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Comprehensive Quality Evaluation Model of College Students Based on Deep Learning

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Abstract: *-* Evaluating college students' quality in higher education institutions is significant for promoting enhancement and innovation in teaching and learning practices. Conventional evaluation strategies mainly depend on subjective evaluation, which limits their ability to capture the multifaceted characteristics of students. In this study, we developed a distinct deep learning (DL) architecture by combining the Convolutional Deep Belief Network and Red Fox Optimization (CDBN-RFO) to evaluate college students' quality. Initially, a database containing academic performance records, extracurricular activities, and other relevant information is collected and fed into the system. Then, the database was preprocessed to make it an appropriate format for subsequent analysis. Further, the proposed CDBN-RFO was created, and the CDBN was trained using the preprocessed database to understand the patterns and relations within data for evaluating college students' quality. Subsequently, the RFO approach was deployed to fine-tune the CDBN hyperparameters to their finest range, which increases the overall system performance. Subsequently, the RFO optimized the CDBN training process by fine-tuning its parameters to the optimal range, enhancing overall evaluation performance. The developed framework was modeled using Python software, and the results were analyzed, including accuracy, error, computational time, etc. Also, a comparative analysis was done with conventional algorithms, which validated that the proposed strategy outperformed them in accuracy.

Keywords: Student quality evaluation, Red Fox Optimization, Convolutional Deep Belief Network.

1. Introduction

The primary objective of evaluating higher education is to enhance teaching and educational quality, and it plays a crucial role in managing and regulating teaching quality in higher education institutions like universities and colleges. Generally, a student quality assessment systematically examines and analyzes the student's data to evaluate the effectiveness of educational practices and the quality of learning outcomes [1]. Conventional evaluation strategies are mostly inflexible, and semester exams are conducted to assess the academic quality of college students. This process is typically time-consuming and not suitable for an advanced learning system. Mostly, the traditional evaluation commences at the beginning or at the semester's end per the college management's scheduled time, and the results are declared either at the beginning or end of the next semester [2].

This kind of assessment has no interconnection with a student's behavior in the classroom, extracurricular activities, student interest, etc., making it ineffective. Moreover, the current generation of students probably lacks interest in this type of quality assessment [3]. This creates a demand for developing an advanced evaluation approach to evaluate the quality of higher education. Current educational systems acknowledge that many factors beyond academic processes heavily impact student performance. These factors include student participation level, engagement level, critical thinking skills, involvement in extracurricular activities, etc., [4]. Therefore, developing an innovative and automatic evaluation strategy is required to assess the college student's quality precisely. This automatic strategy utilizes advanced data-driven technologies such as artificial intelligence (AI) and big data analysis (BA) algorithms [5].

Artificial intelligence methodologies, including deep learning (ML) and machine learning (ML), have emerged as promising tools for improving quality assessment because of their ability to analyze complex multidimensional data. This practical and automatic data analysis enables the capture of long-range interconnections within diverse data sources, providing a comprehensive understanding of college students' qualities [6]. Hence, education institutions focus on designing evaluation methodologies that utilize ML and DL techniques. Most of the studies used algorithms like reinforcement learning, ensemble learning, long short-term memory (LSTM), deep neural networks, k-means clustering (KMC), etc., to evaluate the quality of education in higher education. Although these techniques provide better data analysis than traditional evaluation methods, they face challenges like model complexity, data dependence, high computational time, limited scalability, less adaptability, etc. Moreover, some techniques cannot handle the diverse heterogeneous data, making them ineffective for real-time scenarios. To resolve these challenges, we developed an innovative algorithm leveraging the benefits of meta-heuristic optimization and deep learning to accurately and effectively assess college students' quality.

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The enduring sections of the article are arranged as follows: section 2 reviews the recent studies related to the current research, section 3 provides the motivation, section 4 details the developed strategy, section 5 analyzes the study's results, and section 6 provides the research conclusion.

2. Related Works

A few recent studies related to the proposed work are reviewed below,

Mustafa Yagci [7] developed an innovative data mining approach for analyzing student's academic performances. This data mining technique uses ML techniques to forecast the performances of undergraduate students by analyzing their midterm scores. The study examined different ML techniques such as support vector machine (SVM), k-nearest neighbor (KNN), random forest (RF), and logistic regression for student academic performance evaluation. This work utilized the academic records of 1854 students from Turkey collected from 2019 to 2020 as the data source, and the results depicted that these models achieved an accuracy of 70 to 75%. However, this accuracy is not sufficient for real-time educational settings.

Monika Hooda et al. [8] utilized artificial intelligence to evaluate students' success in higher education. The study aims to enhance the student's quality by effectively supporting learning and teaching. This study developed an Improved Fully Connected Network (I-FCN) to analyze the students' success rate. The implementation outcomes manifest that the I-FCN algorithm outperformed conventional RF, KNN, and SVM techniques. In addition, this data-driven algorithm ensures reliable evaluation, making it more effective for improving learning outcomes.

Mariel F. Musso et al. [9] presented a DL methodology for predicting major outcomes in student academics, such as degree completion, academic retention, grades, etc. This study utilized data collected from 655 students from a private higher education institution. This work developed a multilayer perceptron artificial neural network integrated with a backpropagation algorithm to perform the above prediction task. The experimental results highlight that this algorithm accurately predicted the student's grade. However, this algorithm is prone to overfitting and offers limited generalization.

William Villegas-Ch et al. [10] proposed an innovative and distinct algorithm that combines AI and BA with the learning management system (LMS) to enhance the student's learning quality. This study aims to improve online education through advanced technologies. It utilized data from online educational platforms developed during the COVID-19 pandemic. The findings showed that utilizing advanced and emerging technologies helps improve student quality.

Tongqing Yuan [11] presented an evaluation strategy using an enhanced Markov chain model to assess the teaching quality in the classroom. This study aims to improve and manage educational institutions by evaluating the quality of teaching conducted among college teachers. This mathematical model also helps develop and change the teaching process, and the experimental findings depict that this method offers a reasonable evaluation of teaching quality. However, this methodology relies entirely on assumptions and is ineffective in modern educational settings.

3. Motivation

The higher education landscape is rapidly changing to improve the quality of education and student outcomes. Hence, an optimal evaluation strategy is required to understand the quality of students and regulate higher education management. The traditional evaluation methodologies face difficulty in capturing the multidimensional nature of student characteristics and quality. Currently, the educational needs of students are changing; this creates a demand in educational institutions to develop innovative evaluation strategies to provide a comprehensive understanding of student's abilities and experiences. Over the past decades, the evolution of AI in education has paved the way for automatically assessing college students' quality through intensive data analysis. Deep learning, a subsection of AI, has emerged as an effective tool for resolving the above problems with quality assessment. The DL model can examine large volumes of heterogeneous data and understand the complex, intricate patterns and relations within the data to evaluate college students' unique characteristics and quality. This research focused on developing a distinct hybrid deep learning architecture for comprehensively assessing college students' quality.

4. Proposed CDBN-RFO for College Student Quality Evaluation

In this study, a novel hybrid CDBN-RFO algorithm was presented to accurately and effectively evaluate college students' quality. The developed algorithm leverages the Convolutional Deep Belief Network (CDBN) learning capabilities and the fine-tuning abilities of Red Fox Optimization (RFO). The developed work begins with the collection of heterogeneous data from educational institutions. This heterogeneous database includes a wide range of information, such as academic records, demographic details, student participation records, health records, extracurricular activities, etc. In the next step, this database undergoes preprocessing to standardize the raw database. The preprocessing steps include data cleaning, data balancing, and data transformation. These steps convert the raw database into an appropriate format for subsequent analysis. The preprocessed database was fed into the CDBN-RFO, which evaluates the quality of college students by analyzing the features and patterns within the database.
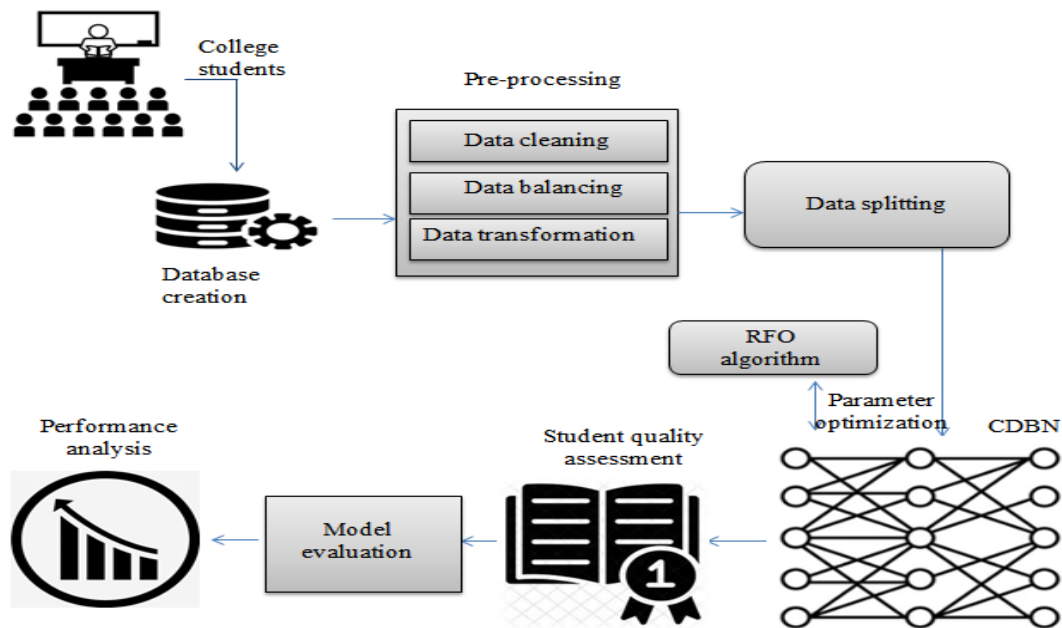
Figure 1: Architecture of the proposed methodology

The CDBN module was trained using the preprocessed database to learn and understand the patterns underlying the effective evaluation of college students' qualities. Consequently, the RFO was utilized to refine the CDBN parameters to their optimal range, which ensures optimal training and enhances the system's overall evaluation performance. The architecture of the developed algorithm is provided in Figure 1.

4.1 Data collection and preprocessing

This section presents a detailed description of the data accumulation and data preprocessing involved in the proposed work.

a) Data collection

The developed work commences with collecting multivariate student performance data from educational institutions. The database collection includes academic records, demographic information, details about a student's participation in various activities, their level of involvement in academic and extracurricular pursuits, and other relevant metrics. This study utilized the database collected from the university information system [12]. This database contains a comprehensive array of attributes spanning academic performance, learning habits and achievements, innovation ability, moral qualities, living habits, and physical and psychological habits. The academic details include college students' grades in practical courses, professional courses, computer knowledge, language proficiency, and communication ability. The learning habits and achievements include information regarding students' creativity, honors and achievements, reading frequency in libraries, etc. Innovation ability includes papers published, problem-solving, critical thinking, and grades of innovative courses done by the students. Moral qualities include disciplinary records, adherence to ethical standards, disposition records, grades of ideological records, and political status. Living habits include information regarding students' lifestyle choices, socioeconomic status, etc. Finally, physical and psychological health includes students' grades in physical courses, mental health status, participation in sports competitions, etc. This dataset contains 34 features, which provide a wide range of information for student quality evaluation.

b) Preprocessing

Data preprocessing is one of the crucial phases involved in data analysis. This phase includes steps like cleaning, balancing, and transformation, and these steps play an important role in converting raw databases into a standardized and clean dataset, making them reliable and effective for subsequent analysis by the deep learning models. The data-cleaning step involves the identification of errors, inconsistencies, and missing values in the database. In this step, we applied a data imputation algorithm to clean the entire dataset. This algorithm effectively detects and handles the dataset's errors, inconsistencies, and missing values. Then, data balancing was performed to address the class imbalance in the dataset. The collected heterogeneous database contains multiple classes; this step balances all the classes through either oversampling or undersampling. Finally, data transformation was done using a min-max scaling algorithm, which scales the dataset features into a common scale. This step prevents the features with greater magnitudes from dominating the subsequent analysis.

4.2 College Student Quality Evaluation using CDBN

The CDBN is a deep artificial neural network containing numerous convolutional restricted Boltzmann Machines (RBMs) layers. These layers are stacked together to perform different intelligent tasks. This is a modified and enhanced deep belief network (DBN) version. This improvement enables us to scale high-

dimensional database features, producing improved data analysis. The RBMs in the DBN comprise an energy function responsible for analyzing the hierarchical features and patterns within the database. The RBM architecture contains two important layers: visible and hidden layers. These layers perform selective functions to analyze the patterns and correlations within the data for accurate analysis of student quality. These layers are interconnected via neuron nodes, and this connection is weighted. The energy function of the RBM is presented in Eqn. (1).

$$E_n(v,h;\theta) = \sum_{i=1}^{t} a_i v_i - \sum_{i=1}^{t}\sum_{j=1}^{u} w_{ij} v_i h_j - \sum_{j=1}^{u} bs_j h_j \tag{1}$$

Where $\theta = \{wt_{ij}, a_i, b_j\}$ defines the RBM's parameter sequence, w_{ij} represents the neuron node weight interconnecting the visible and hidden layer, h_j represents the hidden state, a_i defines the offset of the visible layer, v_i indicates the state of the visible layer, and b_j defines the hidden layer offset. Using weights and biases, the energy function captures the cooperation between the hidden and visible layers. In this training, the RBM learns to adjust the weights and biases and captures the data's intricate patterns and hierarchical attributes.

In CDBN, an extra convolution layer was added to the RBN architecture. The CDBN structure includes an input layer, a visible layer, a convolutional layer, a hidden layer, and an output layer. These layers are locally connected, and the convolution function shares the neuron node weights. Introducing convolutional layers enables the system to learn the hierarchical data representations effectively, offering improved evaluation performances compared to the conventional DBN. The input layer of the CDBN accepts the preprocessed database as input. The input layer size is $k_v \times k_v$. The number of groups of matrices present in the hidden layer is x, and every group defines a binary array $k_h \times k_h$. The groups in the hidden layer are connected through a filter, and the filter size used in the developed work is 3x33x3. The weight matrix, which connects the visible and hidden layers, is defined as $wt_1, wt_2, \ldots wt_x$. During training, the weight matrices connecting the hidden and visible layers are adjusted iteratively to understand and extract the most significant features and patterns within the input database. The energy function governing the CDBN is represented in Eqn. (2).

$$E_n(v,h) = -\sum_{x=1}^{x} h^x(w^x * v) - \sum_{k=1}^{k} b_x \sum_{j=1}^{u} {h_{ij}}^x - c_n \sum v_{ij} \tag{2}$$

Here, b_x denotes the hidden layer bias and c_n indicates the bias globally shared by all visible units; $*$ defines the convolution function; v_{ij} defines the input values of the visible and hidden layer; ${h_{ij}}^x$ indicates the hidden layer; and w^x represents the convolution kernel of the hidden unit. The conditional probability distribution of the proposed CDBN is defined in Eqn. (3) and (4).

$$p_d\left({h_j}^x = 1 \mid v\right) = \sigma\left(w\bar{t}^k * v\right)_j + b_x \tag{3}$$

$$p_d\left(v_i = 1 \mid v\right) = \sigma\left(wt^k * h^x\right)_i + c_n \tag{4}$$

These conditional probability distributions define the relationships between the visible and hidden layers in the CDBN, capturing the long-range dependencies and patterns within the data. The captured patterns and features are fed into the output layer, which converts these hierarchical data representations into student's quality. The student's quality includes their academic performance, thinking ability, cultural interest, social responsibility, communication ability, etc. This quality evaluation is an iterative process, and at each iteration, the weights and biases in the architecture are adjusted using RFO optimization to minimize the training loss.

4.2 Red Fox Optimization

Red Fox Optimization is a nature-inspired optimization algorithm developed by the mathematical modeling of red fox habits, food foraging, and hunting to resolve world optimization problems. In the proposed work, it was deployed to fine-tune the CDBN parameters to their optimal range to enhance the model's training and overall evaluation performances. In the RFO algorithm, exploring territories for searching food is modeled as a global search. In the presented work, the global search phase of the RFO algorithm was utilized to search for the optimal value of the CDBN parameters. The CDBN parameters include bias vector, weights, neuron node count, etc. Initially, the population containing the number of foxes was randomly initialized. Here, the population indicates the parameter sequence containing different parameter subsets. The initialization of the parameter sequence is represented in Eqn. (5).

$$\hat{p}(s) = \{ps_1, ps_2, \ldots \ldots ps_y\} \tag{5}$$

Where $\hat{p}(s)$ indicates the parameter set, and s population size (number of parameter sets in the population). Then, the foxes move in solution space, searching for optimum values based on the objective function. The objective function is to minimize the error during the CDBN training process, represented in Eqn. (6).

$$E_r = \frac{1}{r}\sum_{t=1}^{r}(y' - y)^2 \qquad (6)$$

Where y' and y indicates the actual output and ideal outcome. Based on this criterion function, each parameter set in the population explores the solution space to find its optimal value. Before the exploration phase, the fitness value of each parameter set in the population was determined. The higher fitness indicates that the error incurred by the CDBN is minimal and vice versa. After fitness evaluation, each parameter set in the population is sorted (arranged in ascending order), and the parameter set with greater fitness is considered as best. Then, for the best parameter set, the square of the Euclidean distance to each parameter set in the population was determined, and it is expressed in Eqn. (7).

$$d(ps_i, ps_b) = \sqrt{\|ps_i - ps_b\|} \qquad (7)$$

Further, all parameter sets in the population are moved towards the best one, and it is represented in Eqn. (8).

$$ps_i(t+1) = ps_i(t) + \alpha sign(ps_b(t) - ps_i(t)) \qquad (8)$$

Where $ps_i(t+1)$ denotes the updated parameter set, and $ps_i(t)$ represents the current parameter set. Then, the fitness was evaluated for updated parameter sets in the population. Sort the updated parameter sets based on their new fitness. If the fitness for updated parameter sets is higher than the old fitness, then the updated parameter sets are used for CDBN training. This parameter tuning is a continuous process, and at each iteration, the parameter sets are updated to their optimal value. Thus, integrating RFO with the CDBN enhances its training process and improves the overall system performance. Algorithm 1 tabulates the pseudocode of the developed CDBN-RFO.

Algorithm: 1
Start {
Initialize the student database;
Data preprocessing:
1. Use imputation to clean the data; //*data cleaning*
2. Perform either oversampling or downsampling;//*Data balancing*
3. Apply min-max scaling;//*data transformation*
Design the proposed CDBN-RFO model;
Train CBDN module:
For each iteration:
1. Initialize CDBN parameters;
2. Design input, convolution, visible, hidden, and output layers;
3. Split the database as training and testing sets;
4. Define energy function;
5. Determine Probability distributions;
6. Evaluate student quality;

7. Calculate error;
end for
RFO optimization:
1. Initialize RFO parameters (population size, maximum iteration);
2. Define objective function (error);
for each iteration:
1. Estimate fitness value;
2. Sort the population;
3. Exploration phase;
3. Update parameter sets;
4. Determines new fitness for updated parameters and sorts them;
5. **if (new fitness > old fitness)** returns an updated parameter set,
6. **else** return old parameter set;
end for
Evaluate results;
}End

5. Result and discussion

A hybrid evaluation methodology was developed in the proposed work to assess the quality of college students. The proposed methodology leverages a hybrid deep learning algorithm named convolutional deep belief network and Red Fox Optimization to analyze student quality precisely. The presented evaluation model was modeled in the Python language, version 3.7. The experimental setup includes a Windows 10 operating system, an Intel four-core CPU, 8G memory, and a 1T hard disk. The study results are examined and validated with the existing models regarding metrics like accuracy, mean square error, and computational time.

5.1 Model training and testing

The proposed model was trained and tested across this subsection's publicly available UCI machinery student performance database. The evaluation of model training and testing enables us to determine the system's generalizability and how effectively it prevents overfitting. Firstly, the input database containing 649 instances is fed into the Python system, where it undergoes preprocessing. After preprocessing, the database was split into 3:1 ratios for model training and testing.
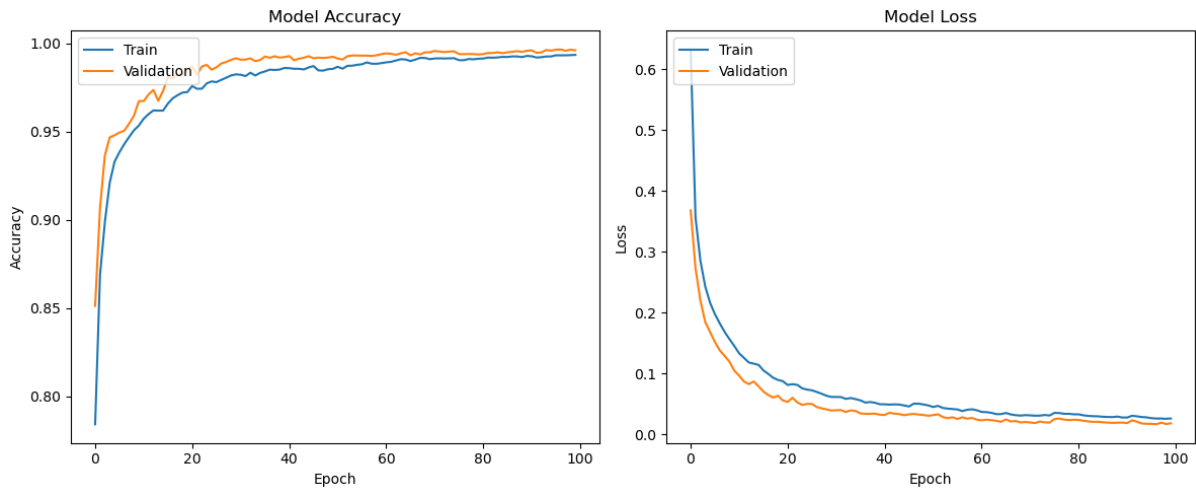
Figure 2: Model training and testing

The training dataset was used to train the model for evaluating the college students' quality, and training performances were assessed as accuracy and loss. The training accuracy measures how precisely and quickly the proposed model learns the patterns and correlations within the training sequence, and the loss metric evaluates the difference between the ideal and real output. Figure 2 presents the model training and testing performances. The proposed algorithm achieved a higher accuracy of 0.95 and a minimum loss of 0.08 during the training process. The testing performances validate the model's generalization and how effectively it prevents the overfitting problem. The testing accuracy measures how the developed model applies the learned patterns and evaluates the student quality, while the loss determines the deviation between the real and the ideal output. The intensive evaluation of the model's testing performances highlights that it achieved a higher testing accuracy of 0.94 and a lower loss value of 0.09. This manifests that the proposed model offers better generalization and prevents overfitting challenges.

5.2 Comparative assessment

In this subsection, we validate the proposed methodology's performance with the existing evaluation models. The existing models include K-means clustering (KMC) [13], Long-Short-Term Memory (LSTM) [14], K-nearest neighbor (KNN) [15], and Deep Belief Network (DBN) [16]. These models are implemented in Python and validated for the same UCI student performance dataset to determine the outcomes.

The accuracy metric measures how effectively the proposed algorithm evaluates college students' quality. It also measures how the ideal output correlates with the real output. Figure 3 (a) presents the comparative analysis of accuracy. The comparison of accuracy with the existing models like KMC, LSTM, KNN, and DBN illustrates that the proposed strategy achieved better accuracy than the conventional models. These existing models obtained an average accuracy of 92.2%, 93.1%, 91.4%, and 94.2%, while the proposed algorithm achieved a higher average accuracy of 99.34%. In addition, compared to the existing models, the developed model almost obtained consistent accuracy over increasing data volume. This highlights that the proposed algorithm accurately evaluates education quality despite rising data volumes.

Similarly, we measured the error obtained by the proposed model. The comparison of errors is presented in Figure 3 (b). The above-mentioned existing techniques incurred error rates of 3.30%, 5.50%, 3.90%, and 4.30%, respectively. On the other hand, the proposed algorithm obtained a minimum error rate of 0.152%. This depicts that the difference between the ideal outcome determined by the proposed strategy and actual output is slight and lower than that of the existing models. This manifests that the proposed algorithm accurately evaluates the quality of the students.
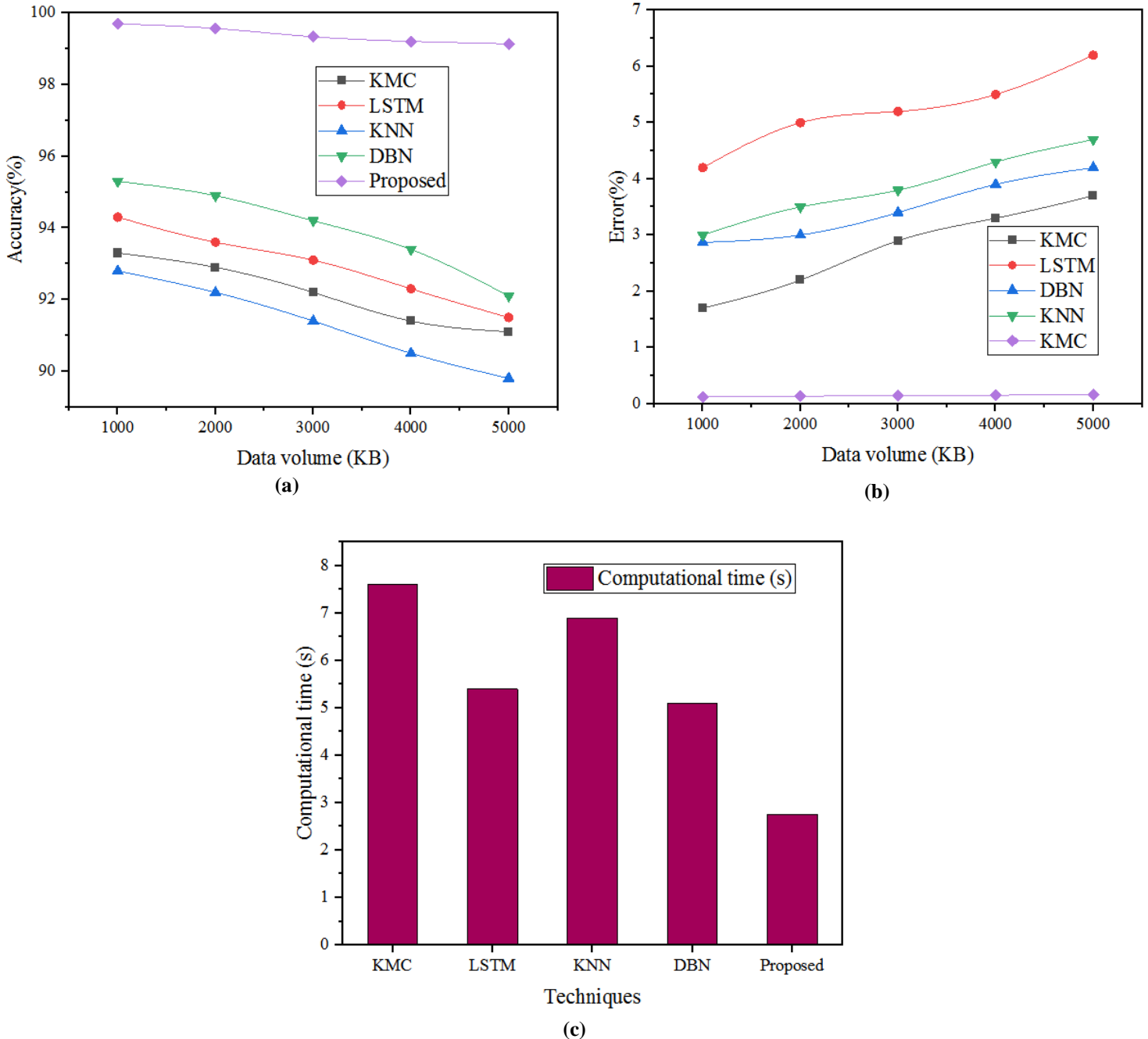
(a)

(b)

(c)

Figure 3: Comparative assessment: (a) accuracy, (b) error, and (c) computational time

Furthermore, the computational efficiency of the developed model was determined as computational time. The computational time measures the overall time the proposed algorithm consumes for performing tasks such as data preprocessing, feature analysis, optimization, and quality evaluation. Figure 3 (c) presents the comparison of computational time. The above-mentioned existing models consumed the computational time of 7.6s, 5.4s, 6.9s, and 5.1s, respectively, while the proposed algorithm consumed a minimum computational time of 2.76s. This highlights that the developed algorithm quickly processes the data and evaluates the quality of college students. This detailed comparative evaluation shows that the developed model is more accurate and computationally effective than the existing evaluation strategies. Moreover, evaluating model performances for increasing data volumes suggests its scalability and reliability in handling large-scale databases, making them practical for modern educational settings.

6. Conclusion

This study proposed an innovative evaluation model developed by combining a convolutional deep belief network and red fox optimization for reliable and practical assessment of quality of college students. The proposed model was experimentally validated using the UCI machinery student performance database, and it achieved a greater accuracy of 99.34%, a minimum error rate of 0.152%, and less computational time of 2.76s.

Also, a comparative analysis was made with the existing models, such as KMC, LSTM, KNN, and DBN, to validate their effectiveness and robustness in student quality evaluation. The comparative assessment highlighted that the accuracy was increased by 5.14% in the developed strategy. Also, the error rate and the computational time are reduced by 3.148% and 2.34s in the designed model. Furthermore, evaluating model performances for increasing data volumes highlights its scalability and reliability in handling extensive data in real-time scenarios. These better performances of the developed work make it practical and reliable for student quality evaluation in modern educational settings.

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