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Attention-Guided Trivariate Sequential Intelligence for Academic Performance Inference and Student Stress Profiling

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ABSTRACT

The increasing adoption of data-driven technologies in education has created a growing demand for intelligent systems capable of accurately analyzing student performance and behavioral patterns. Educational datasets contain valuable information, including study habits, attendance, engagement, and assessment records, which can be utilized to predict academic outcomes and identify factors affecting student success. Conventional Machine Learning (ML) models, including Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GB), Decision Tree (DT), Logistic Regression (LR), and Linear Regression (LinR), provide baseline predictive performance but often struggle to model complex nonlinear relationships, exhibit limited generalization, and lack interpretability. To address these challenges, this study proposes BARM, a hybrid framework that integrates Bidirectional Long Short-Term Memory (BiLSTM) with an Attention mechanism and rule-based models, namely the Optimal Decision Rule List Classifier (ODRLC) and Optimal Decision Rule List Regressor (ODRLR). The proposed framework simultaneously performs two classification tasks, FinalGrade and StressLevel, along with ExamScore regression through a dynamic model selection strategy that identifies the best-performing model based on evaluation metrics. A Flask-based web application enables real-time prediction, batch processing, and Exploratory Data Analysis (EDA) visualization. Experimental results demonstrate that BARM improves prediction accuracy, reliability, scalability, and interpretability, making it well suited for practical educational analytics and academic decision support.

Keywords: Student Performance Prediction; Hybrid Deep Learning; Bidirectional Long Short-Term Memory; Rule-Based Learning; Educational Data Mining.

1. INTRODUCTION

The rapid adoption of Information and Communication Technology (ICT)-based learning environments has significantly transformed modern education, resulting in the continuous generation of large-scale educational data. These data are collected from diverse sources, including Learning Management Systems (LMS), Student Information Systems (SIS), online assessments, video-assisted learning platforms, and other digital educational environments. Such data contain valuable information related to students' academic performance, learning behavior, attendance, engagement, and assessment outcomes, providing opportunities to support evidence-based educational decision-making [1]. Educational Data Mining (EDM) has emerged as an important research area that applies data mining, ML, and artificial intelligence techniques to discover meaningful knowledge from educational data. By analyzing academic records and

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behavioral information, EDM enables institutions to identify learning patterns, predict academic outcomes, support personalized learning, and implement timely intervention strategies for students requiring additional academic assistance [2].

Accurate prediction of student academic performance has become a significant research challenge because early identification of academically at-risk students enables educators to provide appropriate guidance and improve learning outcomes [3]. Existing predictive models primarily utilize structured information such as examination scores, attendance records, demographic attributes, and assignment marks. Although these features provide useful indicators of academic achievement, they often fail to capture the complex behavioral characteristics exhibited during online learning, including learning engagement, study consistency, resource utilization, and interaction patterns. Consequently, important information influencing student performance remains underutilized [4]. Recent advances in ML and deep learning have substantially improved educational prediction by learning complex relationships from heterogeneous datasets [5], [6]. Conventional ML algorithms, including RF, SVM, GB, DT, LR, and LinR, provide reliable baseline performance but often exhibit limited capability in modeling nonlinear relationships, long-term dependencies, and high-dimensional behavioral data. Furthermore, these models may suffer from reduced generalization and limited interpretability when simultaneously addressing multiple prediction tasks within a unified framework [7], [8].

To overcome these limitations, this study proposes BARM, a hybrid educational prediction framework that integrates BiLSTM with an Attention mechanism and rule-based learning models, namely ODRLC and ODRLR[9]. The proposed framework performs a unified 2CA1RT analysis by simultaneously predicting FinalGrade and StressLevel through classification while estimating ExamScore using regression. A dynamic model selection strategy identifies the most effective predictive model based on evaluation metrics, while a Flask-based web application supports real-time prediction, batch processing, and EDA visualization, improving the practical usability and interpretability of the proposed system.

The primary objectives of this research are summarized as follows:

- To analyze and evaluate baseline ML models, including RF, SVM, GB, DT, LR, and LinR, for predicting student academic performance and stress levels.
- To develop the proposed BARM framework by integrating BiLSTM with Attention and rule-based models (ODRLC and ODRLR) for effective learning from complex educational data.
- To design a unified 2CA1RT framework capable of performing dual classification (FinalGrade and StressLevel) together with ExamScore regression within a single predictive system.
- To implement a dynamic model selection mechanism and deploy the proposed framework using Flask for real-time prediction, batch processing, and EDA-based visualization.

2. LITERATURE SURVEY

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Tang, et al. [10] proposed a deep ensemble learning framework for predicting student academic performance by integrating multiple Deep Neural Networks (DNNs) through a weighted voting mechanism. The study optimized the parameters of individual deep learning models before combining their predictions, thereby improving classification accuracy and overall predictive reliability. The proposed ensemble approach demonstrated superior performance compared to standalone deep learning models, highlighting the effectiveness of combining multiple classifiers for educational data analysis. The framework enabled educational institutions to identify students at academic risk more accurately and support timely intervention strategies. Adefemi, et al. [11] developed a hybrid deep learning architecture by combining Convolutional Neural Networks (CNN) and Bidirectional Gated Recurrent Units (BiGRU) to predict student academic performance. The framework incorporated comprehensive data preprocessing techniques, including missing value imputation, feature selection, normalization, and class balancing to improve model robustness and predictive accuracy. Experimental results demonstrated that integrating spatial feature extraction with sequential learning significantly enhanced prediction performance, making the proposed model suitable for complex educational datasets. Yu, et al. [12] proposed ensemble learning models based on bagging and stacking techniques for academic performance prediction. The study evaluated the proposed models using five-fold cross-validation and compared them with individual machine learning algorithms. Experimental findings showed that both fusion-based approaches consistently outperformed single predictive models, achieving classification accuracies of approximately 83% and 84%, respectively. The research demonstrated that ensemble learning effectively improves prediction stability, generalization capability, and decision-making accuracy in educational analytics.

Ruiz-Camacho, et al. [13] investigated the relationship between academic stressors and students' psychological responses using hierarchical regression analysis. The study identified academic workload, examination pressure, and students' performance-related beliefs as the primary factors contributing to negative emotional responses, including anxiety, physical fatigue, irritability, and sleep disturbances. The findings emphasized that prolonged academic stress significantly affects both students' mental well-being and academic achievement, highlighting the importance of early identification and stress management interventions. Hahn, et al. [14] evaluated the applicability of the Study Demands–Resources (SD-R) model across both COVID-19 and post-pandemic educational environments using Structural Equation Modeling (SEM). The study analysed how academic demands, available learning resources, and psychological factors influenced student stress under different learning conditions. Results confirmed that the SD-R model remained stable across both learning environments and effectively explained variations in student stress, demonstrating its usefulness for understanding educational challenges during and after the pandemic. The research further suggested that improving academic resources and institutional support can significantly reduce student stress and enhance learning outcomes.

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Ismiyana Putri, et al. [15] conducted a comprehensive Systematic Literature Review (SLR) on the application of Machine Learning (ML) techniques for predicting student stress and academic performance. The review analysed numerous research studies to identify the most widely adopted predictive algorithms, data preprocessing methods, and influential predictive features used in educational analytics. The findings revealed that Random Forest (RF), Support Vector Machine (SVM), and Neural Networks were among the most frequently utilized algorithms due to their strong predictive capabilities. Furthermore, the review emphasized that combining psychological, behavioral, physiological, and academic features with effective preprocessing techniques such as feature selection, normalization, and class balancing substantially improves prediction accuracy and model robustness. The study concluded that integrating advanced machine learning approaches with comprehensive student-related data enables educational institutions to develop more reliable early warning systems for identifying academically at-risk and psychologically stressed students.

3. PROPOSED SYSTEM

The system integrates data ingestion, preprocessing, model training, evaluation, and deployment into a unified pipeline for student performance prediction. It begins with user authentication and dataset loading, followed by structured preprocessing to prepare data for modeling. Fig. 1 illustrates how both existing ML models RF, SVM, GB, DT, LR and the proposed BARM model operate within the same framework. The architecture supports both classification tasks FinalGrade, StressLevel and regression tasks ExamScore. The BARM model combines BiLSTM, Attention, ODRLC, and ODRLR to enhance predictive performance. A model comparison and selection module evaluates all models using performance metrics. The selected model is deployed through a Flask-based web application. The system supports both single and batch predictions along with visualization through EDA.

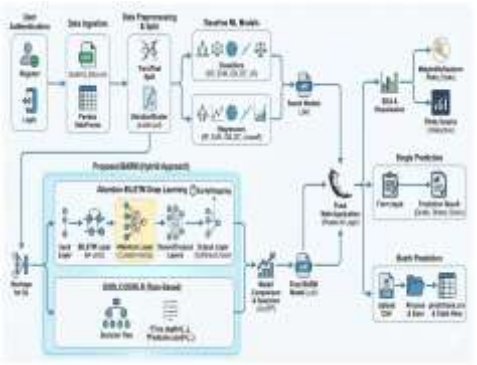


Fig. 1: Proposed system architecture of student performance prediction.

1. Data Acquisition and Ingestion

The system begins by collecting student-related data from structured sources such as CSV files, which include academic, behavioral, and institutional attributes. This data is loaded into a processing environment where it is organized into a tabular format. Proper data ingestion ensures consistency and prepares the dataset for further transformation and analysis.

2. Data Preprocessing and Transformation

In this stage, the collected data undergoes cleaning, normalization, and scaling to remove inconsistencies and improve quality. The dataset is then divided into training and testing subsets to enable proper evaluation of model performance. This step ensures that the data is standardized and suitable for both traditional and advanced analytical methods.

3. Baseline Model Evaluation

Multiple baseline models are applied to the processed data to establish initial

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performance metrics for 2CA1RT. These models help in understanding the dataset characteristics and provide a reference for further improvements. The outputs generated here are stored and later used for comparative analysis.

4. Hybrid Model Processing and Feature Learning

The system utilizes a hybrid framework that processes input data through deep learning layers to capture complex patterns and sequential dependencies. Simultaneously, rule-based components analyze structured decision paths to enhance interpretability. This combined approach enables the system to handle both complexity and transparency in predictions.

5. Model Comparison and Selection

All trained models are evaluated using performance metrics, and a comparison mechanism identifies the best-performing model. This dynamic selection process ensures that the most accurate and reliable model is chosen for deployment. It also helps in improving overall system robustness and adaptability.

6. Deployment and Prediction Interface

The final selected model is integrated into a web-based application that allows users to perform both single and batch predictions. The system provides outputs such as grades, stress levels, and scores along with visualizations for better understanding. This stage ensures practical usability and real-time interaction with the predictive system.

4. RESULTS AND DISCUSSION

The dataset used in this research contains as shown in table 1 student-related features that influence academic performance and behavioral outcomes. It includes attributes such as study habits, attendance, resource usage, and engagement factors. The dataset is structured with both numerical and categorical features representing academic and personal characteristics. It supports both classification and regression tasks within the system. The target variables include StressLevel and FinalGrade for classification and ExamScore for regression. This dataset enables the models to learn patterns between student behavior and performance outcomes. The results and discussion section presents the outcomes obtained after executing the system and evaluating its performance. It focuses on analyzing how effectively the system performs based on defined evaluation metrics. The results include numerical values, graphical representations, and comparisons that help in understanding system behavior. This section interprets the outputs to identify patterns, trends, and performance differences. It also highlights the strengths and weaknesses observed during execution. Visual tools such as graphs and charts are used to support the analysis. The discussion provides meaningful insights derived from the results.

Table 1: Dataset Description of Student Performance

Feature Name	Description	Type
StudyHours	Number of hours spent studying	Numerical
Attendance	Percentage of attendance	Numerical
Resources	Access to study resources (0/1/2)	Categorical
Extracurricular	Participation in extracurricular	Categorical

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	activities (0/1)	
Motivation	Level of motivation (0/1)	Categorical
Internet	Availability of internet access (0/1)	Categorical
Gender	Gender of the student (0/1)	Categorical
Age	Age of the student	Numerical
LearningStyle	Preferred learning style (encoded)	Categorical
OnlineCourses	Number of online courses taken	Numerical
Discussions	Participation in discussions (0/1)	Categorical
AssignmentCompletion	Percentage of assignments completed	Numerical
ExamScore	Final exam score	Numerical (Target - Regression)
EduTech	Usage of educational technology (0/1)	Categorical
StressLevel	Stress level of student	Categorical (Target)
FinalGrade	Final academic grade	Categorical (Target)

Fig. 2 depicts the batch prediction interface of the system, which processes multiple input records simultaneously. It illustrates the structured tabular output containing predicted values for FinalGrade (0–3), StressLevel (0–2), and ExamScore (40–100). The figure shows that predictions are generated for multiple samples, enabling large-scale analysis. The interface supports efficient handling of batch datasets. It highlights the integration of prediction results with input features. The system ensures consistent output formatting for all records.

Table 2 presents the performance comparison of various classification models for predicting final grades. The Proposed BARM model significantly outperforms all baseline models, achieving the highest accuracy, precision, recall, and F1 score (0.9682). Among traditional methods, RF shows strong performance with balanced metrics around 0.85. In contrast, SVM and GB demonstrate moderate results with accuracies below 0.55. DT and LR perform poorly, indicating limited capability in capturing complex patterns. The consistent metrics of BARM suggest robust and reliable classification performance.

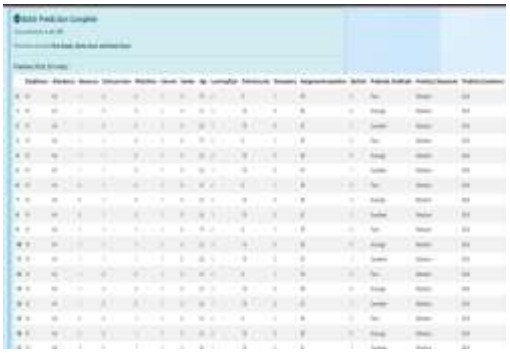


Fig. 2: Batch Prediction Interface

Table 2: FinalGrade – Model Performance

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Model	Accuracy	Precision	Recall	F1 Score
RF	0.8509	0.8514	0.8509	0.8509
SVM	0.4553	0.4605	0.4553	0.4498
GB	0.5026	0.5069	0.5026	0.5003
DT	0.2864	0.1534	0.2864	0.1984
LinR	0.2860	0.2804	0.2860	0.2394
Proposed BARM	0.9682	0.9682	0.9682	0.9682

Table 3: StressLevel – Model Performance

Model	Accuracy	Precision	Recall	F1 Score
RF	0.8985	0.8988	0.8985	0.8986
SVM	0.5344	0.6422	0.5344	0.4119
GB	0.5526	0.6036	0.5526	0.4565
DT	0.5040	0.2541	0.5040	0.3378
LinR	0.5040	0.2541	0.5040	0.3378
Proposed BARM	0.9741	0.9741	0.9741	0.9741

Table 3 compares different models for stress level classification. The Proposed BARM model again achieves the best performance, with all evaluation metrics reaching 0.9741. Random Forest is the second-best model, delivering high accuracy and balanced precision and recall values close to 0.90. SVM, GB show moderate effectiveness but with noticeable drops in recall and F1 score. DT and LR yield relatively weak results, indicating poor generalization. The higher precision of SVM suggests some class bias despite lower overall accuracy. Table 4 presents regression model performance for predicting exam scores using error metrics and R^2 score. The Proposed BARM model achieves the lowest MAE (0.8270), MSE (25.5347), and RMSE (5.0532), along with the highest R^2 score (0.9179), indicating excellent prediction accuracy. RF performs well among baseline models with relatively low error values and a strong R^2 of 0.8409. Other models, including SVM and GB, show higher errors and significantly lower R^2 scores. DT and LinR on exhibit the weakest performance, with minimal explanatory power. The results demonstrate that BARM effectively captures underlying patterns in exam score prediction.

Table 4: Exam Score – Model Performance

Model	MAE	MSE	RMSE	R^2 Score
RF	1.7103	49.5114	7.0364	0.8409

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SVM	14.5936	298.3599	17.2731	0.0412
GB	14.3744	278.4714	16.6875	0.1051
DT	15.1999	308.8406	17.5739	0.0075
LinR	15.2205	310.1464	17.6110	0.0033
Proposed BARM	0.8270	25.5347	5.0532	0.9179

5. CONCLUSION

The research successfully developed an intelligent prediction system for analyzing student performance and stress levels using both ML models and the proposed BARM model. The system integrates preprocessing, EDA, and multiple models including RF, SVM, GB, DT, LR, and LinR within a unified framework. The proposed BARM model, which combines BiLSTM, Attention, ODRLC, and ODRLR, demonstrated superior performance compared to all baseline models. In FinalGrade classification, BARM achieved an accuracy of approximately 0.97, outperforming RF (~0.85) and significantly surpassing SVM, GB, DT, and LR models. Similarly, in StressLevel classification, BARM maintained high accuracy around 0.97–0.98, while other models showed moderate to low performance. In regression tasks, BARM achieved a high R^2 score (0.91) with lower error values, whereas LinR and other models showed limited predictive capability. The hybrid architecture effectively captured both complex patterns and interpretable decision rules, leading to improved generalization and reliability. The integration with a Flask-based interface enabled real-time prediction, batch processing, and visualization, making the system practical and scalable.

REFERENCES

[1] Hasan, R.; Palaniappan, S.; Mahmood, S.; Shah, B.; Abbas, A.; Sarker, K.U. Enhancing the teaching and learning process using video streaming servers and forecasting techniques. *Sustainability* 2019, *11*, 2049.

[2] Romero, C.; Ventura, S. Educational data mining and learning analytics: An updated survey. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* 2020, *10*, e1355.

[3] Du, X.; Yang, J.; Hung, J.-L.; Shelton, B. Educational data mining: A systematic review of research and emerging trends. *Inf. Discov. Deliv.* 2020, *48*, 225–236.

[4] Albreiki, B.; Zaki, N.; Alashwal, H. A systematic literature review of student'performance prediction using machine learning techniques. *Educ. Sci.* 2021, *11*, 552.

[5] Matz, S.C.; Bukow, C.S.; Peters, H.; Deacons, C.; Dinu, A.; Stachl, C. Using machine learning to predict student retention from socio-demographic characteristics and app-based engagement metrics. *Sci. Rep.* 2023, *13*, 5705.

[6] Umer, R.; Susnjak, T.; Mathrani, A.; Suriadi, L. Current stance on predictive analytics in higher education: Opportunities, challenges and future directions. *Interact. Learn. Environ.* 2023, *31*, 3503–3528.

International Journal of
AI ELECTRICAL CIVIL AND MECHANICAL ENGINEERING
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0434 www.zesterapublications.com Original Research Paper

[7] Yang, Z.; Yang, J.; Rice, K.; Hung, J.-L.; Du, X. Using convolutional neural network to recognize learning images for early warning of at-risk students. IEEE Trans. Learn. Technol. 2020, 13, 617–630.

[8] Kong, X.; Luo, C. A novel ConvLSTM with multifeature fusion for financial intelligent trading. Int. J. Intell. Syst. 2022, 37, 8855–8877.

[9] Asif, R.; Merceron, A.; Ali, S.A.; Haider, N.G. Analyzing undergraduate students' performance using educational data mining. Comput. Educ. 2017, 113, 177–194.

[10] Tang, B.; Li, S.; Zhao, C. Predicting the Performance of Students Using Deep Ensemble Learning. J. Intell. 2024, 12, 124. https://doi.org/10.3390/jintelligence12120124

[11] Adefemi, K.O.; Mutanga, M.B.; Jugoo, V. Hybrid Deep Learning Models for Predicting Student Academic Performance. Math. Comput. Appl. 2025, 30, 59. https://doi.org/10.3390/mca30030059

[12] Yu, F.; Liu, X. Research on Student Performance Prediction Based on Stacking Fusion Model. Electronics 2022, 11, 3166. https://doi.org/10.3390/electronics11193166

[13] Ruiz-Camacho, C.; Gozalo, M. Predicting University Students' Stress Responses: The Role of Academic Stressors and Sociodemographic Variables. Eur. J. Investig. Health Psychol. Educ. 2025, 15, 163. https://doi.org/10.3390/ejihpe15080163

[14] Hahn, E.; Kuhlee, D.; Zimmermann, J.; Serrano-Sánchez, J. The Mediating Role of Perceived Stress and Student Engagement for Student Teachers' Intention to Drop Out of University in Germany: An Analysis Using the Study Demands–Resources Model Under Pandemic and Post-Pandemic Conditions. Educ. Sci. 2025, 15, 719. https://doi.org/10.3390/educsci15060719

[15] Ismiyana Putri, Dwi & Putra, Mardi Yudhi & Nurul Alfian, Ari & Arifin, Rita & Shadiq, Jafar & Indaryani, Putri. (2025). Machine Learning Models for Student Stress and Academic Performance Prediction: A Systematic Literature Review. 1-5. 10.1109/ICIC68054.2025.11309547.