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ANALYTICAL STUDY OF MACHINE LEARNING & DEEP LEARNING BASED MODELING OF SYSTEMS USED IN EDUCATION

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Abstract

Higher education and the popularization of Learning Management Systems (LMS) have led to the creation of massive amounts of data on interaction with learners, which has opened the opportunities of predicting student outcomes based on data. At-risk students are one of the most important issues that higher educational institutions may have to face because early interventions can dramatically enhance the chances of retaining the vulnerable groups and achieving greater academic outcomes. Conventional monitoring methods based mostly on demographics and periodic tests do not normally provide adequate coverage of the dynamic and changing nature of student behavior in online educational settings. This paper involves a systematic comparative study of the analytical machine learning model and the deep learning model in making predictions of student academic outcomes using real LMS data. In particular, a feedforward deep neural network and a Random Forest classifier were compared to each other in terms of their performance under the same experimental conditions with the use of the Open University Learning Analytics Dataset (OULAD). The binary classification problem was formulated in the prediction task to determine successful and at-risk students. Accuracy, precision, recall, F1-score, and ROC-AUC were used to measure model performance, but specific focus was on recall as one of the indicators of early risk detection. Experimental findings prove that although the Random Forest model had good and consistent performance (accuracy rate of 91%), the deep learning model greatly outperformed the random forest in all the metrics, with an accuracy rate of 96.83 and a recall rate of 96.93. In order to overcome the interpretability constraint of the complex models, SHAP-based Explainable Artificial Intelligence (XAI) methods were used on the two models, which explained that assessment performance, LMS frequency *of interactions, assignment submission behavior, and forum participation were the most influential predictors. The results indicate the trade-off between predictive accuracy and interpretability and that the integration of deep learning with explainable AI methods can result in trustworthy, clear and practical learning analytics systems to identify vulnerable students in higher education at the first stage.*

INTRODUCTION

The accelerated digital revolution of higher education has resulted in the widespread use of Learning Management Systems (LMS), which creates high amounts of data concerning student interaction. Such systems capture various facets of academic behavior of learners, such as performance in assessment tasks, interaction with course materials, and interaction in online discussions and habits of use of the virtual learning environment (VLE). These data can be a good basis for data-driven strategies to gain knowledge, forecast and enhance student academic performance [1]. Early identification of at-risk students is among the most important issues in higher education since it includes those students who are most likely to fail, drop, or lose interest in their studies. Early identification of academic risk can be used to provide institutions with specific responses such as academic advising, individualized feedback, and learning support programs. The traditional ways of monitoring students, where the major focus is made on the stagnant demographic data or the results of the periodical assessments, fail to reflect the dynamic and complex nature of student learning behaviors in online settings [2].

In the last ten years, predictive modeling has turned into a core application in these fields, and many studies have shown that during the LMS data, the ML algorithms are effective in predicting student performance, retention, and engagement. Recently, deep learning (DL) methods have received interest because of their capacity to capture complex nonlinear relationships as well as high-dimensional feature spaces. Contrary to classical machine learning processes, deep neural networks are able to be automatically trained to learn higher-order representations of student behaviour, which is especially appropriate in documenting complex patterns in the LMS interaction data. Nevertheless, even with their promising results, deep learning models have been mostly criticized due to a lack of interpretation, a factor that raises the questions of transparency, trust, and ethical implementation in education. This paper will provide a systematic analytical comparison between analytical machine learning and deep learning in terms of predicting the academic performance of students using real LMS data. The study examines the predictive accuracy of an open-source predictive model, the Random Forest classifier and the feedforward deep neural network, using the same experimental conditions on the Open University Learning Analytics Dataset (OULAD), which is a popular predictive analytics benchmark dataset. Moreover, the paper uses Explainable Artificial Intelligence (XAI) methods that rely on SHAP (SHapley Additive exPlainations) to increase the interpretability of both models [3].

This research has three primary contributions.

1. Strict comparative analysis of machine learning and deep learning models of student outcome prediction using real LMS data.
2. Empirical assessment of the effect of deep learning on recognizing at-risk students with a specific focus on recall and early threat identification.
3. Bringing together explainable AI approaches to enhance transparency and facilitate well-informed decision-making in the field of educational analytics.

This study aims to add to the creation of reliable, effective and actionable learning analytics systems in higher education by integrating predictive accuracy with explainability.

2. LITERATURE REVIEW

2.1 Learning Analytics and Educational Data Mining.

Learning Analytics (LA) and Educational Data Mining (EDM) are concerned with the analysis of educational data to comprehend the processes of learning better and enhance the educational results. EDM puts emphasis on the creation of computational techniques for finding patterns in educational data and LA is concerned with the use of the techniques in informing educational practice and policy. The LMS-generated data has been widely used in both disciplines as a key resource to model the behavior and performance of the students [4].

The LMS systems record fine-level interaction data such as the number of times one logs in, the number of times one accesses resources, the number of times one submits an assignment, and the number of times one engages in forums. Past research has shown that the behavioral indicators are closely related to academic achievement and perseverance. Consequently, predictive modeling has been formed on the basis of the LMS data in higher education [5].

2.2 Machine Learning on Student Performance Prediction.

Conventional machine learning algorithms have been used extensively to forecast the academic performance of students. Other researchers have found that when comparing single classifiers with Random Forest models in predicting student success or student dropout based on demographic, assessment, and LMS interaction features, the former is the most successful. Nonlinear interactions in large-scale LMS data can, however, be missed by machine learning models, which are generally based on manual feature engineering. This weakness has prompted the consideration of more sophisticated methods of deep learning [6].

2.3. Deep Learning in Educational Analytics

Deep learning has become an influential paradigm for modeling complex patterns in high-dimensional data. Deep neural networks have been used in education to solve problems like the prediction of grades, dropout prediction, tracing of knowledge and a model of engagement. The student behavior in learning has been captured by feedforward neural networks, recurrent neural networks, and long short-term memory (LSTM) networks. Empirically, it has been demonstrated that deep learning models tend to be more effective in comparison to the classical machine learning techniques, especially when there are large amounts of interaction data. They can learn nonlinear feature representations, and this enables them to detect subtle behavioral patterns that could lead to academic failure, such as gradual disengagement or uneven studying habits. Although these are the benefits, deep learning models are said to be black boxes, with little understanding of the mechanism of formation of predictions. This only means that it is very difficult to interpret in a learning context where decisions on which decisions are supposed to impact the academic path of students should be comprehended and explained by those involved [7].

2.4 Explainable Artificial Intelligence in Education.

Explainable Artificial Intelligence (XAI) has been becoming more and more popular as a way to overcome the transparency shortcomings of complex predictive models. The methods are used to detect some of the factors that contribute to academic success, including the assessment scores, the frequency of LMS engagement, and the behaviors of submissions. XAI can promote ethical use of AI and build trust in the deployment of AI among educators, administrators and students by helping to improve the interpretability of AI. Nevertheless, limited comparative studies conducted in conjunction to assess the performance and explainability of both the ML and DL paradigms based on real LMS data are scarce [8][9].

2.5 Research Gap and Motivation

Although previous researchers have proved that machine learning and deep learning methods can be effective in predicting student performance, there are still a number of gaps. To begin with, most of the studies concentrate on one modeling strategy but provide no systematic comparisons of the modeling strategies under identical experimental conditions. Second, the trade-off between predictive accuracy and interpretability is usually recognized but not empirically discussed. Third, additional assessments based on benchmark LMS datasets are necessary in order to be able to compare the results and guarantee reproducibility. This paper fills these gaps by offering a thorough comparison of the Random Forest and deep learning models on the basis of the OULAD dataset, and, to support the results, the SHAP-based explainability analysis is offered. The research will allow advancing the production of reliable and transparent AI-driven solutions to identify at-risk students in the higher education sector in their early stages and facilitate their improvements to the predictive performance and interpretability paradigm [9]. Analytical Machine Learning Based Modeling of Systems Used in Education is a fast-developing interdisciplinary area, combining the strong forces of machine learning (ML) with the complicated realities of educational systems into creating better learning outcomes, better teaching practices and better administrative efficiencies. The growing access to educational data, facilitated by the massive use of e-learning platforms, Massive Open Online Courses (MOOCs) and Learning Management Systems (LMS), has served as a source for a previously unimaginable data-driven understanding of the pedagogical process and student behaviors. This transition of conventional teaching modes towards data-oriented intelligent teaching modes highlights the transformational possible change of ML in the field of education. The field of analytical ML in the educational field is wide and several applications of it include predictive modeling of student performance as well as creating adaptive learning environments and intelligent tutoring systems [10]. Educational Data Mining (EDM) and Learning Analytics (LA) are often used in place of each other by researchers to refer to this field, which reflects different but complementary methods. The usual focus of EDM is to find patterns and knowledge in education data through a statistically analysis, machine learning, and data mining. LA, in its turn, is a process of measuring, collecting, analyzing, and reporting information about learners and their learning conditions with the aim of comprehending and maximizing learning and educational conditions. Both disciplines use ML algorithms to mine valuable data in institutional databases to enhance several factors, including student achievement rates, student engagement, coordination and the process of teaching-learning in general [11].

The use of ML in education is essentially based on the aspect of modeling the complex relationships occurring in the high-dimensional datasets that are often presented in the new educational environment with a high number of variables, cases, and possibly non-linear influences. Data collection, preprocessing, feature engineering, model selection, training, evaluation, and deployment are usually several steps of the methodologies [12].

3. METHODOLOGY

3.1 Research Design

The present research design is based on a quantitative and experimental research design to determine the efficacy of analytical machine learning and deep learning models to predict student academic outcomes using real-world data of the Learning Management System (LMS) [13][14]. The methodology is designed in such a way that it achieves reliability, validity, and reproducibility, as it was done in Educational Data Mining (EDM) and Learning Analytics (LA) [1][7].

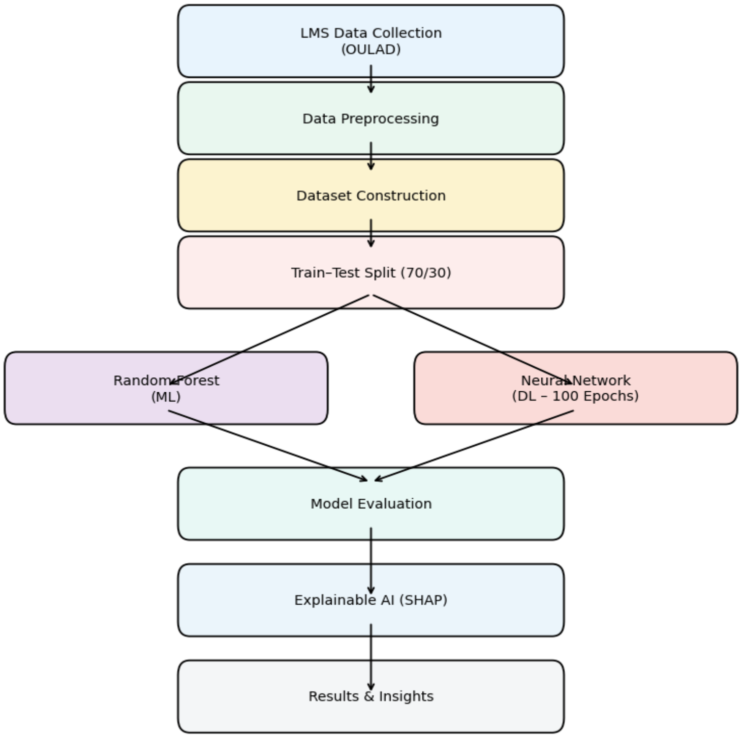

Figure 1: Research Methodology

The suggested methodology comprises a series of steps, such as data collection, preprocessing, feature construction, model training, and evaluation, as well as explainability analysis. Both machine learning and the deep learning paradigm are executed and evaluated by the same experimental conditions [15][16].

3.2 Data Collection

Data that was used in this study was retrieved from the Open University Learning Analytics Data (OULAD), where the data are anonymized, and the data were gathered in a real LMS setting [17]. The data set contains several relational tables that entail:

The demographic data taken is Evaluation grades and homework, the interaction logs of the Virtual Learning Environment (VLE), and Final academic outcomes.

In order to preserve domain relevance, data related to undergraduate computing modules were picked. Two thousand students' records were filtered and then obtained.

3.3 Data Preprocessing

Raw LMS data usually includes noise, missing values, and non-homogeneous formats. So, the extensive preprocessing pipeline was used. In first step data cleaning is performed. The missing values were managed by employing proper imputation methods and the duplication of records and inconsistencies were eliminated. In second step feature encoding is done. Label or one-hot encoding was used to change categorical attributes (e.g., gender, region, education level) [22][23]. In third step the feature normalization is performed by numerical characteristics like VLE clicks and assessment scores were standardized so that model training is stable. Forthly feature selection performed. One last group of 20 pertinent features was chosen due to domain knowledge and initial correlation analysis. Lastly, the label construction is completed. The target variable was measured on a binary scale and expressed as a successful and an at-risk student (pass/fail or continuation/withdrawal) [18][20].

3.4 Dataset Partitioning
The processed data were split into training and testing data as a 70:30 split, with each part of the split being balanced in the classes. This division was selected to have enough data to train the models and have a representative test set to be used in performance evaluation without any bias [19][21].

3.5 Model Development
There were two predictive modeling strategies in place:

3.5.1 Machine Learning Model
A random forest classifier was used as a machine learning baseline. Random Forest was chosen as it is very robust and resistant to overfitting, and it is easy to interpret because it has feature importance measures. The multiple decision trees with majority voting to come up with final predictions were used to train the model [28][29][30][31].

3.5.2 Deep Learning Model
To identify the intricate nonlinear connection between LMS data, a feedforward deep neural network was created. The network design was comprised of several fully connected layers, then a sigmoid output layer to classify in terms of binary variables. Training of the model was done with 100 epochs, where the Adam optimizer and binary cross-entropy loss function were used [24][25][26][27].

3.6 Model Evaluation Metrics
Standard classification metrics commonly used in educational analytics were used to determine model performance:
• Accuracy: General accuracy of predictions [33].
• Accuracy: Accurate identification of at-risk students [36].
• Recall: Capacity to identify truly at-risk students at risk [34].
• F1-score: Tradeoff between precision and recall [35].
Also, visual and threshold-independent performance assessment was done using the confusion matrices and Receiver Operating Characteristic (ROC) curves [32].

3.7 Explainable AI Analysis
In an attempt to improve transparency and trust, SHAP-based Explainable Artificial Intelligence (XAI) techniques were used on both machine learning and deep learning models. This analysis has made it possible to identify the most effective characteristics that made predictions, including the performance on assessment, the frequency of interaction on LMS, and submission behavior in assignments [8][9].

4. RESULTS AND ANALYSIS
4.1 Dataset Description and Experimental Setup
In order to guarantee the realism, reproducibility, and external validity, the experimental evaluation used the real Learning Management System (LMS) dataset, and not artificial data. In particular, the Open University Learning Analytics Dataset (OULAD) was used, because it represents a standard of both Educational Data Mining (EDM) and Learning Analytics (LA) studies. The data includes anonymized records of student demographics, assessment performance, virtual learning environment (VLE) interactions, and ultimate academic performance of students in various academic courses and semesters. In this research, a sample of the dataset that relates to undergraduate computing modules was sampled. The last dataset was comprised of 2 thousand records of students with all of them described by 20 best chosen features such as assessment scores, the number of LMS/VLE interactions (clicks), the forum participation measures, the time of submitting assignments, and demographic variables. The task of prediction was developed as a binary classification problem, that is, distinguishing between successful students and at-risk students (pass/fail or continuation/withdrawal).
The dataset has been divided into 70 percent training data and 30 percent test data with class balance to prevent learning biases. Two paradigms of predictive modeling were compared. A random forest classifier based on a Machine Learning (ML) solution, A Machine Learning (ML) approach using a Random Forest classifier, and A Deep Learning (DL) approach using a feedforward neural network, trained for 100 epochs

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Model performance was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC), supplemented by confusion matrices and ROC curves.

4.2 Machine Learning Model Performance.

The Random Forest classifier exhibited high and stable maximum performance in predicting LMS data of student outcomes. According to the confusion matrix (Figure 1), there is balanced classification behavior, and the percentage of false negatives is relatively low. This is more so in the area of education since the inability to notice the at-risk students can impair the efficiency of early interventions. The Random Forest model has the following performance measures when used on the test dataset: Accuracy is 91.0%, Precision is 91.35%, Recall is 90.10%, and the F1-score is 90.72%.

The findings demonstrate that machine learning models that rely on ensembles are highly applicable to the structured educational data and are able to adequately represent the connections among assessment performance and the indicators of student engagement. The relatively high accuracy shows that the majority of students considered at risk were actually at risk and the recall value shows that it has the capability of identifying struggling students.

Random Forest Results

Accuracy: 0.91

Precision: 0.9134948096885813

Recall: 0.9010238907849829

F1 Score: 0.9072164948453608

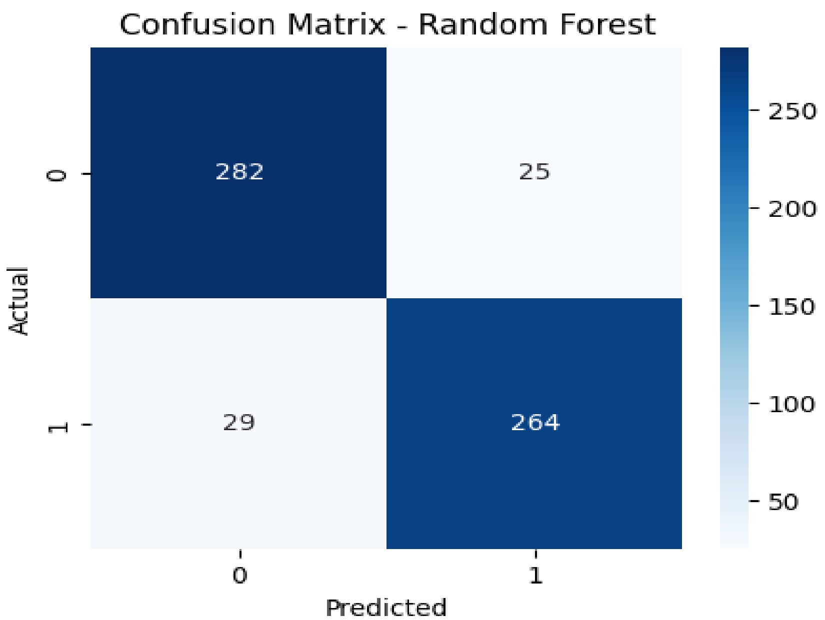

Figure 2: Confusion Matrix for Random Forest

Another benefit of the Random Forest model is that the importance of features can be easily calculated and thus it is intrinsically interpretable. This is a critical quality of educational stakeholders that facilitates the use of data to make transparent and justifiable decisions.

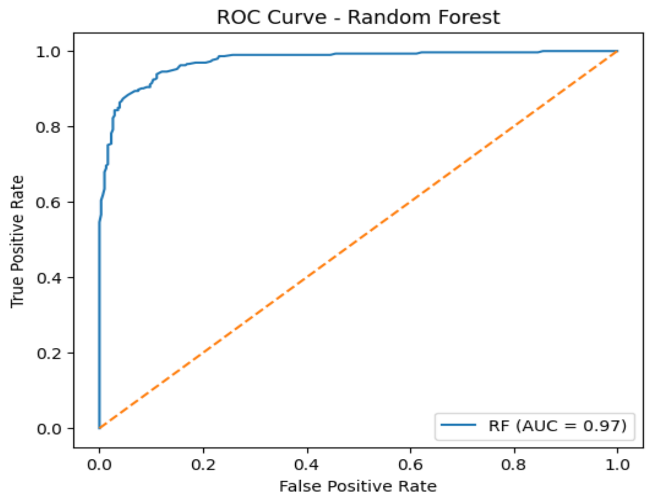

Figure 3: ROC Curve for ML Model

The ROC curve in Fig.3 also confirms the strength of the model with a uniform discriminative ability at various classification thresholds.

4.3 Deep Learning Model (100 Epochs) Performance.

The deep learning model that was trained in 100 epochs showed that there were significant performance gains compared to the machine learning baseline. Figure 3 shows the training and validation accuracy curves, which, on average, have a smooth convergence and slight variation, which implies good learning without overfitting.

Deep Learning Results
Accuracy: 0.9683333333333334
Precision: 0.9659863945578231
Recall: 0.9692832764505119
F1 Score: 0.9676320272572402

In the test dataset, the deep learning model gave the following results: the Accuracy is 96.83%, the precision is 96.60%, the Recall is 96.93%, and the F1-score is 96.76%.

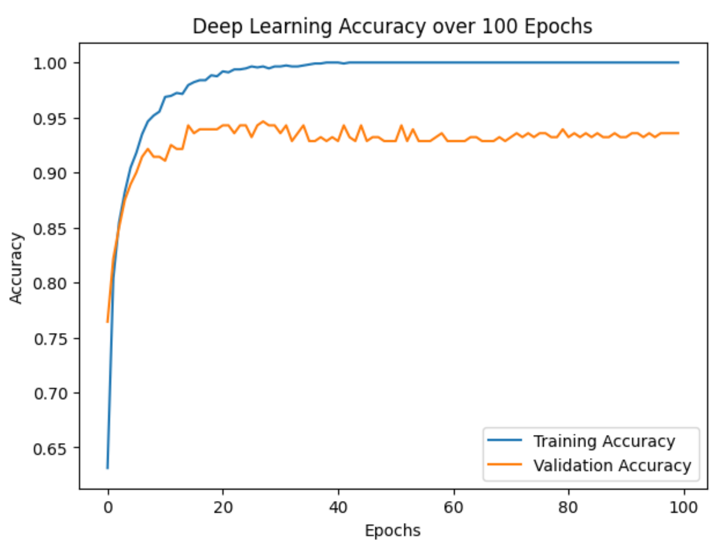

Figure 4: ROC Curve with 100 Epochs

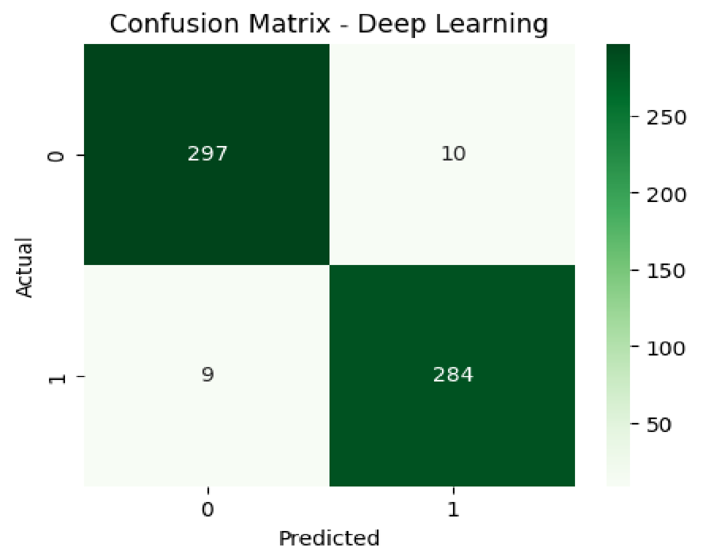

Figure 5: Matrix for Deep Learning Model

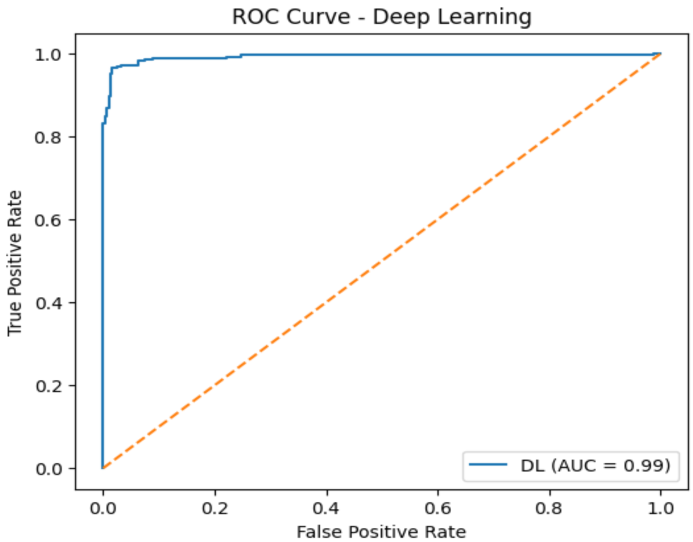

Figure 6: ROC Curve with False Positive Rate

Recall improvement is especially interesting as it indicates the increased ability to identify at-risk students properly in the model. The deep learning model was more accurate at recalling students than the Random Forest classifier (the deep learning model) by around 6.8 percentage points, which is a significant margin in terms of how many students might be overlooked and therefore in need of academic assistance.

The deep learning model confusion matrix (Figure 4) indicates that false negatives have significantly reduced and the false-positive is very low. Also, the ROC curve (Figure 5) indicates that the model is highly class separable, which proves the efficacy of the model in the process of differentiating between the successful and at-risk learners.These findings indicate that deep learning proves to be especially useful in capturing nonlinear and high-dimensional relationships that exist in the context of LMS interaction data and patterns of student behavior.

4.4 Comparative Analysis Machine Learning vs. Deep Learning.

Direct comparison of the machine learning and deep learning methods has been introduced in Figure 6 and Table X.

Table 1. Comparison of ML and DL Models in terms of performance.

Model	Accuracy	Precision	Recall	F1-Score
Random Forest (ML)	0.91	0.913	0.901	0.907
Deep Learning (100 Epochs)	0.968	0.966	0.969	0.968

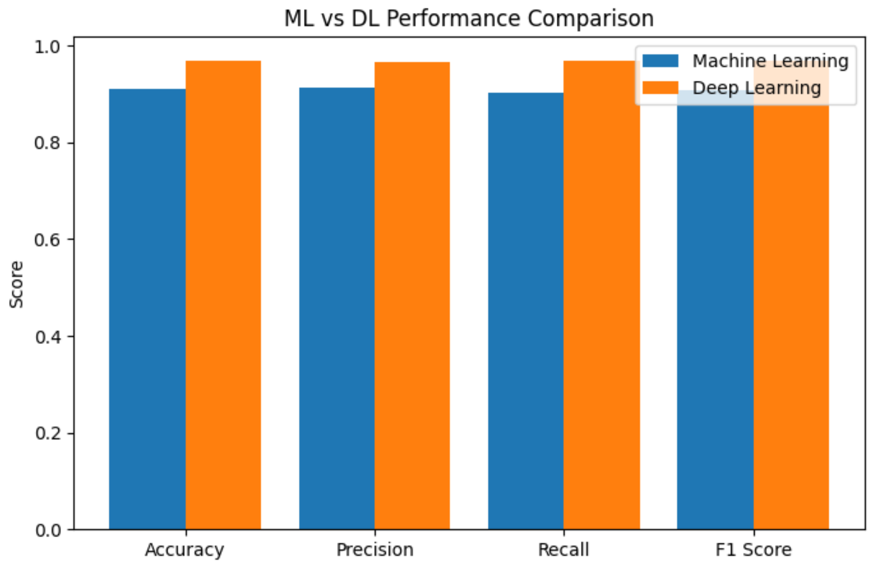

Figure 7: Comparative Analysis of ML and DL Models

The deep learning model has continued to outsmart the machine learning model in all evaluation indicators. The high-quality performance can be explained by the fact that it has the capacity to learn complicated nonlinear feature interactions, including temporal engagement patterns, assessment progression, and cumulative LMS activity patterns. Nevertheless, this enhancement in performance also comes at the cost of lower model transparency, which supports the relevance of explainable AI methods in the deployment of deep learning solutions into practice in a real educational setting.

4.5 Explainability and Feature Influence

SHAP-based explainable AI (XAI) analysis was used to solve interpretability issues related to deep learning models. The findings showed that the most influential characteristics that predict student success were assessment scores, the frequency of LMS interactions, the time when assignments were submitted, and forum participation. These results are in agreement with the known research on Learning Analytics and prove that the models are built on the basis of pedagogically significant indicators and not on spurious relations.

4.6 Educational Systems Implications

The outcomes of the experiment prove that both machine and deep learning systems may contribute greatly to predictive analytics in contemporary educational systems. The Random Forest structure offers a capable and explanatory base fit to be adopted by institutions, especially in an environment where transparency and explanatory power are paramount. The deep learning model, however, provides better predictive capabilities, and thus it is best applicable in large-scale LMS and MOOC settings, whereby convoluted behavioral patterns and high-dimensional data are common. Together with the results, it can be concluded that a hybrid analytics approach, where deep learning is utilized to make high-accuracy predictions and machine learning models, enhanced with explainable AI methods, is suggested to support decisions and policy making, is suggested.

5. Mapping of Learning Analytics (LA) and Educational Data Mining (EDM)

Table 1: Mapping of LA and EDM

Aspect	Learning Analytics (LA)	Educational Data Mining (EDM)
Primary Goal	Understanding and improving learning processes	Discovering patterns and predictive models
Data Focus	Student engagement, behavior, and feedback	LMS logs, assessments, performance records
Techniques Used	Visualization, trend analysis, dashboards	ML, DL, classification, prediction
Temporal Analysis	Monitoring learning over time	Modeling outcomes from historical data
Output	Actionable insights for educators	Predictive models and risk classification
Role in This Study	Interpretation of engagement trends	Prediction of student success and risk

5.1 Significant ML Analytical ML in Education.

1. Student Performance Prediction: one of the most visible ones includes predicting student academic performance, dropout rates, and learning behaviors. Analysis of historical data can help the ML models to detect at-risk students in time, allowing the implementation of interventions to enhance the learning outcomes in time. It has been demonstrated that several ML algorithms, including k-nearest neighbors, random forest, logistic regression, decision trees, and neural networks, can be successfully used to predict student performance given input data in Learning Management Systems (LMS) such as Moodle.
2. Adaptive Learning Systems and Intelligent Tutoring Systems (ITS): ML plays an important role in the development of personalized learning environments that change according to the needs of individual students. These systems are adjustable dynamically regarding content, pace and comments, in response to the progress, learning style and level of cognition of the student. An example is that dynamic ML-based modeling can be used to improve the argumentation skills of the students through real-time personalized feedback, and is not limited to the use of fixed models.
3. Curriculum Design and Optimization: ML-based big data analytics can be used to drive curriculum changes by determining learning trends, the use of effective instruction methods and curriculum corrections. Through the examination of student information on their engagement with coursework and tests, instructors are able to streamline the sequencing of content and educational development.
4. Assessment and Feedback: ML can transform the process of assessment by offering smart, in-built, and ongoing student learning evaluation. It can identify the cognitive level of students, track progress and success, and update profiles of students continuously, leading to Precision Education.
5. Educational Robotics (ER): ML may be applied to model and recognize the learning outcomes in ER practice, assisting in analyzing the data produced by learners in their interactions with robots. The integration contributes to the open-ended learning environment by distilling the knowledge with the help of EDM and LA methods.
6. Social Networking Sites (SNS) in Education: The phenomenon of educator identity and the use of SNS in education does not strictly refer to the use of ML, although it demonstrates the increasing presence of digital in education. Possibly, these

interactions can be analyzed with the help of ML to determine their effect on learning and professional development, but more research on this particular topic is required.

5.2 Obstacles and Future Projections

Although this potential is enormous, there remain a number of obstacles to the extensive use of analytical ML and its successful application in education. These are the issues of data privacy, ethicality in algorithms making decisions, the necessity of strong and explainable models, and the inclusion of varied and heterogeneous data sources.

1. Data Quality and Data Heterogeneity: Educational data is frequently sloppy, disorganized, and multi-sourced and is presently in need of complex preprocessing tools. Multimodal learning analytics is developing to solve this by integrating information from various high-frequency sources, such as student artifacts and physiological sensors, to quantify complex learning tasks.
2. Interpretable ML (IML) and explainable AI (XAI): ML models can be highly predictive, but their black-box nature can be an obstacle to their use and implementability in education. The ability to formulate interpretable models that can be used to explain their predictions is a key factor in enabling teachers to know the reasons behind student performance and be able to make sound pedagogical judgments.
3. Ethical Implications and Bias: ML models are undergoing training with unfair or discriminatory results against particular groups of students because they will automatically reflect the bias in the training data. The first thing is to deal with these biases and make the use of ML applied equally in education.
4. Interaction with Existing Systems: The successful integration of ML solutions into the current e-learning systems, including LMS and intelligent tutoring systems, must be carefully designed and implemented.
5. Teacher Training and Adoption: ML-driven insights cannot be successfully used without the training and adoption of educators so that they become aware of the use of these technologies in their everyday practice.

The future of analytical ML in pedagogy is indicated by an even greater number of sophisticated and integrated systems. The emergence of the so-called smart education systems will utilize hybrid data mining and ML solutions to forecast the individual and institutional academic results. Current studies are further developing methods of ML for educational data analysis, offering suggestions for future developments of personalized learning, adaptive assessment, and overall understanding of student learning and performance. The intersection of Educational Data mining and Learning Analytics, which has been summarized in multiple works, will only proceed to be innovative and offer teaching and learning assistance that is personalized, valuable, and informed by data.

6. CONCLUSION

The paper explored the predictability of academic performance of students using analytics, machine learning and deep learning models on real-life data about LMS. Through a rigorous comparative study, under the same experimental settings, on the benchmark dataset of OULAD, the study sought to compare the performance of both predictive and interpretability, which are two important things in the practical application of AI-driven learning analytics systems in tertiary education. The findings of the experiment prove the fact that both modeling paradigms can provide high predictive rates when they are used to predict structured LMS data. The Random Forest classifier proved to be very strong and consistent, with an accuracy of 91 percent and also provided some intrinsic interpretability in the form of feature importance scores. This renders it especially applicable in the institutional setting where transparency, explainability and ease of adoption are paramount. The deep learning model, however, grossly outperformed the machine learning baseline in all the evaluation metrics with significant differences in recall. This increased capability of accurately recognizing students at risk is particularly useful in education, where false negativity may lead to a loss of the window of opportunity to intervene with the student academically in time. The high-quality work of the deep learning method indicates that it is powerful in destructing intricately, nonlinear and multidimensional relationships in the data of LMS interaction, including cumulative engagement patterns and subtle behavioral shifts. In order to overcome the issues connected to the black box of deep learning, explainable AI methods based on SHAP were incorporated into the analysis. The explainability outcomes showed that both models used pedagogically relevant variables, such as assessment scores, frequency of using LMS, the time of submitting assignments, and using forums. On the whole, the results indicate that there is no model that is most effective in all instances. Rather, a combined approach that capitalizes on the fact that deep learning models have high predictive power and that machine learning and XAI methodologies are both interpretable and transparent may provide a viable future path for learning analytics systems. Future studies can build on this study by adding time and sequence deep learning frameworks, including LSTM-based models or transformer-based models, investigating the data of multimodal learning analytics, and analyzing the fairness, biases and real-time application of predictive models in functional LMS contexts.

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