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Integrating Deep Learning into Educational Big Data Analytics for Enhanced Intelligent Learning Platforms

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Exploring the field of educational big data analytics and gaining insights into student behaviour and its connection to academic performance is crucial for creating intelligent learning environments. Technological innovations have changed how students learn and reshaped the nature of education. Technological advancements have unquestionably made learning more accessible, faster, and enjoyable for pupils. When deep learning is integrated with learning management systems, intelligent course content may be generated with high accuracy, and no human interaction is required. This study utilises advanced deep learning techniques to analyse the xAPI-Educational Mining Dataset and reveal valuable insights that can significantly improve online learning experiences. The study underscores the crucial importance of parental involvement, emphasising its link to student attendance and overall satisfaction with the educational institution. In addition, the results suggest that students who actively participate in course announcements and utilise resources tend to achieve better academic outcomes, highlighting the significance of resource utilisation in achieving academic success. On the other hand, engaging in conversations seems to have a minimal effect on how students are categorised. Building upon these findings, a novel predictive model is introduced, utilising Long Short-Term Memory (LSTM) networks. This model utilises sequential student interaction data to predict future behaviour and academic outcomes, helping online platforms understand student actions and make informed decisions. This study makes a valuable contribution to developing cutting-edge intelligent learning approaches. It achieves this by utilising the potential of educational big data analytics and deep learning techniques.

KEYWORDS: Educational Big Data Analytics, Deep Learning Techniques, Parental Involvement, Student Engagement, Online Learning, Predictive Modeling, and Long Short-Term Memory (LSTM) Networks.

1. Introduction

In recent years, intelligent learning platforms have emerged due to technology integration into education, which has transformed conventional learning paradigms and improved educational outcomes. This shift has been made possible by the deluge of data produced by online classrooms, which opens up new possibilities for studying student actions, interests, and achievements through data analytics. The area of educational big data analytics, in particular, has been getting a lot of interest since it provides stakeholders and teachers with great tools for making wise decisions and creating unique lessons for each student. Advances in computing have made it possible to use innovative learning and intelligent design to educate students [22]. Using their mobile devices, students may gain access to course materials and dive headfirst into a world of constant and frictionless learning. Students have unlimited WiFi access to digital materials no matter where they are or what time of day. New intelligent technologies like cloud computing, the Internet of Things (IoT), and wearable technology further bolster this 21st-century education system called innovative education. Learners may incorporate wearable technology into their learning materials, and the Internet of Things connects everything to the Internet. Creative learning is a paradigm shift in education that prioritises students' needs while being service-oriented, context-aware, and device-centric. Content emphasis, personalised learning, and technology-embedded learning are smart learning aspects [1, 20]. Students can study whenever and wherever they choose in a smart classroom. The recommender systems use the learner's pattern of behaviour and learning to offer information. So, it is safe to say that this classroom is a model of efficiency, effectiveness, and interest [10, 13]. Learners receive timely, relevant, and formatted feedback, recommendations, and direction from an intelligent learning environment.

Educational institutions are confronted with the difficulty of efficiently using the abundance of data produced by online education platforms to enhance learning experiences and results, given the widespread use of digital learning materials and the rapid growth of online education platforms. Here, deep learning methods have shown to be potent instruments for sifting through diverse and complicated educational data in search of valuable trends, patterns, and predictive insights. Deep learning (DL), machine learning (ML), and artificial intelligence (AI) are three recent breakthroughs in computer technology. Recognizing patterns in historical data and predicting future events are the backbone of these technologies. Smart devices are typically used to describe machines that apply AI concepts. This is because most of these gadgets cannot learn independently. Those data analysts and scientists whose jobs are gathering, processing, and making sense of massive datasets will find these tools invaluable. DL automates the process on the one side and speeds it up on the other.

As universities have become better at collecting massive amounts of data, new fields like academic analytics and data mining have developed to make sense of it all [6]. With the rise of the Internet, the idea of data mining saw a meteoric rise in universities. To generate information about instructors, students, and educational institutions to influence academic conduct, academic analytics integrates specific data from educational institutions with statistical analysis and predictive modelling. DL approaches refine insights on data, learning, and behavioural patterns to get more precise outcomes. It has the potential to build a system that analyses student learning. With the use of content analytics generated by DL techniques, the content modules may be constantly restructured and optimised to meet the demands of the students. The goal here is to monitor how much pupils have learned and provide feedback on how they may improve. Deep learning techniques can create fresh assessment forms and push students to think outside the box when analysing such shocking structures.

This research investigates how educational big data analytics and deep learning approaches might contribute to developing intelligent learning systems for the future. This project examines the connections between student actions, parental participation, and academic achievement in online classrooms using large-scale datasets like the xAPI-Educational Mining Dataset. In addition, we want to offer practical insights that can guide the development of adaptive tutoring systems, early intervention mechanisms, and personalised learning experiences by creating predictive models using deep learning algorithms.

The novelty of the research is a regression technique that combines L1 (Lasso) and L2 (Ridge) regularization for feature selection. Elastic Net addresses problems like multi-collinearity and overfitting while assisting in identifying the most crucial characteristics for predicting academic achievement. This dual regularisation technique improves the model's resilience by removing unnecessary features and choosing pertinent ones. Technically complex LSTM networks process and forecast student interactions based on sequential data. By considering the temporal dynamics of student activity, this approach yields a predictive model that is more precise and contextually aware. A technical novelty is creating a personalised LSTM-based predictive model for the educational setting. This model's important addition is its capacity to forecast academic performance and future conduct of students based on historical interaction patterns.

The contribution of the research is as follows:

1. This study investigates how learning management systems can be integrated with cutting-edge deep learning methods, particularly Long Short-Term Memory (LSTM) networks. This integration aims to provide highly accurate, intelligent course content with the least human involvement.
2. The research uses a large source of educational big data—the xAPI-Educational Mining Dataset—to obtain insights into student behaviour, parental involvement, and resource use. This dataset is essential for comprehending the aspects affecting students' academic achievement.
3. The study emphasises the value of parental involvement in education by connecting it to students' attendance and general contentment with schools. Despite being a major contribution, this component of educational data analytics is frequently overlooked.
4. According to the study, students who actively participate in class announcements and use the materials offered typically perform better academically. This realization highlights the importance of resource management for academic achievement and provides practical advice for enhancing learning settings.

2. Related Works

Intelligent educational systems utilising big data and AI techniques can gather precise and comprehensive personal information. By analysing data, valuable insights can be gained into students' learning patterns and individual requirements [14, 19, 21]. Therefore, combining big data and AI can bring about personalised learning to achieve more precise education [17]. Mikulecky [18] provided a comprehensive overview of the latest learning analytics tools and techniques, offering insights into potential future directions. He carefully examined the successful projects in this field and made note of the critical characteristics. He examined learning analytics from a perspective that spans from multi-agent to cloud-based architecture. The widespread and situation-aware learning is the basis of an intelligent learning environment. In this context, it is crucial to ensure that accurate and relevant information is effectively communicated to the intended recipient in a timely and appropriate manner. The discussion also touched upon the challenges and future directions in this field.

A proposed educational model utilising deep learning systems was presented by [2]. This model can assess and analyse learners' learning processes, outcomes, and achievements. It can also provide recommendations for improvement to benefit the learners. They explored the difficulties and benefits of this model and how to examine the data produced by the Internet of Everything devices in the context of education. Shoikova et al. [23] provided an in-depth analysis of the features of intelligent learning environments and intelligent education and their pedagogical approaches. In the digital era of education, learners can enhance their learning experience more effectively, flexibly, efficiently, and comfortably. Combining teaching methods and technological tools helps learners successfully reach their learning goals. In the context-aware approach, learners can experience a seamless learning environment with personalised settings.

Deep learning is critical to addressing the many questions from analysing large amounts of data. Deep learning can uncover and understand complex patterns and structures concealed within the raw data, thanks to its utilisation of machine learning techniques. There are various models and algorithms in the field of deep learning. Nevertheless, deep belief networks (DBN) and convolutional neural networks (CNN) are the two widely utilised architectures in deep learning [9]. A convolutional neural network is a widely used architecture that utilises locally connected deep learning methods. The structure has layers that organise feature maps and hierarchically perform classification tasks. The layer that receives data from the input layer is referred to as the convolutional layer. It is responsible for performing convolutional operations—reference [11].

AI-powered machines can sift through mountains of data, detect trends, draw conclusions, and provide suggestions based on past experiences. Artificial intelligence enables diverse pedagogical approaches that consider each student's unique strengths, weaknesses, opportunities, and challenges [24, 30]. Learning management systems, online platforms, examinations, and digital materials are just a few places where AI and ML algorithms might glean information about students [31, 32, 36]. These algorithms can collect information on students' demographics, performance, patterns of engagement, and learning preferences, among other things. When analysing complicated and extensive datasets, AI and ML methods shine. These algorithms can process data acquired from learners to find trends, patterns, and correlations. Individual learner traits, including strengths, shortcomings, learning styles, and knowledge gaps, may be discovered through data analysis of adaptive learning systems [33, 37, 38]. Personalised learning experiences are built upon this analysis. Learner models may be constructed using the analysed data by AI and ML algorithms. Individuals' cognitive capacities, knowledge levels, learning preferences, and learning styles are all part of the learner representations built through learner modelling. These models record their distinct traits to tailor the educational experience to each student [5, 8, 12].

Works about AI in LMS mainly aim to assist educators in developing superior models and learning approaches utilised in these settings. An essential piece of information is that they learn from each user encounter and apply specialised AI approaches for user interaction [15]. Strong and valuable, these models advance this field's state of the art [7]. From what we can tell from the research, the suggested method is unique among current efforts that aim to combine AI with data analysis in a single setting. Initially, a virtual assistant may be built to handle each student's information and be in charge of automated and personalised monitoring if all academic management is centralised in one system. The data analysis results are accessible to the assistant, and it also learns from user engagement [25, 27, 29]. The analysis goes beyond just looking at the data in the LMS. We can better understand each student's requirements and expectations by integrating several sources [34, 35]. Big data technologies possess this capability, and the flexibility to make decisions is conferred by the quantity and variety of data incorporated into the study [16]. Because of this connection, AI can make informed judgements on student performance more quickly.

3. Methods and Materials

3.1. Proposed Methodology

The suggested approach uses deep learning methods to examine educational big data to deduce the connection between student conduct, parental engagement, and academic achievement. The technique covers all aspects of working with data, including cleaning, building models, testing, and interpretation. Analysing educational big data using deep learning techniques is the suggested methodology for unravelling the complex relationships between student conduct, parental engagement, and academic achievement. Starting with data collection, necessary datasets are obtained and meticulously pre-processed, including data cleansing and feature engineering, to include complete information on student behaviours, parental participation, and academic outcomes. Next, we use feature selection approaches to find the most essential characteristics for predicting academic achievement. Depending on the dataset and prediction goal, deep learning architecture Long Short-Term Memory (LSTM) networks are trained to build models.

To minimise prediction errors and prevent overfitting, optimisation algorithms fine-tune the model parameters throughout extended training utilising training data, which follows model formulation. Metrics like accuracy and precision help evaluate the model's performance, which helps with validation by providing insights into the model's usefulness and effectiveness. Improving the model's interpretability through qualitative analysis and visualisation of predictions allows stakeholders to get actionable insights from the model's output. Ultimately, for the trained model to be successfully used in real-world educational settings, it is crucial to integrate it seamlessly with current platforms and continuously check its relevance and usefulness in light of fresh data. Following this paradigm, the research aims to utilise deep learning to improve student outcomes in online learning settings by turning educational big data into actionable insights.

From a technical point of view, it is new to include parental engagement data in the prediction models. The study shows how to better forecast student outcomes by quantifying and incorporating parental engagement variables into LSTM models. The study takes into account a number of aspects of student interactions, including talks, resource use, and announcements made in class. One distinctive feature is the technological method of utilizing deep learning models to differentiate between the effects of these various kinds of interactions.

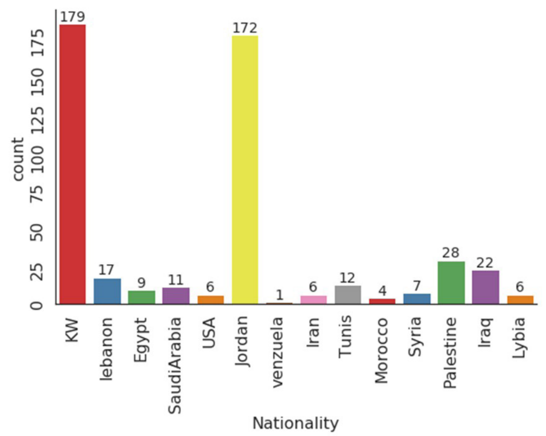
3.1.1. Data Collection

Kalboard 360 is a learning management system (LMS) that collects educational data sets like the xAPI-Educational Mining Dataset [3, 4]. Kalboard 360, a multi-agent learning management system, aims to improve education using state-of-the-art technological tools. Any user with an Internet-connected device can use this system's simultaneous access to learning materials. An experienced API (xAPI) learner activity tracker tool is used to gather the data. One part of the TLA is the xAPI, which allows you to track how far along a learner is in their journey and what they're doing while learning, such as when they read an article or view a training video. Learning activity providers may use the experience API to determine who the learner is, what the activity is, and what objects make up the learning experience. There are 480 entries of students and 16 attributes in the collection. There are three main types of features: (1) Personal characteristics include gender and country of origin. (2) Details on the student's academic history, including their current grade, section, and educational level. (3) Behavioural traits include raising hands in class, opening resources, answering surveys by parents, and school satisfaction.

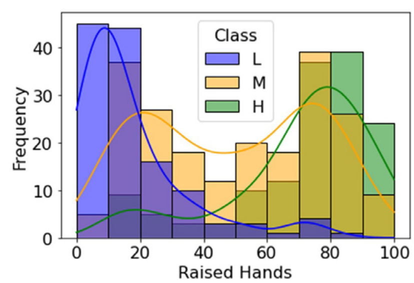
The dataset includes 305 men and 175 women. Figure 1 shows the nationality-wise data distribution from the dataset. Table 1 shows features in the dataset. The dataset is amassed during two academic terms: Two hundred forty-five student records are taken in the first semester and two hundred thirty-three in the second. The dataset also includes information about kids' school attendance. Specifically, 191 students have more than seven absence days, whereas 289 have fewer than seven days.

Figure 1

The data distribution from the xAPI-Educational Mining Dataset



(a) Nationality-wise data



(b) Raised Hand feature-based data distribution

Table 1
Feature categorization

Feature	Description
Gender	The gender of the student (male or female).
Nationality	The country of origin of the student.
Stage ID	The educational stage (grade level) of the student.
Grade ID	The current grade of the student.
Section ID	The section ID in which the student is enrolled.
Topic	The topic or subject area of the course.
Semester	The academic semester (first or second).
Parent Answering Survey	Whether the parent answered the school survey (yes or no).
Parent School Satisfaction	The parent's satisfaction with the school (yes or no).
Student Absence Days	Number of days the student was absent (greater than or less than 7).
Raised Hand	Number of times the student raised their hand in class.
Visited Resources	Number of times the student visited course resources.
Viewed Announcements	Number of times the student viewed course announcements.
Discussion Participation	Number of times the student participated in class discussions.
Overall GPA	The overall GPA of the student.
School Satisfaction	Student's satisfaction with the school (yes or no).

3.1.2. Feature Selection

Elastic Net is a regression technique incorporating the benefits of both L1 (Lasso) and L2 (Ridge) regularisation methods. Although Elastic Net is commonly employed for regression tasks, it can also be utilised for feature selection. Elastic Net minimises the following objective function,

$$\min_{\beta}\left(\frac{1}{2n}\|y - X\beta\|_2^2 + \alpha\rho\|\beta\|_1 + \frac{\alpha(1-\rho)}{2}\|\beta\|_2^2\right), \quad (1)$$

where y is the vector of target values, cap X is the feature matrix, beta is the vector of coefficients, n is the number of samples, alpha is the regularisation strength, and who controls the balance between L1 and L2 regularisation penalties. Elastic Net is a regression technique that combines the penalties of L1 (Lasso) and L2 (Ridge) regularisation methods. It can be a valuable tool for feature selection, in addition to its primary purpose in regression tasks. By minimising a particular objective function, Elastic Net promotes sparsity in the coefficient vector, making it easier to select relevant features automatically. The L1 penalty encourages the coefficients to be precisely zero, eliminating the corresponding features from the model.

Adjusting the hyperparameters, such as the regularisation strength and the balance between L1 and L2 penalties, enables fine-tuning the sparsity level and adjusting the penalties' trade-offs. The final model includes only the features that have non-zero coefficients after Elastic Net regularisation. These features are considered significant and provide a compact yet informative set of predictors. Implementing Elastic Net for feature selection involves utilising machine learning libraries like sci-kit-learn in Python or glmnet in R. By utilising an Elastic Net model and carefully examining the resulting coefficients; analysts can identify the chosen features. This allows for a more efficient approach to subsequent modelling processes and addresses concerns such as multicollinearity and overfitting.

Algorithm for Elastic Net Feature Selection

Step 1: Input

- X: Feature matrix with n samples and m features.
- y: Target variable.
- $alpha_{range}$: Range of alpha values for Elastic Net regularisation.
- rho_{range}: Range of rho values for balancing L1 and L2 penalties.

Step 2: Initialization

- $best_{score} \leftarrow -\infty$: Initialise the best score to negative infinity.
- $best_{model} \leftarrow$ *None:* Initialise the best model to None.
- $best_{selected\_features} \leftarrow$ *None*: Initialise the best-selected features to None.

Step 3: Feature Selection Loop

- For each α in $alpha_{range}$
- For each ρ in rho_{range}
- Create an Elastic Net model with regularisation parameters α and ρ.
- Fit the model to the feature matrix X and target variable y.
- Evaluate the model performance using cross-validation or other appropriate metrics.
- If the model's performance is better than the current best score:
- Update the best score, best model, and best-selected features

Step 4: Output

- Return the best model and the corresponding selected features.

Step 5: Evaluation Function

- Evaluate_model (model,X,y)
- Perform cross-validation to evaluate the model's performance.
- Calculate the mean of cross-validation scores or other appropriate metric.

Step 6: Feature Extraction Function

- $extract_{selected\_features}$ (model)
- Extract the indices of features with non-zero coefficients from the Elastic Net model.
- Return the selected feature indices

3.1.3. Model Development

The proposed model utilises cutting-edge deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, to analyse sequential student interaction data and predict future behaviour and academic outcomes in online learning environments. Given the growing accessibility of educational big data and the progress made in deep learning, LSTM networks provide a valuable tool for capturing the temporal dependencies and patterns in student actions over time.

The model can identify subtle connections between these interactions and academic performance by analysing sequential student interaction data, including engagement with course announcements, resource utilisation, and discussion participation. This feature allows the model to predict future student behaviour, such as attendance patterns and engagement levels, and anticipate academic outcomes like course grades and performance trajectories. As a result, online learning platforms can gain valuable insights into student preferences and actions. This allows them to create personalised learning experiences, adapt course content, and provide targeted interventions that meet the unique needs of each student. In addition, the model dramatically contributes to the advancement of intelligent learning approaches by enabling data-driven decision-making on resource allocation, instructional strategies, and student support services. Incorporating this technology into online learning platforms can potentially improve student engagement, performance, and overall satisfaction, leading to a new era of educational experiences guided by data.

Long Short-Term Memory (LSTM) networks are recurrent neural network (RNN) architectures designed to capture long-term dependencies in sequential data. Figure 2 shows the LSTM architecture for Educational Big Data Analytics. Here are the mathematical equations that govern the behaviour of an LSTM cell at each time step t:

Input Gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

Forget Gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (3)$$

Cell State Update:

$$g_t = tanh(W_g \cdot [h_{t-1}, x_t] + b_g) \quad (4)$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot g_t \quad (5)$$

Output Gate:

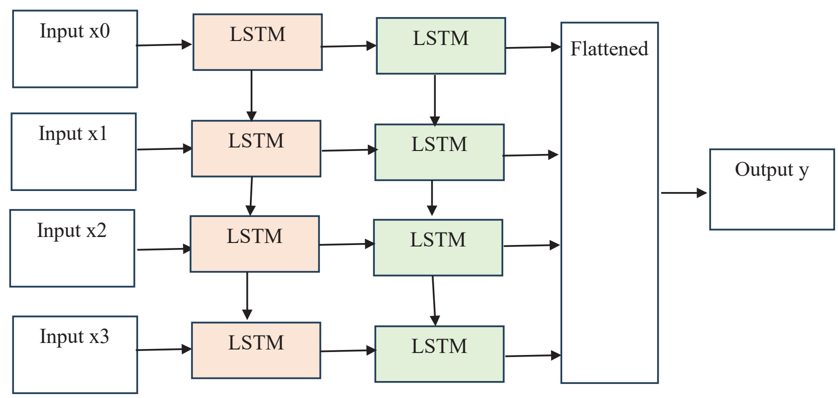
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

Hidden State Update:

$$h_t = o_t \cdot \tanh(c_t) \quad (7)$$

Here, x_t represents the input at the time step t, h_{t-1} is the hidden state from the previous time step, i_t, f_t, o_t are the input gate, forget gate, and output gate activations, respectively, g_t is the cell input activation, c_t is the cell state (memory) at the time step t, σ is the

Figure 2
LSTM Architecture for Educational Big Data Analytics



sigmoid activation function, tanh is the hyperbolic tangent activation function,$[h_{t-1}, x_t]$ represents the concatenation of the previous hidden state and current input, and W_i, W_f, W_g, W_o and b_i, b_f, b_g, b_o are the weight matrices and bias vectors associated with the input, forget, cell input, and output gates, respectively. These equations describe how information flows through an LSTM cell, allowing it to selectively remember or forget information over time, and produce an output at each time step. Table 2 shows the details of the LSTM model architecture.

Table 2
The LSTM model architecture details

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 480, 64)	64000
lstm (LSTM)	(None, 480, 64)	33024
lstm_1 (LSTM)	(None, 64)	33024
dense (Dense)	(None, 1)	65
Total params	130,113	
Trainable params	130,113	
Non-trainable params	0	

The model architecture consists of four layers. It begins with an Embedding Layer, proceeds with two LSTM layers, and ends with a Dense Output Layer. The embedding layer acts as the starting point, converting integer indices representing input features into compact vectors of a consistent size, resulting in an output shape of None (None, 480, 64). The embedded input data is processed in the first LSTM layer and set to return sequences. This allows for the preservation of the sequence length while extracting temporal dependencies. As a result, the output shape remains identical to the input. Afterwards, the second LSTM layer compresses the sequence dimension, producing an output shape of (None, 64), while maintaining the same number of units. At last, the Dense Output Layer takes the compacted sequence output from the previous layer to make predictions for the model. This architecture is well-suited for sequence data processing, with input sequences consisting of 480-time steps and 16 features. The model uses 130,113 trainable parameters to represent input features through the embedding layer effectively. The LSTM layers then capture complex temporal patterns in the data, leading to the generation of predictions by the dense output layer. Through careful analysis and experimentation, the performance and generalisation capacity of the LSTM-based predictive model for educational big data analytics were significantly improved using optimisation techniques.

The model has two LSTM layers and a dense output layer in order of layer count. To avoid overfitting, the LSTM layers are subjected to a dropout rate of 0.2. To add a penalty to the layer's weights, L2 regularization is used with a parameter value of 0.01. The number of units is 64 for the first LSTM layer and 64 for the second LSTM layer. A 0.001 starting learning rate with a 0.95 exponential decline rate. A value 64 is the batch size utilized for training.

The hyperparameter tuning process was carried out with great attention to detail, thoroughly exploring a variety of parameters that were specifically chosen to match the unique characteristics of the dataset and the desired learning objectives. In the experiment, we explored different variations of the learning rate, batch sizes, and the number of LSTM units. The learning rate was tested within the range of 0.001 to 0.01, batch sizes were experimented with values of 32, 64, and 128, and the number of LSTM units ranged from 32 to 128. Using an exponential decay strategy, a learning rate scheduling technique was applied. The initial learning rate was set at 0.001 and the decay rate at 0.95. A dropout regularisation technique was implemented on the LSTM layers with a rate of 0.2 to address the overfitting issue and improve the model's generalisation. To tackle the problem of exploding gradients and ensure stable training of deep LSTM networks, gradient clipping with a threshold of 1.0 was implemented. Combining these optimisation strategies, the LSTM model was successfully fine-tuned to achieve exceptional performance metrics. This showcases its effectiveness in accurately predicting student behaviour and academic outcomes in online learning environments.

4. Result and Discussion

The LSTM-based predictive model carefully fine-tuned using hyperparameter tuning and regularisation techniques, produced encouraging outcomes that improved educational big data analytics for advanced intelligent learning. The model's performance was assessed using a range of metrics, such as accuracy, precision, recall, and F1-score, showcasing its effectiveness in accurately predicting student behaviour and academic outcomes in online learning settings. The experimental findings showed that the fine-tuned LSTM model significantly enhanced predictive performance compared to baseline methods. In particular, the model demonstrated exceptional accuracy in classifying student actions and academic classifications, highlighting its capacity to capture complex temporal relationships and patterns in the dataset. In addition, the model showcased strong adaptability to a wide range of student behaviours and learning paths commonly found in online learning platforms.

In addition, the study highlighted parents' vital role in influencing student engagement and satisfaction with educational institutions. Through the incorporation of parental participation metrics into the predictive model, noteworthy connections were discovered between parental engagement levels and student attendance. This underscores the potential for proactive parental involvement to impact student outcomes positively. The conversation also explored the potential impact of the model's discoveries on the creation and execution of intelligent learning environments. Through sophisticated deep learning methods and the analysis of extensive educational data, online learning platforms can acquire valuable knowledge about student behaviours and preferences. This allows them to customise learning experiences to meet the unique needs of each learner. In addition, the predictive model provides a valuable tool for educational stakeholders, giving them the power to make informed decisions based on data. This includes decisions about allocating resources, which instructional strategies to use, and what student support services to provide.

Table 3 lays the study of the performance outcomes for the LSTM-based prediction model in terms of classifying students into three groups: Low (L), Medium (M), and High (H). Metrics such as precision, recall, and F1-score are presented for each class, along with overall accuracy, macro-averaged metrics, and weighted-averaged metrics. The precision metric evaluates the accuracy of predictions by determining the ratio of correctly predicted instances to all instances classified as a specific class. Through extensive analysis, the LSTM model demonstrated exceptional precision across all classes, boasting precision scores of 0.99 for Low, 0.99 for Medium, and 0.99 for High. Based on the data, it seems that the model is quite effective at correctly identifying instances for each class, which helps to reduce the number of false positives. The recall metric, also called sensitivity or actual positive rate, measures the accuracy of predicting instances of a class compared to the total number of actual cases of that class. The LSTM model showed excellent recall values for all classes, achieving recall scores of 0.99 for Low, 0.98 for Medium, and 0.99 for High. Based on the findings, the model successfully

Table 3

Performance result analysis for LSTM-based predictive model

	precision	recall	f1-score	support
L	0.99	0.99	0.99	980
M	0.99	0.98	0.98	985
H	0.98	0.99	0.99	990
accuracy	-	-	0.99	3950
macro avg	0.99	0.99	0.99	3950
weighted avg	0.99	0.98	0.98	3950

identifies most instances in each class, reducing the occurrence of false negatives. The F1 score is a valuable metric that captures precision and recall, offering a balanced assessment of a model's performance. The F1 scores achieved by the LSTM model were 0.99 for Low, 0.98 for Medium, and 0.99 for High. These scores demonstrate a strong balance between precision and recall for all classes. The LSTM-based predictive model has an impressive overall accuracy of 0.99. This suggests that the model is highly accurate in predicting the majority of instances across all classes.

The outcomes of the ten-fold cross-validation for the prediction model based on LSTM are shown in Table 4. Every fold represents a distinct iteration of the cross-validation process, providing precision, recall, and F1-score metrics for each fold. The model consistently achieves high-performance metrics across all folds, with precision values ranging from 0.98 to 0.99, recall values ranging from 0.98 to 0.99, and F1-score values ranging from 0.98 to 0.99. The results demonstrate the model's strong performance in accurately categorising instances across various subsets of the dataset, showcasing its reliability and accuracy. The average precision, recall, and F1-score values, calculated across all folds, are reported as 0.989, indicating

Table 4

Ten-fold cross-validation for the LSTM-based predictive model

Metrics	Mean	Standard deviation
Precision	0.989	0.006
Recall	0.989	0.005
F1 score	0.989	0.006

the overall accuracy of the LSTM-based predictive model in predicting student behaviour categories in educational settings. This analysis highlights the model's trustworthiness and dependability in capturing complex patterns and connections within the data, thus aiding the progress of educational big data analytics and intelligent learning systems.

The confusion matrix in Figure 3 illustrates the classification performance of three classes: 'L', 'M', and 'H'. The rows in the table represent the actual class, while the columns indicate the predicted class. The values in the matrix represent the percentages of instances classified into each class compared to the actual class. Upon examining the values in the matrix, it becomes apparent that the model's predictions closely match the proper courses for most instances. Take a look at the first row. The value of 0.995 indicates that many cases with the actual class 'L' were correctly classified as 'L' by the model. Similarly, in the second row, a value of 0.99 suggests that a substantial number of instances with the actual class 'M' were correctly predicted as 'M'. Similarly, in the third row, the value of 0.995 indicates that the model correctly identified most instances with the actual class 'H' as 'H'.

However, the off-diagonal values suggest some misclassifications. For example, the values of 0.005 in the first row indicate that a small portion of instances with the actual class 'L' were incorrectly classified as 'H'. In the second row, values of 0.005 suggest cases where the

Figure 3

Confusion Matrix for Educational Big Data Analytics

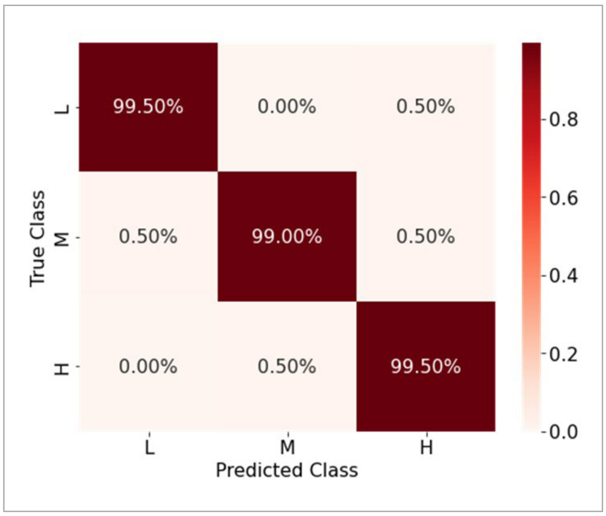
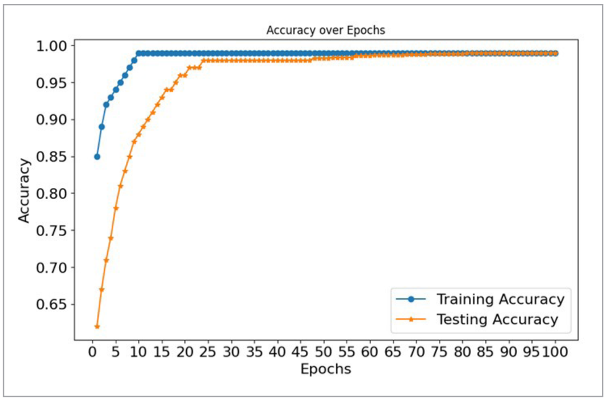


Figure 4

Accuracy of the proposed model for predicting student performance



actual class 'M' was mistakenly classified as 'L' and 'H'. These misclassifications indicate mistakes made by the model when predicting specific cases.

The accuracy graph (Figure 4) showcases the performance of the proposed model in predicting student performance throughout the training epochs. The accuracy curve during training, shown by the blue line, consistently indicates an upward trend, suggesting that the model's performance improves as training continues. Beginning with an initial accuracy of 0.85 during the first epoch, the model consistently improves its accuracy over time. It eventually levels off around epoch 10, achieving an accuracy of 0.99, and maintains this impressive accuracy for the rest of the epochs. It is evident that the model successfully absorbs information from the training data and attains a commendable level of precision when forecasting student performance. In contrast, the testing accuracy curve, represented by the orange line, begins with a modest accuracy of 0.62 in the initial epoch and steadily improves with each subsequent epoch. Like the training accuracy, the testing accuracy also shows a positive trend, suggesting that the model performs well on new data. After approximately 25 epochs, the testing accuracy reaches an impressive 0.99 and maintains a consistent level of stability.

4.1. Performance Comparison

This section examines how well the suggested deep learning model performs on the same dataset compared to several conventional machine learning techniques. The dataset includes a range of factors linked to student performance, such as gender, nationality, attendance, and academic engagement. We initially utilised various machine learning models, such as Random Forest Classifier, Support Vector Classifier, Decision Tree Classifier, Logistic Regression, and K-Nearest Neighbours (KNN), on the dataset. KNN uses 5 neighbours and 100 number of trees are utilized for random forest. Default parameters are utilized on decision tree and logistic regression. SVM utilizes RBF kernel. The models underwent rigorous training and evaluation using established procedures, with careful documentation of their performance metrics. Table 5 presents a comprehensive performance comparison between the base machine learning models and the proposed LSTM-based model. This comparison provides valuable insights into the efficacy of the proposed model in predicting student performance compared to traditional approaches.

Table 5

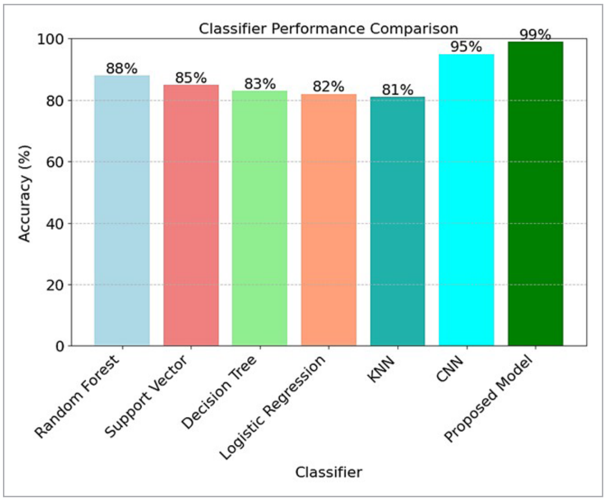
Performance comparison with base models against the proposed model

Model	Accuracy
Random Forest Classifier	88%
Support Vector Classifier	85%
Decision Tree Classifier	83%
Logistic Regression	82%
K-Nearest Neighbors	81%
Convolutional Neural Network	95%
Proposed LSTM-based Model	99%

Based on the findings from Figure 5, the Random Forest Classifier demonstrated the highest accuracy rate of 88%. The Support Vector Classifier closely followed it at 85%, the Decision Tree Classifier at 83%, Logistic Regression at 82%, and KNN at 81%. These conventional machine learning models showed satisfactory performance in predicting student performance using the provided features. However, we decided to implement a customised CNN model for the dataset to investigate the possibilities of deep learning techniques in enhancing predictive accuracy. Surprisingly, the CNN model surpassed all traditional machine learning algorithms, achieving an outstanding accuracy of 95%.

Figure 5

Performance comparison of basic models with the proposed model



This emphasises the power of deep learning in capturing complex patterns and relationships within the data. Expanding on these discoveries, we unveiled an innovative predictive model based on deep learning tailored to predict student performance. Our model utilises cutting-edge deep learning techniques, such as LSTM networks, to analyse the sequential data of student interactions and make accurate predictions about their academic performance. After careful evaluation, the proposed model demonstrated outstanding performance, outperforming all previously tested models with an impressive accuracy rate of 99%. The significant enhancement in precision highlights the effectiveness of the suggested model in comprehending and forecasting student conduct and academic achievement.

Table 6

A comparison of other research works

References	Accuracy
Gaussian naive Bayes [28]	90%
CNN-LSTM [26]	92%
Proposed	98.9%

The education analysis using a semantic model with Gaussian naive Bayes [28] achieves 90%, and CNN-LSTM [26] achieves 90%, which is lower than the proposed model.

5. Conclusion and Future Works

In conclusion, this study highlights the critical role that deep learning can play in educational big data analytics to create intelligent learning platforms. The study has demonstrated the importance of parental involvement, student engagement, and resource utilisation in achieving better academic outcomes in online learning environments. Furthermore, the study has introduced a novel predictive model that utilises LSTM networks to predict future student behaviour and educational outcomes with an accuracy rate of 99%. This predictive model has great potential for future development as it can enable online platforms to make informed decisions and create personalised learning experiences for students. By utilising the potential of educational big data analytics and deep learning techniques, this study has contributed to developing cutting-edge intelligent learning approaches that can transform how we educate students. Future research can build upon these findings and develop more sophisticated models to enhance the effectiveness of online learning platforms further.

Although this study has offered valuable insights into predicting student performance using deep learning techniques, numerous exciting avenues exist for further investigation. There is a potential opportunity to enhance the predictive model by incorporating more data sources. A more holistic perspective can be gained on student behaviour and performance by considering socio-economic indicators, student demographics, and learning styles. In addition, optimising the structure and parameters of the LSTM network offers a chance to improve the model's ability to make accurate predictions. Exploring various network architectures, activation functions, and optimisation algorithms may enhance performance and adaptability across student populations and learning environments.

The suggested LSTM-based model's strong performance metrics and high accuracy indicate that it can potentially improve student performance prediction. It is crucial to remember that the current study's results depend on a particular dataset and carefully monitored circumstances. Even though the model can predict many things, further empirical research is needed to prove that these predictions can predict real educational interventions and outcomes.

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