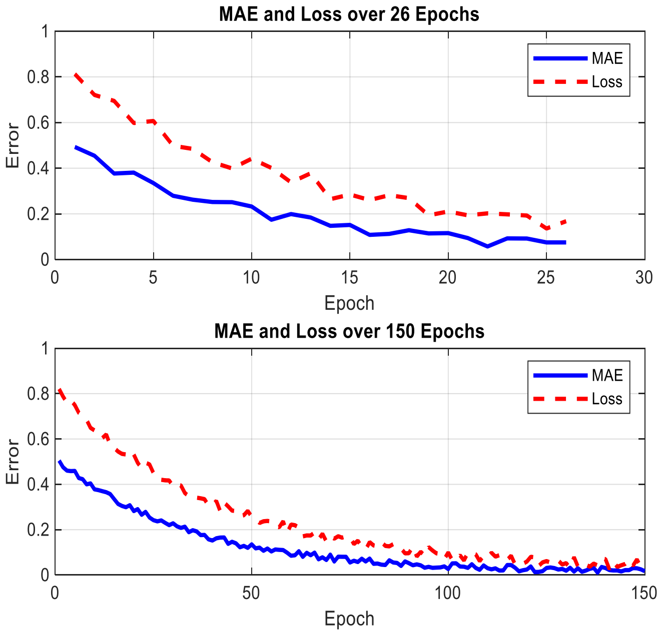


Fig 9. MAE and Loss Over (a) 26 Epochs (b) 150 Epochs.

This study offers a deep learning-based methodology for predicting student performance by combining behavioral traits, academic records, MOOC involvement, and NPTEL. Variants of GBU-based LSTM models were used as baseline techniques in studies to confirm the efficacy of the suggested framework. Character characteristics and enriched word embeddings were then used to create improved models. The outcomes showed that the suggested models performed better than conventional methods, demonstrating their ability to forecast student performance without the need for a large collection of data or outside sources. This paradigm can be modified for educational environments with limited resources and integrating it with current systems can improve their ability to forecast student outcomes.

V. CONCLUSION

Implementing cutting-edge teaching strategies and utilizing data-driven insights are essential for raising educational standards and improving student results. Predictive models that can precisely anticipate student performance must be developed in order to facilitate proactive interventions and individualized support. Conventional methods of predicting student performance frequently depend on a small number of hand-picked characteristics, which has poor generalizability and may lead to overfitting because of a lack of data. In order to reliably forecast student performance, this study suggests a deep hybrid framework that combines behavioral traits, academic records, MOOC involvement, and NPTEL. This framework attempts to offer a more thorough and trustworthy method of predicting student success by utilizing deep learning and the merging of many data sources, thus increasing the efficacy of online learning. A web-based survey was sent to Pakistani academic institutions in order to gather data for this study, and undergraduate, graduate, and PhD students responded. The effectiveness of the suggested GBU-based LSTM models in forecasting student performance was then assessed using the data that had been gathered. The LSTM model was determined to be the best option using a Chi-aquare selection process, demonstrating how well the suggested deep hybrid framework predicts student performance by combining behavioral traits, academic records, MOOC involvement, and NPTEL.

CRediT Author Statement

The authors confirm contribution to the paper as follows:
Conceptualization: Kannan M, Albert Antony Raj S and Ananthapadmanaban K R; **Methodology:** Kannan M; **Software:** Albert Antony Raj S and Ananthapadmanaban K R; **Data Curation:** Kannan M; **Writing- Original Draft Preparation:** Kannan M, Albert Antony Raj S and Ananthapadmanaban K R; **Visualization:** Albert Antony Raj S and Ananthapadmanaban K R; **Investigation:** Kannan M; **Supervision:** Albert Antony Raj S and Ananthapadmanaban K R; **Validation:** Kannan M; **Writing- Reviewing and Editing:** Kannan M, Albert Antony Raj S and Ananthapadmanaban K R; All authors reviewed the results and approved the final version of the manuscript.

Data Availability Statement
The Datasets used and /or analysed during the current study available from the corresponding author on reasonable request.

Conflict of interest
The authors declare no conflicts of interest(s).

Funding
Authors declare no funding for this research.

Competing Interests
There are no competing interests.

References:
[1]. S. Srivastava and N. SINGH Bhati, “A SEM Approach to Assess M-Learning Intentions Among Students of Design: An Empirical Analysis Using the TRUTAUT Model,” Journal of Information Technology Education: Research, vol. 23, p. 015, 2024, doi: 10.28945/5306.
[2]. Ok'Onkwo, C. "Smart Education Recommendation Framework with Dashboard in the Smart City: Smart Education Context." PhD diss., University of East London, 2025.
[3]. Muthuswamy, P. R. *New age education models: Innovation and reform in the 21st century*. Notion Press, 2022.
[4]. I. Ahmad et al., “Inclusive learning using industry 4.0 technologies: addressing student diversity in modern education,” Cogent Education, vol. 11, no. 1, Mar. 2024, doi: 10.1080/2331186x.2024.2330235.
[5]. Kaushik, K. E. S. H. A. V., NEELU JYOTHI Ahuja, and A. N. A. N. D. Nayyar. "Blended learning tools and practices: a comprehensive analysis." (2021).
[6]. Y. Bai, Z. Liu, T. Guo, M. Hou, and K. Xiao, “Prerequisite Relation Learning: A Survey and Outlook,” ACM Computing Surveys, Apr. 2025, doi: 10.1145/3733593.
[7]. A. Kumar., “Blended Learning Tools and Practices: A Comprehensive Analysis,” IEEE Access, vol. 9, pp. 85151–85197, 2021, doi: 10.1109/access.2021.3085844.
[8]. Fayyaz, Nosheen, Muhammad Sajjad. "A Systematic Mapping Review on MOOC Recommender Systems."
[9]. P. Kaliraj, G. Singaravelu, and T. Devi, Transformative Digital Technology for Disruptive Teaching and Learning. Auerbach Publications, 2024. doi: 10.1201/9781032675176.
[10]. S. Patil and S. Shirgave, “Advancements in Video Content Analysis using Machine Learning for Educational Applications: A Comprehensive Review,” 2024 2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI), pp. 1–6, Nov. 2024, doi: 10.1109/idicaiei61867.2024.10842838.
[11]. Der, sunil h., and ch varalakshmi. "artificial Intelligence in Indian Education: A Transformative Force."
[12]. Das, Partha Pratim. "Perspective Chapter: MOOCs in India: Evolution, Innovation, Impact, and Roadmap." *arXiv preprint arXiv:2501.14780* (2025).
[13]. S. Kavitha, S. Mohanavalli, and B. Bharathi, “Predicting Learning Behaviour of Online Course Learners’ using Hybrid Deep Learning Model,” 2018 IEEE 6th International Conference on MOOCs, Innovation and Technology in Education (MITE), pp. 98–102, Nov. 2018, doi: 10.1109/mite.2018.8747136.
[14]. S. Rizwan, C. K. Nee, and S. Garfan, “Identifying the Factors Affecting Student Academic Performance and Engagement Prediction in MOOC Using Deep Learning: A Systematic Literature Review,” IEEE Access, vol. 13, pp. 18952–18982, 2025, doi: 10.1109/access.2025.3533915.
[15]. N. V V, “Automatic Classification of Presentation Slides in Educational Lecture Videos for Bi-Modal Visual Content Analysis Using Multiclass Mw-Svm,” 2023, doi: 10.2139/ssrn.4367601.