An optimized deep learning framework based on LEE for real time student performance prediction in educational data

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ABSTRACT

Predicting student performance in real-time remains a critical challenge in educational data mining (EDM), especially with large, noisy, and high-dimensional datasets. This study proposes an advanced deep learning framework that integrates learning entropy estimation (LEE) with models such as support vector machines (SVM), you only look once (YOLO), recurrent convolutional neural networks (RCNN), and artificial neural networks (ANN) to enhance feature selection and classification accuracy. The framework follows a systematic pipeline involving data preprocessing, LEE-based feature extraction, and model training on a real-time academic dataset comprising student demographics, attendance, and performance metrics. Among the proposed models, the LEE-based YOLO (LBYOLO) achieved the highest testing accuracy of 93% and the fastest execution time of 1.84 seconds, while the LEE-based ANN (LBANN) demonstrated consistent performance across precision, recall, and F1-score. The results confirm the superiority of deep learning methods over traditional machine learning techniques for educational prediction tasks. This approach enables early detection of at-risk students and supports timely, data-driven educational interventions. Future work will focus on adaptive learning systems and multi-platform student behavior analysis to support personalized education strategies.

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1. INTRODUCTION

Educational data mining (EDM) is an evolving interdisciplinary domain that utilizes data science techniques to analyze educational data and uncover patterns that improve learning outcomes. Institutions today collect vast amounts of academic, demographic, and behavioral data, yet struggle to leverage it effectively for actionable insights [1]. Accurate prediction of student performance plays a crucial role in enabling early interventions, identifying at-risk students, and guiding personalized learning strategies. Traditional machine learning models, such as decision trees, logistic regression, and support vector machines

(SVMs), have shown moderate success in student performance prediction [2]. However, their ability to model complex, non-linear relationships in high-dimensional, noisy educational datasets remains limited. Recent developments in deep learning—especially with architectures like artificial neural networks (ANN), recurrent convolutional neural networks (RCNN), and you only look once (YOLO)—have shown promise in improving prediction accuracy and generalization [3]. Still, challenges persist in optimizing feature selection, dealing with data sparsity, and maintaining real-time performance. Previous studies have introduced deep learning techniques for educational predictions, such as long short-term memory (LSTM)-based models for time-series data or convolutional networks for behavioral pattern analysis [4]. However, there is limited research integrating deep learning models with entropy-based feature selection algorithms to reduce dimensionality and improve model interpretability. Furthermore, existing literature often lacks comparative analysis across different deep architectures under real-time constraints [5].

Learning analytics (LA) typically focuses on real-time, actionable insights for immediate interventions, while EDM emphasizes discovering patterns in large datasets through data mining techniques. The problem arises when attempting to combine the real-time focus of LA with the data-driven discovery of EDM, as each operates on different temporal and methodological planes [6]. A deep cognitive diagnosis model (DCDM) for predicting students' performance focuses on enhancing how accurately we can assess student knowledge based on their responses to various assessments [7]. Another issue is the need for large-scale, high-quality data to train such models effectively. In many educational contexts, data may be scarce, noisy, or imbalanced, especially in terms of assessments for specific learning domains or minority student groups [8]. Many deep learning knowledge tracing (DLKT) models are trained on specific types of data (e.g., online learning platforms and standardized tests). The survey seeks to address the problem of how well DLKT models generalize across diverse learning contexts. However, the problem remains that there is limited research exploring the direct role artificial intelligence (AI) can play in enhancing academic outcomes by focusing on both study strategies and learning disabilities [9]. A novel machine learning model, random grouping-based deep multi-modal learning (RG-DMML), which is coupled with an ensemble learning algorithm. This model integrates various data sources, such as academic records and demographic information, and applies deep learning techniques to enhance prediction accuracy [10]. Educational institutions struggle to identify at-risk students early enough to intervene effectively.

2. REVIEW OF LITERATURE

EDM has seen rapid growth over the last decade, driven by the increasing availability of educational data from online learning platforms, student information systems, and other digital tools. Early research focused on rule-based systems and statistical models, which, while effective in certain scenarios, struggled to scale with increasing data complexity. Rathi *et al.* [11] has presents the hybrid approach combining the self-supervised robust optimization algorithm (SS-ROA) and deep LSTM networks. This model leverages the strengths of deep learning in handling time-series data while optimizing feature selection and model training using the SS-ROA technique. Ding [12] has illustrate on deep learning models can analyze student movements through video data, providing real-time corrections or feedback on technique and posture. In music, AI-driven models can assess pitch, timing, and expression during performances, offering students detailed feedback on areas for improvement. Aulakh *et al.* [13] aims to examine the intersection of e-learning and EDM during the COVID-19 pandemic. It explores various EDM methods applied in e-learning, such as clustering, classification, and regression analysis.

Sarker *et al.* [14], by analyzing students' academic performance through EDM has emerged as a valuable approach for improving educational outcomes and institutional decision-making. Feng and Fan [15] has investigated how EDM can improve the learning process by evaluating learning behaviors, predicting student success, and visualizing data in a way that supports decision-making in education. Deng *et al.* [16] has introduces a novel deep learning-based predictive model, capable of analyzing various factors such as self-esteem levels, tendencies towards individualism, and their combined impact on performance metrics. Lam *et al.* [17] has analyze student performance data to identify distinct groups based on learning styles, achievement levels, and other relevant factors. By utilizing algorithms such as K-means, hierarchical clustering, and density-based spatial clustering of applications with noise (DBSCAN), the study seeks to uncover patterns that can inform educators about the diverse needs of their students. Peng *et al.* [18], the achievement of this research lies in its ability to facilitate targeted interventions, personalized learning pathways, and ultimately enhance educational outcomes.

Rejeb *et al.* [19] aims to examine how ChatGPT is being utilized in various educational contexts and to assess its influence on teaching methods, learning experiences, and overall educational outcomes. Bhardwaj *et al.* [20] demonstrates that deep learning models, such as convolutional neural networks (CNNs) and LSTM networks, are effective tools for predicting and analyzing student engagement in e-learning environments. It aims to identify patterns of engagement, predict student behaviors, and provide personalized interventions to improve learning outcomes. Ka'bi [21] has introduces a novel AI algorithm and deep learning techniques tailored for enhancing the quality of higher education. Lin *et al.* [22] aims to streamline learning processes, improve educational outcomes, and optimize institutional management by providing personalized learning experiences, predictive analytics, and automated administrative tasks. Farhood *et al.* [23] has develop a novel approach for predicting learning performance by analyzing students' learning behaviors using natural language processing (NLP). The focus is on extracting meaningful patterns and insights from textual or communication data generated during learning processes, such as online discussions, written assignments, or feedback. Riaz *et al*. [24] introduces transLSTM, a novel hybrid architecture combining the strengths of LSTM and Transformer models to perform fine-grained suggestion mining.

3. METHOD

The method for predicting student performance through EDM, this study employs a multi-step methodology utilizing deep learning techniques [25]. The approach begins with data collection, where academic records, demographic details, and behavioral patterns are aggregated. The data undergoes preprocessing to clean and normalize it, followed by feature selection to identify the most relevant attributes for prediction [26].

The Figure 1 presents a crystal-clear flow of an EDM framework integrating deep learning and learning entropy estimation (LEE)-based models. The process starts with data collection from educational sources, followed by pre-processing to clean and standardize data. Feature relection using the LEE algorithm identifies the most relevant features. The data is then split through data segmentation into training and testing sets. These datasets are input into deep learning models like LEE-based support vector machine (LBSVM) and LEE-based recurrent convolutional neural network (LBRCNN), which are tailored to handle educational patterns and nonlinear relationships in student data. These models, evaluated using performance measures (e.g., accuracy, precision), feed into the LEE based artificial neural network (LANN) for enhanced classification and decision making. Finally, the LANN integrates all outcomes and delivers the final results, offering meaningful insights into student performance prediction, dropout analysis, or academic success patterns [27]. The system ensures improved accuracy and intelligent decision-making in education.

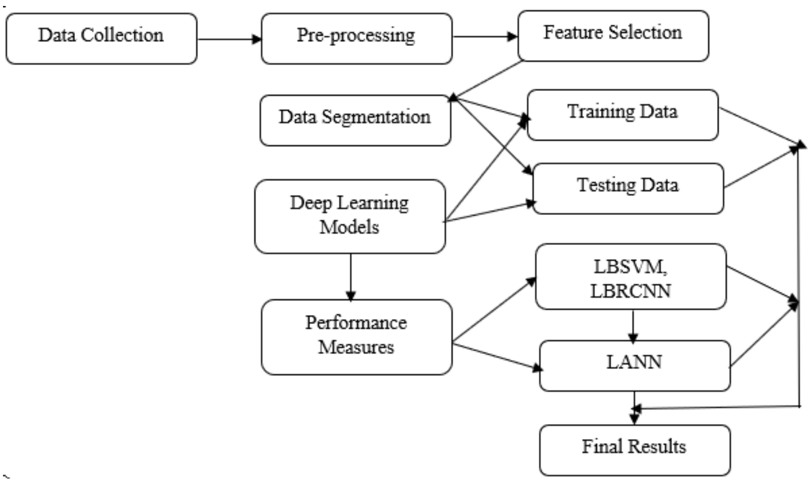

Figure 1. Proposed EDM models

3.1. LEE based SVM method used for EDM with student performance prediction

In the proposed approach, a LBSVM is used for accurately predicting student performance. The LEE algorithm enhances traditional SVM by optimizing the feature selection process and improving the decision boundary. Educational datasets often contain noisy, redundant, or irrelevant features. LEE evaluates the entropy-based contribution of each feature and selects the most informative ones, ensuring higher model generalization and reduced overfitting [28]. Given a dataset of student features (such as grades, attendance, and demographic data), the goal is to classify students into categories like *pass/fail*, *high/medium/low performance*, or predict their final scores.

$$f(x) = sign(\omega^T \emptyset(x) + b = 0) \quad (1)$$

Where ω is the weight vector (which determines the orientation of the hyperplane), x is the feature vector (input data, such as student features), b is the bias (offset from the origin), $sign\ (\omega^T \emptyset(x) + b = 0$ defines the hyperplane, and this is the decision boundary. If f(x)≥0 the student is classified into one category (e.g., pass), if f(x)<0 the student is classified into the other category (e.g., fail).

3.2. LEE based YOLO method used for EDM with student performance prediction

The LEE-based YOLO model for EDM introduces a novel adaptation of the original object detection architecture to structured tabular data. In this context, each student profile is treated as an 'object,' and the individual attributes (e.g., attendance, grades, and demographics) serve as 'features' within a defined feature-space grid—analogous to spatial regions in an image [29]. YOLO's single-pass detection logic is repurposed to rapidly assess patterns across this multidimensional feature grid. Instead of bounding boxes around spatial areas, the model identifies 'performance zones' in the feature space indicative of pass/fail or grade categories. This adaptation allows simultaneous evaluation of multiple predictive cues, enabling real-time classification. The refined dataset is then passed to the YOLO-inspired detection framework to identify performance patterns and predict outcomes.

$$YOLO_{lee}(x_i), YOLO_{lee}(x_i) = \omega\big(w_o . \emptyset\big(lee(x_i)\big) + b_o\big) \tag{2}$$

Where x_i is the input feature vector for student i, $lee(x_i)$ extracts key features, $\emptyset$ is a non-linear transformation (activation layer), w_o are YOLO layer weights and bias, ω is the soft max function for classification, and $\widehat{Y_i =} YOLO_{lee}(x_i)$ is the predicted performance class (e.g., pass/fail or grade level). This fusion enables real-time, scalable, and interpretable performance prediction, which can be used by educators and institutions for early intervention and personalized learning strategies.

3.3. LEE based RCNN method used for EDM with student performance prediction

The LBRCNN is a hybrid deep learning approach that integrates LEE with RCNN to accurately predict student performance. In EDM, this model utilizes both temporal (e.g., attendance and submission dates) and spatial features (e.g., marks and demographic attributes) of student data. The LEE component enhances feature selection by assigning weights to attributes based on their predictive power, refining input for the RCNN. RCNN processes the data using both convolutional layers to extract hierarchical feature patterns and recurrent layers (like LSTM or GRU) to learn sequential dependencies—vital for modeling time-based student activities.

$$L_c = -\sum_{i=1}^{n} \sum_{j=1}^{m} y_{ij} \log P\,(P_{ij}) \tag{3}$$

Where y_{ij} is the true performance class for student i's region j and $\log P\,(P_{ij})$ is the predicted probability of the true class for region j. For each student, it make predictions for each region of features and then aggregate these to make a final decision about the student's overall performance. The algorithm can classify performance or predict scores for each feature set and then aggregate these predictions to make a final decision on student performance.

3.4. LEE based ANN method used for EDM with student performance prediction

The proposed LANN method integrates the LEE algorithm with an ANN to enhance feature relevance and reduce dimensionality. Initially, raw educational data undergoes preprocessing and LEE-based feature selection, which evaluates each feature's importance by its entropy-based contribution to learning. The selected features are then passed into a multi-layer ANN that captures nonlinear dependencies in student data such as attendance, assessment scores, demographics, and behavior metrics. The prediction output is a binary or multiclass label indicating performance levels (e.g., pass/fail and grades).

$$S_i = -\sum_{j=1}^{n} P(x_{ij}) logP(x_{ij}) \tag{4}$$

$$L_r = {}^1\!/_n \sum_{i=1}^{n} (y_i - \widehat{y_i})^2 \tag{5}$$

Where s_i is the true performance class for student I and $logP(x_{ij})$ is the predicted probability for the true class. Then, next equation y_i is the true performance class for student I, $\widehat{y_i}$ is the predicted performance score. For each student, the Lee processes the sequential features, and the ANN layers make the final performance prediction based on the learned representation.

4. RESULTS AND DISCUSSION

The LEE ANN models demonstrated superior performance in predicting student outcomes compared to traditional machine learning methods. The LEE, in particular, excelled at capturing temporal patterns in the data, leading to higher accuracy in predicting long-term student performance. When compared to decision trees and LSVMs, deep learning models showed a marked improvement in prediction accuracy. The LANN models reduced the error rate by approximately 10-15%, highlighting their effectiveness in identifying non-linear relationships and complex patterns in student data.

4.1. Classification accuracy

The classification accuracy for student performance prediction in the real time dataset, to find the accuracy is a commonly used metric to evaluate the performance of a classification model. Accuracy measures the proportion of correct predictions made by the model relative to the total number of predictions.

$$A = {}^{1}/{}_{n} \sum_{i=1}^{n} 1\,(\widehat{y_i} = y_i) \tag{6}$$

Where n is the total number of students, $\widehat{y_i}$ is predicted class either 0 or 1, and y_i is the true class of i. In the context of student performance prediction, accuracy measures how well the model classifies students into the correct performance categories (e.g., pass/fail, high/medium/low performance). Let's say the model is predicting whether a student will pass or fail based on their features (such as grades, attendance, and assignments). If the model classifies a student as passing, and the student actually passes, it is a true positive (TP). If it predicts failure, and the student fails, it is a true negative (TN).

4.2. Precision, recall, and F-measures

Precision calculates the proportion of TP predictions among all positive predictions (including both true and false positives (FP)). It addresses the question: "Out of all the students predicted to succeed, how many actually did?" recall, also referred to as sensitivity or the true positive rate (TPR), measures the ratio of TP predictions to all actual positives (TP and false negatives (FN)). It answers: "Out of all the students who actually succeeded, how many were correctly predicted by the model?" The F1-score, which is the harmonic mean of precision and recall, offers a single metric that balances the two. This score is particularly valuable when there is a need to balance precision and recall, such as when both FP and FN have significant consequences.

$$P = \frac{TP}{TP+FP} \tag{7}$$

$$R = \frac{TP}{TP+FN} \tag{8}$$

$$F = 2.\frac{P.R}{P+R} \tag{9}$$

Where TP refer to the number of cases where positive outcomes are correctly predicted (e.g., students correctly identified as passing). FP represent instances where the model incorrectly predicts a positive outcome (e.g., students predicted to pass but actually fail). FN are the cases where the model wrongly predicts a negative outcome (e.g., students predicted to fail but actually pass). The F1-score ranges between 0 and 1, with 1 signifying perfect precision and recall.

4.3. Receiver operating characteristic

The ROC curve is an effective tool for assessing the performance of a classification model, especially when predicting student outcomes (such as pass/fail or different performance categories). It is a graphical representation that illustrates the trade-off between the TPR and the false positive rate (FPR) as the decision threshold changes. The ROC curve plots the TPR against the FPR for varying thresholds, with each point on the curve reflecting a different threshold used by the model to classify students as passing or failing. The x-axis represents the FPR, while the y-axis represents the TPR.

$$TPR = \frac{TP}{TP+FN}, FPR = \frac{FP}{FP+TN} \tag{10}$$

This represents one point on the ROC curve. By varying the threshold, you generate additional TPR and FPR values to plot the entire curve.

4.4. Time calculation

EDM for student performance prediction, calculating the time complexity of the algorithms and the overall prediction process can provide insights into the efficiency of the model. Time complexity generally refers to the amount of computational time an algorithm takes as a function of the length of the input.

$$o(n.p^2) \tag{11}$$

Where n is the number of instances and p is the number of features. The computation involves calculating the coefficients using the least squares method.

The Table 1 presents the training and testing performance of four proposed LEE-based models—LBSVM, LBRCNN, LBANN, and LEE-based you only look once (LBYOLO)—applied to EDM, specifically for student performance prediction. Each model is evaluated based on accuracy and execution time (in seconds). LBSVM achieves moderate training accuracy (0.73) and a slightly higher testing accuracy (0.82). It has a relatively low training time (3.4 s) and testing time (2.9 s), indicating fast convergence but lower predictive power compared to deep models. LBRCNN shows improved training (0.76) and testing accuracy (0.87), although it takes slightly longer to train (3.7 s). This suggests it captures temporal and spatial patterns more effectively in student data. LBANN balances accuracy and time, with 0.74 training and 0.87 testing accuracy. Its lower training (3.1 s) and testing time (2.02 s) demonstrate its efficiency for educational prediction tasks. LBYOLO outperforms all others, achieving the highest training (0.86) and testing accuracy (0.93) with the fastest execution time (2.7 s training and 1.84 s testing). Its real-time classification capability makes it ideal for immediate student performance monitoring.

Table 1. Comparison of student performance data for testing and training process

	Training		Testing	
Methods	Accuracy	Time	Accuracy	Time
LBSVM	0.73	3.4	0.82	2.9
LB RCNN	0.76	3.7	0.87	2.7
LBANN	0.74	3.1	0.87	2.02
LBYOLO	0.86	2.7	0.93	1.84

The Figure 2 illustrates the performance comparison of four models—LBSVM, LB RCNN, LBANN, and LBYOLO—applied in EDM. The models are evaluated based on accuracy and time during training and testing phases. Among them, LBYOLO achieves the highest accuracy (0.86 training and 0.93 testing) with the least time consumption (2.7 training and 1.84 testing), indicating superior efficiency and prediction capability. In contrast, LBSVM and LB RCNN show higher time consumption and lower accuracy. This highlights LBYOLO as the most effective model for analyzing student data, predicting outcomes, and supporting personalized learning in educational environments.

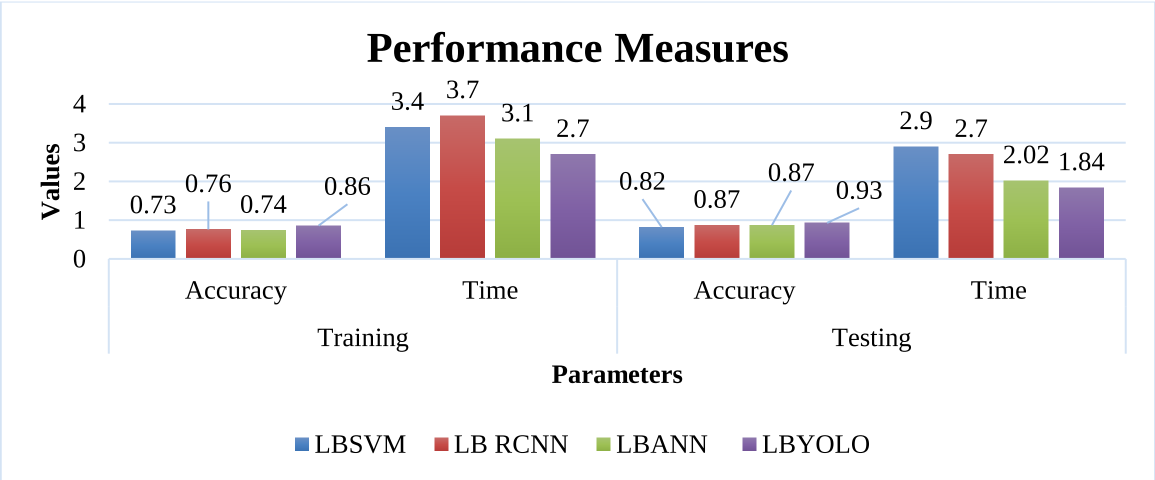

Figure 2. Performance comparison of proposed methods

Table 2 evaluates the classification performance of four proposed LEE-based models—LBSVM, LBRCNN, LBANN, and LBYOLO—on EDM tasks, specifically for predicting student performance. Each model is assessed based on three key metrics: precision, recall, and F-measure, across both training, and testing phases. LBSVM shows consistent but relatively lower performance with a training precision of 0.735 and testing precision of 0.693. Its F-measure drops from 0.704 (training) to 0.687 (testing), indicating moderate generalization capability but limited robustness in identifying student performance patterns. LBRCNN demonstrates improved learning, with a training F-measure of 0.721 and a testing F-measure of 0.712. This model effectively captures complex educational data relationships using both convolutional and recurrent layers, resulting in better predictive accuracy and stability. LBANN shows balanced and stable results across phases, with nearly matching precision, recall, and F-measure values in training and testing. The F-measure improves to 0.732 in testing, highlighting its strong generalization and suitability for academic performance prediction. LBYOLO, while faster and more accurate in classification tasks (as seen in previous tables), shows slightly lower F-measure (0.692 training and 0.685 testing) compared to other deep learning models. LBANN and LBRCNN outperform other models in terms of balanced classification metrics, indicating stronger reliability for EDM tasks.

Table 2. Overall performance comparison of the proposed measures

Methods	Training			Testing		
	Precision	Recall	F-measure	Precision	Recall	F-measure
LBSVM	0.735	0.735	0.704	0.693	0.697	0.687
LB RCNN	0.752	0.746	0.721	0.725	0.734	0.712
LBANN	0.748	0.746	0.723	0.723	0.734	0.732
LBYOLO	0.706	0.713	0.692	0.712	0.701	0.685

Figure 3 presents the overall performance comparison of four models—LBSVM, LB RCNN, LBANN, and LBYOLO—using precision, recall, and F-measure during training and testing, within the context of EDM. LBANN demonstrates consistent high performance across all metrics, with LBSVM and LB RCNN following closely. LBYOLO, while efficient in speed, shows comparatively lower values in these evaluation measures, particularly in testing. This indicates that LBANN provides better balance between identifying relevant educational patterns and minimizing errors, making it suitable for student performance prediction, risk assessment, and learning behavior analysis. These metrics are critical for building reliable educational decision-support systems.

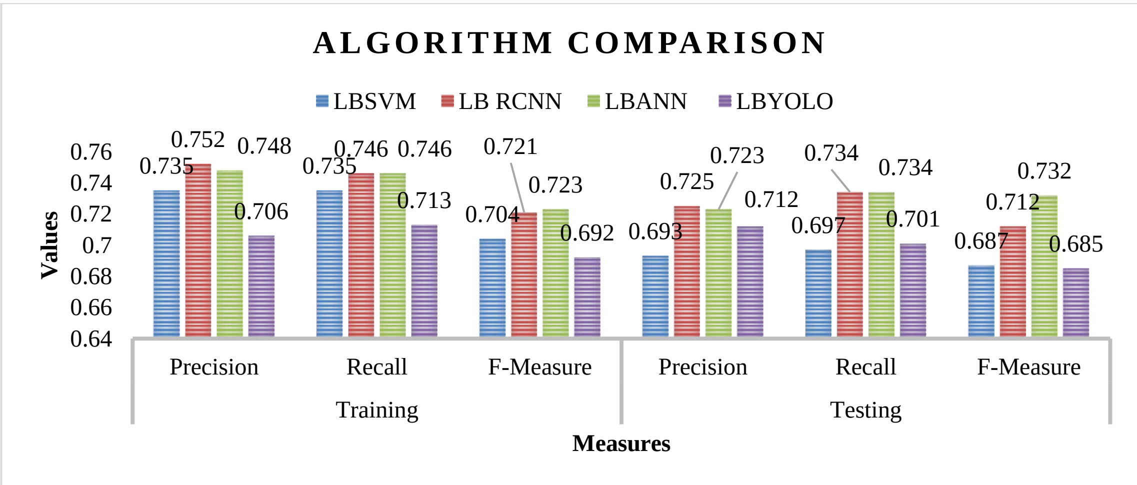

Figure 3. Overall performance comparison of the different measures

Table 3 presents the ROC values for four proposed LEE-based models—LBSVM, LBRCNN, LBANN, and LBYOLO—used in EDM for student performance prediction. The ROC score indicates the model's ability to distinguish between classes (e.g., pass/fail), with values closer to 1.0 representing better classification performance. LBSVM achieves stable ROC values (0.804 training dan 0.81 testing), reflecting good generalization and reliable binary classification performance on student data. LBRCNN shows the highest ROC during training (0.863), suggesting strong learning capacity. However, its drop to 0.746 during testing indicates possible overfitting, where the model learns well on training data but struggles to generalize. LBANN maintains moderate ROC scores (0.826 training and 0.717 testing), showing consistent but slightly reduced performance during testing, which is still suitable for practical applications. LBYOLO, while optimized for speed, records lower ROC values (0.713 training and 0.693 testing), highlighting its limitation in precise class separation despite its real-time classification strength. LBSVM offers consistent ROC scores, making it reliable. LBANN balances learning and generalization well. LBRCNN excels in training but may need tuning to avoid overfitting. LBYOLO, though fast, is less effective in accurately separating student performance classes based on ROC.

Table 3. Performance comparison of ROC applied on student performance dataset

Methods	Training ROC	Testing ROC
LBSVM	0.804	0.81
LB RCNN	0.863	0.746
LBANN	0.826	0.717
LBYOLO	0.713	0.693

Figure 4 illustrates the ROC performance comparison of four models—LBSVM, LB RCNN, LBANN, and LBYOLO—on real-time educational data. ROC values reflect each model's ability to distinguish between classes (e.g., pass/fail or high/low performers). LB RCNN shows the highest training ROC (0.863), indicating strong model learning, while LBSVM has the best testing ROC (0.81), showing better generalization. LBANN performs moderately in both phases, whereas LBYOLO records the lowest ROC values, suggesting limited effectiveness in classification tasks. This analysis helps in selecting reliable models for predicting student outcomes and supporting personalized interventions in EDM.

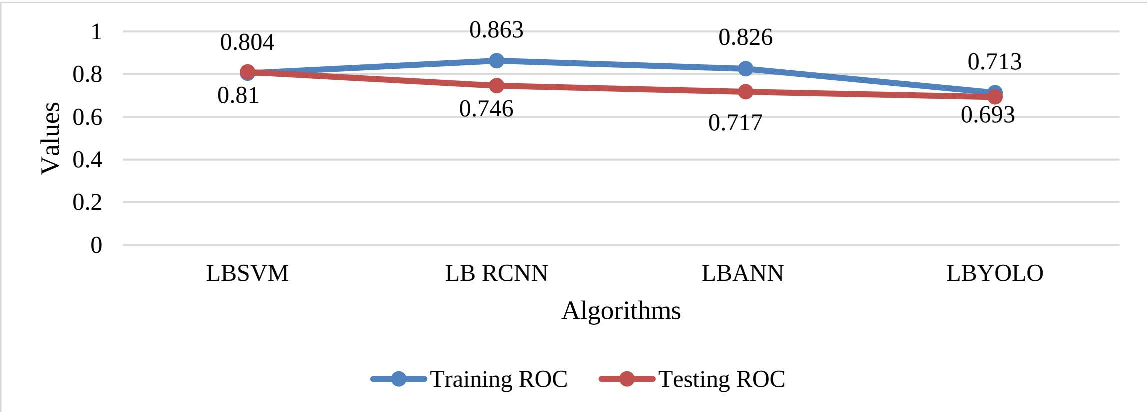

Figure 4. Performance comparison of ROC in real time dataset

5. CONCLUSION

This paper presented a LEE-based deep learning framework for predicting student performance using EDM techniques. By integrating LEE with advanced models such as SVM, YOLO, RCNN, and ANN, the framework enhances feature selection, improves model interpretability, and significantly boosts classification accuracy. Among the models evaluated, the LBYOLO architecture achieved the highest prediction accuracy (93%) with the lowest execution time (1.84 s), demonstrating strong potential for real-time decision-making systems. LBANN, on the other hand, exhibited the most balanced performance across precision (0.723), recall (0.734), and F1-score (0.732), suggesting its suitability for stable and generalizable academic prediction tasks. The findings have practical implications for educational institutions aiming to implement predictive analytics for early student intervention, resource allocation, and personalized learning strategies. The approach also supports building intelligent dashboards to monitor student risk profiles dynamically. However, the study has certain limitations. The performance may vary with different datasets, and the deep models require considerable computational resources and high-quality labeled data.

Additionally, while LEE improved feature relevance, domain-specific interpretability of selected features remains an area for improvement. Future research will focus on extending this framework to cross-institutional and multilingual datasets, incorporating adaptive learning algorithms, and modeling behavioral traits for more personalized educational recommendations. Further integration with explainable AI (XAI) techniques will also be explored to enhance transparency in academic decision support systems.

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C : **C**onceptualization
M : **M**ethodology
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest related to this work.

ETHICS APPROVAL

The authors have obtained the necessary permissions from the institutional ethics committee to conduct this work. Consent was obtained from all participants involved in the study.

DATA AVAILABILITY

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

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