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Student Learning Based Data Science Assisted Recommendation System to Enhance Educational Institution Performance

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Abstract: The student feedback data possesses to be the fundamental influencers of decision-making process in diverse applications. The performance prediction based on student's feedback about the educational institution helps for better solution recommendation. The automated solution recommendation based on student's feedback extensively support the educational institution to make better decisions for improvisation. In most of the existing research works, the performance can be analysed, but suitable solution recommendation is not provided. Also, the existing recommendation works fail to generate accurate outcomes, consumes more time with higher error rates. Hence on diminishing the existing issues, this research work presents a Data science-based solution Recommendation model based on hybrid deep learning approaches. Pre-processing, feature extraction, feature clustering, performance prediction, and recommendation are the steps in the suggested model. In this research, the student feedback data is collected from Kaggle source and some of the attributes are added manually. Pre-processing techniques for the text data include stop-word-removal, tokenization, case-folding, and stemming. The features are extracted using Enhanced Lexicon bidirectional encoder representations from transformers (ELexBert) model. The significant attributes are selected using Adaptive Coati optimization (ACoaT) algorithm. The selected features are clustered based on feature similarity using Upgraded density based k-means clustering (Uden_KMC) model. A new type of hybrid deep learning model known as Channel Block Densnet with Dilated Convolution BiLSTM (ChaBD-BiL) is employed for recommending better decisions. The recommendation performances using feedback data are evaluated using PYTHON where the overall accuracy of 98.19%, specificity of 98.25%, F1 score of 91.28%, sensitivity of 97.41% and Kappa score of 91.28% are obtained.

Keywords: Student feedback, Lexicon BERT, Coati optimization, Density clustering, Channel block DenseNet, Dilated convolution.

1. Introduction

Due to the development of immense database and information technologies, the data science holds a greater impact for promoting the progress of data analysis [1]. Diverse studies insists that the applications of data science can be categorized into several technologies like machine learning, deep learning, and ensemble approaches. The education system is computerized nowadays to render better education to the students [2, 3]. The data science can effectively manage the requirements of students, gather better knowledge, make better decisions and also examine the performance of the educational Institution in a great way. The key role of Educational Data Mining is to discover and overcome the research issues in the field of education [4]. The collection of student feedback related to teaching and other learning activities can assist for the investigation [5]. Through the optimal investigation process, the opportunities, strengths, threats, and weakness in the education system can be analysed properly and further actions can be taken.

Effective recommendations can be provided to educational institutions to support the students in enhancing their studies and assisting the instructors to improve their teaching effectiveness [6]. Due to lack of relevant information, the educational institutions are suffering extensively to support the students by resolving the issues [7]. The only way to gather the information from students is getting direct feedback from the students. One of the traditional feedback mechanisms to gather data are filling of forms directly by the students [8]. Those mechanisms possess huge number of issues like only a certain question set are provided to the students [9, 10]. The chances to expose other forms of issues related to the educational system are not provided to the students. As the traditional mechanism is highly time consuming, online feedback mechanism is pursued in most of the institutions.

The online feedback mechanism is highly significant to gather student's feedback based on different attributes [11]. The students can give the suggestions to the educational institutions more effectively using online feedback mechanism compared to the traditional mechanism. The faculty members are supposed to utilize the feedback to determine their strengths and areas of improvement [12, 13]. Even though online feedback mechanism serves to be better, the analysis of each feedback and appropriate actions to be taken are highly complex [14]. There is so much of research carried out previously on processing the student feedback data. But in most of the works, only sentiments associated to the input data are analysed whereas appropriate recommendation is still lagging [15]. The recommendation system for enhancing the performance of educational institution have attracted huge attention for enhancing the student performance.

To overcome the challenging issues and to recommend better suggestions to the educational institution, an automated recommendation system based on effective feedback prediction is highly required [16]. Many recommendation-based research is carried for improving the student's future based on the student details [17]. However, suggestions for improving the functioning of educational institutions based on student feedback are quite innovative. Numerous models based on machine learning (ML) and Artificial Intelligence (AI) are used for promoting effective recommendation [18, 19]. But more time complexity, inefficiency in generating precise outcomes, increased rates of error and degraded training ability are found to be the challenging issues. Different software solutions are built utilising familiar programming languages to make it easier for designers to use machine learning technology and predictive analytics. [32]. Recently, deep learning (DL) [20] based models are widely used as it produces faster and precise outcomes.

2. Motivation

The educational data science insists the use of data collected from educational environments for overcoming the issues through suitable decisions. Data science is a concept employed to merge the analysis of data, statistics, and feedback by using effective technologies. Various algorithms which addressed the classification problems are evaluated within the education science sector [31]. Algorithms for optimisation can be classified as probabilistic or deterministic which can be used for selection of the optimized features [34]. In the educational institution, the feedback of students is highly necessary for improving the performance further. In the recent days, computerization process is widely used by the educational institutions tending to the creation of huge amount of data. The collected feedback data from the students would be highly helpful for the teachers, administrators and so on for better decision making. Anyhow based on the student's feedback, recommendation of appropriate solutions to the educational institution is highly challenging and consumes more time. The existing research highly concentrates on data processing and categorizing the input texts based on sentiments like positive, negative and neutral, but effective solution recommendations are not performed. Also, the outcomes cannot be predicted much accurately and if predicted also, often results in increased rates of error. There is lack of research performing recommendation of suitable solutions based on student's feedback to enhance the educational institution performance. Due to ineffective consideration of student's feedback, the performance of educational institution as well as the students are influenced. Hence, an automated recommendation model is highly required to fulfil the student's requirement. Motivated by the existing challenges, data science assisted hybrid Deep Learning model is presented in the suggested study to obtain enhanced recommendation solutions.

The following lists some of the major contributions made by the suggested model:

To extract the effective features using Enhanced Lexicon bidirectional encoder representations from transformers (ELexBert) model and choose the best features utilising Adaptive Coati optimization (ACoaT) algorithm.

To generate clusters using Upgraded density based k-means clustering (Uden_KMC) by considering the similarity of features.

To introduce a data science-based solution recommendation model using Channel Block densenet with Dilated Convolution BiLSTM (ChaBD-BiL) network with enhanced accuracy and less rates of error.

To utilize Channel Block densenet for prediction and Dilated Convolution BiLSTM for recommending a suitable solution.

The suggested method's higher performance would be demonstrated by assessing its performances with the current state-of-the-art approaches using several performance indicators.

The suggested research work is well structured into different sections. In Section-2, a few prediction and recommendation works conducted by different researchers are surveyed. The new approaches to text processing are shown in Section-3 to explain how the recommended methodology operates. In Section-4, the models used to analyse the performance are covered. The suggested research work's Conclusion and Future scope is presented in Section-5 along with the appropriate references.

3. Related works

Some of the recent prediction and recommendation works in text processing are specified as follows.

Karaoglan Yilmaz, Fatma Gizem, and Ramazan Yilmaz [21] investigated the opinions of aspiring educators about personalised recommendations based on learning analytics. Based on the flipped learning model, the research was undertaken on 40 teachers in computer course. The outcomes of learning analytics were obtained based on user activity in the learning management system (LMS) of students. Semi-structured opinion surveys were used to gather research data, and content analysis was done based on that data. The effective aspects and demerits of guidance feedback and personalized recommendation dependent upon the learning analytics can be analysed through this research. The research says student- centric learning analytics can be considered, and student opinions can be evaluated for decision making process. Recommendations can be provided to the students to enhance the metacognitive thinking skills.

Sood, Sakshi, and Munish Saini [22] utilized an integrated approach comprising of Cluster-based Linear Discriminant Analysis (CLDA) and Artificial Neural Network (ANN). The major focus of this research was to recommend the motivational comments to the probable students. As a result, students can choose relevant courses, and the suggested remarks help students understand why they may have dropped out. Through this research, the number of dropouts can be extensively minimized with the suitable selection of courses to enhance the overall performance. One benchmark and one synthetic dataset were used, and they are pre-processed initially to process this research. This research talks about the usage of IoT with the wearable devices in the next works to collect the real-time data and to compare the student performance which can reduce the student dropouts.

Yangsheng, Zhang [23] constructed an intelligent model for sports evaluation with the integration of AI based teaching system based on neural network modelling. The final evaluation and process determination are where the AI model starts. The recurrent neural network (RNN) was employed for data analysis and training. In addition, a new decoder was established to process data and a simplified gated neural network (GNN) was developed to construct the internal model structure. In accordance with this, a control experiment was designed to examine the model execution. Through this research, a better outcome can be obtained in predicting the performance by considering the sports students. This research also says about the usage of enhanced neural network and AI based algorithms in future for student performance prediction with better analysis and accuracy.

Kanetaki, Zoe, Constantinos Stergiou, Georgios Bekas, Christos Troussas, and Cleo Sgouropoulou [24] explored the prediction of grades in online engineering education. After being eliminated from statistical analysis, a hybrid model with 35 variables was created and found to have a good correlation with students' academic achievement. Initially, a Generalized Linear- Model was involved and later its errors were employed as an additional related variable to the Artificial Neural Network (ANN). This research predicts that grade as a dependant variable can be a best variable for success of the model. The survey answers of 158 students were validated in this work by dividing the dataset into three subsets. The particulars like standard error, p-value and coefficients were estimated for all variables. The future work of the research talks about the model performance prediction for the next batch of students. A confusion matrix can be used, statistical significance can be found for the variables and model accuracy can be tested for that batch of students.

Ouyang, Fan, Mian Wu, Luyi Zheng, Liyin Zhang, and Pengcheng Jiao [25] combined AI based

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performance prediction approaches and learning analytic methods to boost the learning effects of students in Collaborative learning context. The major purpose of this research was to show the predicted outcomes to students as well as course instructors which can improve the learning quality and teaching performance. It has shown the differentiations of collaborative learning effect over students with and without the integrated approach. The quasi-experimental research was carried on the online engineering courses. Effective enhancement of students, enhanced performances of collaborative learning and student satisfaction strengthening were the outcomes analysed in this research. The future work of this research should use the expanded educational contexts with an increased sample test set . It mainly suggests to propose a integrated approach of AI and LA, conduct the statistical studies using the integrated approach to provide a clear path between AI and Education Domain.

Kusuma, Purba Daru, and Ashri Dinimaharawati [39] proposed The extended stochastic coati optimizer (ESCO), a new metaheuristic, is presented in this paper. The flaw in the coati optimisation algorithm (COA) is expanded to create ESCO. The amount of searches and references included in COA is increased by ESCO. This research work has helped to get a good understanding of Coati Algorithm and its extended version which splits the population into two fixed groups, each performing its strategy for feature optimisation.

To conquer the future works and drawbacks faced in the existing algorithms, a novel hybrid DL model is presented to promote effective recommendation solutions based on the input student feedback data. The procedure of proposed methodology has been provided step by step as follows.

4. Proposed methodology

The student feedback holds to be the fundamental influencers of decision-making process. The performance prediction of student's feedback about the educational institution helps for better solution recommendation. The automated solution recommendation based on student's feedback extensively support the educational institution to make better decisions for improvisation. In most of the existing research works, the performance can be analysed but suitable solution recommendation is not provided. Also, the existing recommendation works fail to generate accurate outcomes, consumes more time with higher error rates. Hence on diminishing the existing issues, this research work presents a data science-based solution recommendation model based on hybrid deep learning approaches. Fig. 1 explains the schematic representation of suggested workflow.

The student feedback data is collected from online Kaggle source. Additionally, some of the attributes and recommendation solution are manually added in the dataset to process this research work. The steps involved in student feedback-based solution recommendation model are listed as follows.

- Pre-processing
- Feature - Extraction
- Feature - selection
- Feature - Clustering
- Performance - prediction
- Recommendation

Initially, pre-processing is carried using stemming, tokenization, case folding and stop word removal. The characteristics are extracted from the pre-processed data using ELexBert model. The most relevant features are selected using ACoaT algorithm. The selected features are clustered into diverse groups based on feature similarity using Uden_KMC model. From the generated clusters, the performances of educational institution based on student feedback are predicted and suitable solutions can be recommended based on that prediction. This can be performed using a novel hybrid DL model called ChaBD-BiL. Here, Channel Block dense net is used for prediction where the educational feedback given by the student can be predicted as good, not bad and poor. Based on the predicted outcomes, Dilated Convolution BiLSTM recommends for a suitable solution to overcome the issues.

4.1 Text pre-processing

The gathered input text data is subjected to abundant irrelevant data that highly declines the quality of text and overall system performance. To attain enhanced performance, significant input text data is necessary and so text data pre-processing [26] is initially carried out in the proposed DL model. Through pre-processing, structured text data can be attained that is significantly crucial for precise recommendation system. In the proposed recommendation model, steps like stemming, tokenization, case folding and stop word removal are used for pre-processing the text data. The explanation of every pre-processing step undertaken are clearly described as follows.

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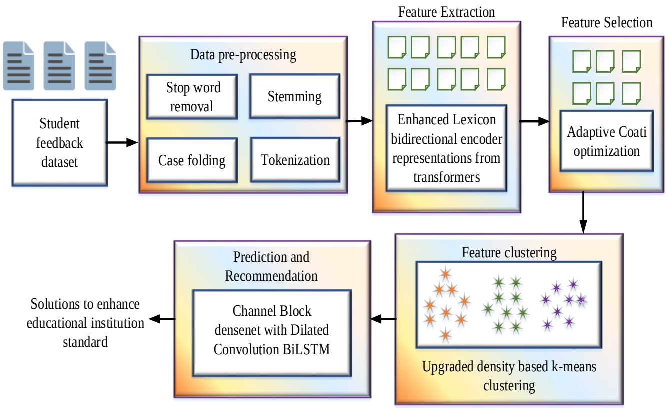

Figure. 1 Block architecture of proposed model

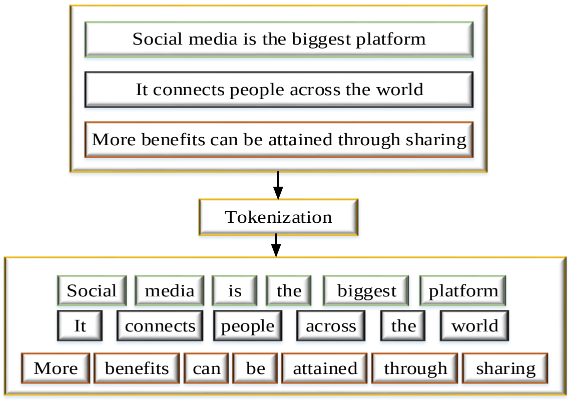

Figure. 2 Instance of Tokenization process

4.1.1. Case folding

Case folding process is performed in the proposed model to convert the letters from text documents to corresponding lower or upper case. In text pre-processing, case folding has been utilized to convert letters into lowercase format.

4.1.2. Tokenization

The process of tokenization is considered as one of the most effective tasks in text data processing. The process of separating a sentence, paragraph, entire text or phrase into small units or words is called as tokenization. The smaller units separated from text data are said to be tokens. In text language processing, the words that determine character string must be recognised and so tokenization process acts as a significant step. An instance of tokenization process performed in the text data are insisted in Fig 2.

4.1.3. Stop word removal

Removal of stop words from text data tends to be a crucial process that is undertaken during pre-processing stage. The major objective of stop word eradication is to remove the words that are usually found through the textual data. Essentially in pronouns, English verdicts, articles, and prepositions present in the given data are considered to be stop words. In text mining-based applications, stop word removal is carried out for analysing relevant words. An example for stop - word - removal for the given text input data is established in Table 1.

4.1.4. Stemming

The process of producing morphological variant of base word is known as stemming. Stemming assists in reducing a word over its corresponding

Table 1. An example for stop – word - removal

A text sample with stop words	Text after stop word removal
He wishes to eat an apple	"Wish", "Eat", "Apple"
The dress appears very pretty	"Dress", "Appear", "Pretty"
How to deliver a book in office	"Deliver", "Book", "Office"
The woman brings bag on her hands	"Woman", "Bring", "Bag", "Hand"

Table 2. An instance for Stemming

Sample word	After Stemming
Connecting	Connect
Introducing	Introduce
Call	Call
Building	Build

word stem that merges the root words. An instance of stemming dependent upon the sample word is given in Table 2.

4.2 Feature extraction

Feature extraction is the process of identifying important features from pre-processed text material to improve performance overall. The principal objective of feature extraction is identification of relevant features for enhancing the recommendation efficiency. Various Deep Learning models can be applied for Feature extraction [38]. In DL model, BERT [27] is considered as one of the significant word embeddings and it can efficiently learn the word contexts. To enhance the efficiency of BERT model further, ELexBert is employed in the recommended model. The design idea of ELexBert model is to utilize Lexicon selected N-grams, convert lexicons into vectors and apply BERT embedding algorithm to obtain a relevant set of

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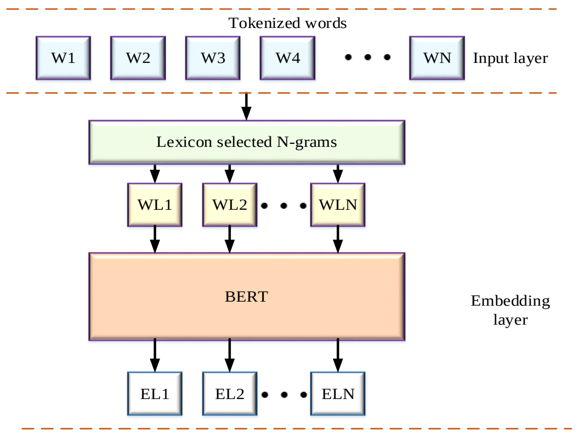


Figure. 3 ELexBert model representation

features. The architecture of the proposed ELexBert model can be seen in Figure 3.

The N-grams denote the combination of words from a sentence that generates a markovian process and is used to determine the subsequent word in a string of words. Also, it generates co-occurrence of words from text in a more significant manner. For instance, the N-grams considered from the sentence is given as follows.

$$\text{Sentence} = \{W1, W2, W3, \ldots, WN\} \tag{1}$$

From the above expression, WN denotes the number of N- gram words. For diverse values of N (uni - gram, bi – gram), the set of lexicon selected N-grams get varied. For example,

$$\text{For } N = 1,\ N1 = \{W1, W2, W3, \ldots, WN\} \tag{2}$$

$$\text{For } N = 2,\ N2 = \{W1\_W2, W2\_W3, W3\_W4, \ldots, WN-1\_WN\} \tag{3}$$

With the utilization of N-grams, it is applicable to choose a section from overall input text. This condition guarantees that the relevant words can be utilized when constructing the text vectors. Every word is converted into vectors using Lexicon to vector approach. To obtain better representation of vectors, a transformer structure is used by the BERT model to acquire contextual knowledge. The model makes extensive use of a multi-headed self-attentive mechanism to mine the data.

4.3 Feature selection

Feature selection is the process of eliminating duplicate and unnecessary information from a dataset using evaluation criteria to increase accuracy [35]. The use of metaheuristic algorithms has been crucial in the solving of complex issues [36]. The higher dimensionality features may tend to maximize the computational complexity whereas precise outcomes cannot be obtained. Hence from the extracted features, the most optimal features of diverse text attributes are chosen using ACoaT algorithm.

Each process in the algorithm is described with a detailed formalisation in Eq. (4) to Eq. (14). The list of annotations used in this model are shown below.

Z_p position of the feature in search space
$Z_{p,q}$ value of the feature
X Number of features
F objective function
Iguana search space position of iguana
Low , Upp lower and upper bounds of the decision variable
T iteration counter
T_c tent chaotic map
t maximum number of iterations

The Coati optimization algorithm [28] is developed on analysing diverse coati behaviours. The coati positions or the features are initialized randomly using the below expression.

$$Z_p : z_{p,q} = Low_q + Random(Upp_q - Low_q), \text{ where } p = 1,2,3,\ldots,X,\ q = 1,2,3,\ldots, \tag{4}$$

Here, Z_p indicates the position of p^{th} feature in search space, $z_{p,q}$ symbolises the value of q^{th} variable and X specifies the number of features. Low_q and Upp_q signifies the lower and upper bound of q^{th} decision variable. Random represents the random real number between the range 0 to 1.

The strategy of attacking and hunting iguanas

The initial stage, known as the exploration phase, modifies the search space's properties while using the fitness function of minimised error rate. The place of best solution among the features is considered as the iguana position. According to popular belief, some coatis climb the tree while others wait for the iguana to fall. The following can be used to indicate how coati's position is updated at each iteration.

$$Z_p^{t+1} : z_{p,q}^{t+1} = z_{p,q} + Random(Iguana_q - \delta . z_{p,q}), \text{ where } p = 1,2,\ldots[X/2], q = 1,2,\ldots,Y \tag{5}$$

From the above expression, δ specifies the integer chosen randomly as equal to 1 or 2. The iguana is placed in an arbitrary location inside the search area as it hits the ground. The coatis move and are replicated in the following expressions based on it.

$$\mathrm{Iguana}_G: \mathrm{Iguana}_G^q = \mathrm{Low}_q + \mathrm{Random}(\mathrm{Upp}_q - \mathrm{Low}_q), \text{ Where } q = 1,2,3,\ldots Y \quad (6)$$

$$Z_p^{T1}: z_{p,q}^{T1} = \begin{cases} z_{p,q} + \mathrm{Random}(\mathrm{Iguana}_G^q - \delta . z_{p,q}), & F_{\mathrm{Iguana}_G} < F_p \\ Z_{p,q} + \mathrm{Random}(z_{p,q} - \mathrm{Iguana}_G^q), & \text{else,} \\ \text{for } p = \left\lfloor \frac{X}{2} \right\rfloor + 1, \left\lfloor \frac{X}{2} \right\rfloor + 2, \ldots X \text{ and } q = 1,2,\ldots Y \end{cases} \quad (7)$$

If the new coati position meets the fitness function, it can be updated at a reasonable cost; if not, the original position is retained. The revised strategy for $p = 1,2,\ldots. X$ is simulated using the below given expression.

$$Z_p = \begin{cases} Z_p^{T1}, & F_p^{T1} < F_p \\ Z_p, & \text{else} \end{cases} \quad (8)$$

From the above expressions, Z_p^{T1} denotes the new position estimated for p^{th} coati, $Z_{p,q}^{T1}$ denotes its q^{th} dimension, F_p^{T1} indicates the objective function and Iguana indicates the search space position of iguana. Iguana_G shows the iguana position on ground. F_{Iguana_G} indicates the objective function value, $\lfloor . \rfloor$ represents the greatest integer function.

The technique of escaping from predators

The animal flees from its place during the exploitation phase when it is attacked by a predator. In order to replicate the updating behaviour, a random position is generated in close proximity to the current coati location, as stated below.

$$\mathrm{Low}_q^{Local} = \frac{\mathrm{Low}_q}{T}, \mathrm{Upp}_q^{Local} = \frac{\mathrm{Upp}_q}{T}, \text{ Where } T = 1,2,3,\ldots t \quad (9)$$

$$Z_p^{T2}: z_p^{T2} = z_{p,q} + (1 - 2\mathrm{random}).\left(\mathrm{Low}_p^{Local} + \mathrm{Random}(\mathrm{Upp}_p^{Local} - \mathrm{Low}_p^{Local})\right), \text{ where } p = 1,2,\ldots,X, \; q = 1,2,\ldots,Y \quad (10)$$

The newly estimated point is adequate if it enhances the actual function value and the requirement simulates using the below given expression.

$$Z_p = \begin{cases} Z_p^{T2}, & F_p^{T2} < F_p \\ Z_p, & \text{else} \end{cases} \quad (11)$$

The new position estimated for p^{th} coati based on exploitation phase is denoted as Z_p^{T2}. The q^{th} dimension is denoted as $Z_{p,q}^{T2}$, F_p^{T2} denotes the objective function value, T indicates the iteration counter, Low_q^{Local} and Upp_q^{Local} represents the lower and upper bound of q^{th} decision variable. The ACoaT algorithm is utilised to improve the efficiency of selection performance. Tent chaotic map is used in the initialization strategy to swap random generation, and equation (4) can be rephrased as follows:

$$Z_p: z_{p,q} = \mathrm{Low}_q + T_c(\mathrm{Upp}_q - \mathrm{Low}_q), \text{ where } p = 1,2,3,\ldots,X, \quad q = 1,2,3,\ldots,Y \quad (12)$$

$$T_c^{t+1} = \begin{cases} \frac{T_c^t}{k}, & \mathrm{Tent}^t \in (0,k) \\ \frac{1-T_c^t}{1-k}, & \mathrm{Tent}^t \in (k,1) \end{cases} \quad (13)$$

The coati position is adjusted using T_c tent chaotic map that assists to enhance the global searching performance. During the attack phase, the coati position is updated by the dynamic weight factor ρ. At the iteration end, ρ reduces adaptively where the coati performs a well local searching by maximizing the speed of convergence. Equation (7) can be reframed as below.

$$Z_p^{T1}: z_{p,q}^{T1} = \begin{cases} \eta = \frac{e^{2(1-\frac{t}{T})} - e^{-2(1-\frac{t}{T})}}{e^{2(1-\frac{t}{T})} + e^{-2(1-\frac{t}{T})}} \\ z_{p,q} + \mathrm{Random}(\mathrm{Iguana}_G^q - \delta . z_{p,q}), \\ F_{\mathrm{IguanaG}} < F_p \\ z_{p,q} + \mathrm{Random}(z_{p,q} - \mathrm{Iguana}_G^q), \text{ else} \end{cases} \quad (14)$$

The iteration counter and the maximum number of iterations are represented by the expression above. By selecting only, the most relevant features for prediction, this technique helps to solve the dimensionality problems by identifying the best features. One of the research works reiterates that, contrary to many other metaheuristics, interacting with as many individuals as possible has been shown to be more effective than doing so with only a limited group of people [40].

4.4 Grouping of features

The selected features are clustered into diverse groups based on feature similarity using Uden_KMC model. The K-means Clustering Algorithm (KCM) [29] is a separation-based cluster analysis approach. The initial step of KCM is to choose R number of objects or features as primary cluster centres. Assign each data point to the cluster associated with the nearest centre. The average of all data points assigned to each centroid is calculated. This average becomes the new centroid for the cluster. Each centroid is moved to the mean of its associated data points. The process is repeatedly carried out until a better convergence is accomplished. The KCM is extremely delicate over principal cluster centres and hence the clustering results vary based on principal cluster centres. This influences the mean point valuation, diverges the cluster center and so declines the clustering result. Hence, Uden_KMC approach is employed for clustering in the proposed method.

In density based outlier detection, k- nearest neighbour (knn) distance and k-neighbourhood of every object is created primarily by Local Outlier factor (LOF). The distance between every object in its k-neighbourhood is estimated. Finally, the local outliers are identified by LOF and the outlier detection process is given as follows. The list of annotations used in Eq. (15) to Eq. (19) are shown below.

u object

(u,v) KNN distance

n Number of Features

Lde Local Density Estimator

LOF Local Outlier Factor

r Number of Features as primary cluster centers

R number of objects or features as primary cluster centres

Step 1: Estimate the knn distance as $(u, v)(v \in N_k(u))$ of every object u. The distance (u, v) is expressed as the straight distance connexion between objects $u$and$v$,

$$\mathrm{Distance} = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \dots\dots + (a_n - b_n)^2} \quad (15)$$

In the above expression, $n$represents the number of features.

Step 2: Assess the object density of u and it replicates the neighbourhood data distribution represented as the reciprocal of knn mean. The knn local density of u is indicated below. 'r' is the number of features as primary cluster centres.

$$\mathrm{Lde(u)} = \frac{1}{\frac{1}{r}\sum_{s=1}^{r} \mathrm{Dist(u,v)}} \quad (16)$$

Where Lde is Local density estimator.

Step 3: Estimate the LOF value of$u$.

$$\mathrm{LOF(u)} = \frac{\sum_{s=1}^{r} \frac{\mathrm{Lde(v)}}{\mathrm{Lde(u)}}}{r} \quad (17)$$

Where LOF is Local Outlier Factor

The knn local density of $u$is indicated as Lde(u) and LOF(u) replicates the extent of $u$as an outlier. If LOF(u) is particularly greater than 1, $u$subjects to be isolated and so the object is not considered. The generated features are clustered using Uden_KMC model and the procedure is listed as follows. The features to be clustered are $C\{f_1, f_2, \dots . f_n\}$ and the output is to accomplish 'n' number of clusters. In Uden_KMC model, LOF(u) is evaluated using equation (17) and if LOF(u) value is greater than one, the isolated points are eradicated. The mean of F features is estimated as the first cluster center which is given as follows.

$$\mathrm{F_1} = \frac{1}{r}\sum_{s=1}^{r} \mathrm{W_s} \quad (18)$$

Evaluate the following cluster center and then assess the distance between cluster center and residual points using the below expression.

$$\mathrm{M_r} = \sum_{l=1}^{R} \mathrm{Max}(z_{k-1}^{l} - \|W_r - W_l\|^2, 0) \quad (19)$$

From the above expression, W_r indicates the sample point whose M_r is the largest upcoming cluster center. Assess the distance between every $W_s$object, cluster center and allocate to the nearby cluster. Repeat the distance and mean calculation until active convergence is accomplished. Through Uden_KMC model, the isolated feature points are lost from the data and the similar features of student review data can be grouped into diverse clusters.

4.5 Recommendation model for better solutions

From the generated clusters, the performances of educational institution based on student feedback are predicted and suitable solutions can be recommended based on the prediction. This can be performed using a novel hybrid DL model called ChaBD-BiL. Here, Channel Block densenet is used for prediction whereas the educational feedback given by the student can be predicted as good, not bad, and poor. Based on the predicted outcomes, Dilated Convolution BiLSTM recommends for a suitable solution to overcome the issues. The BiLSTM model effectively addresses the issues of parameter count and data stability [37]. Fig. 4 describes the schematic representation of proposed ChaBD-BiL model.

The DenseNet-201 construction learns the attributes by utilizing its learnable weights. It is parametrically effectual because of likelihood of feature reuse using diverse layers. Straight links are obtainable from all preceding layers through following layers to indorse connectivity. In order to effectively optimise features, CBAM(Convolutional Based Attention Module), an efficient attention module, infers the attentional map along channel and spatial dimensions. To obtain weighted results, the characteristics are first passed via the channel attention module and then the spatial attention module to obtain the final weighted results. The list of annotations used in Eq. (20) to Eq. (29) are shown below.

F	*Feature map*
C(F)	*Channel attention module*
S(F)	*Spatial attention module*
λ	*Sigmoid function*
AP	*Average Pooling function*
MP	*Maximum Pooling function*
MLP	*Multi layer perceptron*
W	*Weight matrix*
B	*Bias factor*

The following is the evaluation formula for the channel and spatial attention modules.

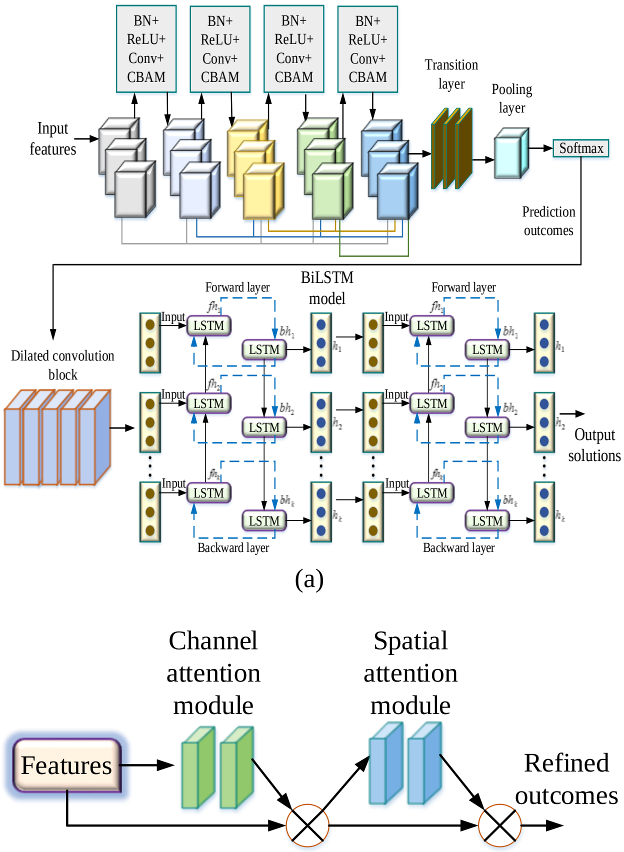
$$C_A(F) = \lambda(MLP(AP(F) + MLP(MP(F)))) \quad (20)$$

$$S_A(F) = \lambda\left(F\left(Concat(AP(F), MP(F))\right)\right) \quad (21)$$

From the above expressions, F indicates the feature map, $C_A(F)$ denotes the channel attention module and $S_A(F)$ indicates the spatial attention module, λ represents the sigmoid function, AP indicates average pooling function, MLP indicates Multi – Layer Perceptron and MP represents maximum pooling function. The feature concatenation can be expressed as below.

$$F^I = N_I([F^0, F^1, \ldots\ldots, F^{I-1}]) \quad (22)$$

From the above expression, $N_I(.)$ signifies the non-linear transformation that is represented as a composite function including Batch Normalization (BN), ReLU, Convolution and CBAM. The amalgamation of feature maps equivalent to layer 0 to $I-1$can be designated as$[F^0, F^1, \ldots\ldots F^{I-1}]$. For the purpose of down sampling, dense blocks comprising of BN, convolutional, ReLU, CBAM and average pooling layers are produced. The pooling layer slowly reduces the size of feature to diminish the parameters and prediction complexity. The grouping of feature maps from dense block is carried out and the dimensions are minimized through the transition layer. Finally, the features can be predicted into good, not bad and poor. From this, the performance outcomes of educational institution can be predicted based on the student review data. Corresponding to the predicted outcomes, the solutions can be recommended using Dilated Convolution BiLSTM to enhance the educational institution performance. The dilated convolution can subjectively increase the receptive field of small convolution kernels to enhance the recommendation accuracy. Without maximizing the number of parameters, the Dilated Convolution BiLSTM can sample the underlying feature maps. The neurons present in the LSTM [30] model comprises of output gate, input gate, forget gate and memory cell. The forget gate is used for data identification from the



(a)

(b)

Figure. 4 Model architecture of (a) ChaBD-BiL (b) CBAM module previous state m_{t-1} that is not to be remembered based on current input.

$$d_t = \phi(W_{ud}u_t + W_{vd}m_{t-1} + B_d) \tag{23}$$

From the above expression, φ means sigmoid activation function, W_{ud} indicates the weight matrix between u_t and d_t. W_{vd} signifies the weight matrix between m_{t-1} and d_t. The trainer input at time t is indicated as d_t, output of previous hidden layer is meant as m_{t-1} and the bias factor is given as B_d. Similarly, the input gate can be expressed as follows.

$$e_t = \phi(W_{ue}u_t + W_{ve}m_{t-1} + B_e) \tag{24}$$

The output gate can be mathematically expressed as follows.

$$g_t = \phi(W_{ug}u_t + W_{vg}m_{t-1} + B_g) \tag{25}$$

The final results of LSTM cell are cell output state(C_t) and layer output (m_t) which can be given as follows.

$$C_t = d_t \otimes C_{t-1} + e_t \otimes \widehat{C_t} \tag{26}$$

$$m_t = g_t \otimes \tanh(C_t) \tag{27}$$

The intermediate cell input state is meant as $\hat{C}_t$ and it can be expressed as follows.

$$\widehat{C_t} = \tanh(W_{uc}z_t + W_{vc}m_{t-1} + B_c) \tag{28}$$

As, LSTM cannot use the suitable information, BiLSTM includes both LSTMs that assimilate information from mutual directions. The forward LSTM directs the input from left to right and evaluates the hidden state ($\overrightarrow{m}_t$) based on z_t and $\overrightarrow{m}_t - 1$. The backward LSTM directs the input from right to left and examines $\overleftarrow{m}_t$ hidden state based on z_t and $\overleftarrow{m}_t - 1$. In a BiLSTM network, the forward and backward parameters are unrelated to one another. The final hidden state of BiLSTM model integrating the forward and backward directional vector at time (t) can be expressed as follows.

$$m_t = [\overrightarrow{m_t}, \overleftarrow{m_t}] \tag{29}$$

Through the proposed ChaBD-BiL model, the solutions like minor improvements are required, no further improvement required and need to improve a lot can be recommended effectively. Based on the recommendation decisions obtained from student review data, the educational institution can promote appropriate actions.

Table 3. Hyper parameter details

Sl. No	Hyper-parameters	Proposed model
1.	Batch size	60
2.	Initial learning rate	0.0001
3.	Learning algorithm	Adam
4.	Maximum epoch size	100
5.	Activation function	ReLU
6.	Maximum iteration	100

5. Results and discussion

The proposed ChaBD-BiL model is explored with varied stages like pre-processing, feature extraction, selection, clustering, and recommendation. The experimental outcomes of the proposed ChaBD-BiL model are signified in this section. The performances of the proposed model are evaluated using PYTHON simulation platform. Various existing approaches are associated with the recommended model to evaluate the performance. The dataset details, description of the performance metrics and its mathematical formulation, performance analysis and analogy are established in the succeeding sections. Combining and changing the different parameters can affect the accuracy of the machine learning algorithms [33]. Table 3 illustrates the hyper parameter setting of suggested model.

5.1 Dataset description

Student review dataset is utilized in the proposed model and has been collected from online Kaggle source given as follows https://www.kaggle.com/datasets/brarajit18/student-feedback-dataset?resource=download . The dataset is acquired from North India students belongs to a prominent university. The overall institutional report is gathered based on the student feedback data. The dataset includes six categories like course content, teaching, library facilities, examination, lab work and extracurricular activities. In addition to the dataset some attributes like accommodation facilities, hostel food facility, transport facility, cleanliness, canteen, prediction outcomes and recommendation solution are added manually.

Table 4. Performance metrics and its formulation

Performance Metrics	Description	Mathematical formulation
Accuracy	Accuracy can be defined as the total of true positive and false metrics added to the total of true and false metrics.	$A = \frac{W + X}{W + X + Y + Z}$ W -True positive, X -True negative, Y -False positive, Z -False negative.
Kappa	The stability of prediction and employment of probabilistic assessments amongst the predictable scores in case of agreement and disagreement is terms as Kappa Score.	$K = \frac{\lambda_0 - \lambda_f}{1 - \lambda_f}$ λ_0- Score agreement between predicted and actual value λ_f- Score disagreement between actual and predicted ones.
Specificity	Specificity is the quantity of negative results to the total sample that are actually negative.	$SPE = \frac{X}{X + Y}$ X -True negative, Y -False positive,
F1 score	The combination of precision and recall to a single value is termed an F1 score.	$F1S = 2 * \frac{PPV * TPR}{PPV + TPR}$ PPV - Positive predictive value TPR -True positive rate
Sensitivity	Recommendation outcomes are highly sensitive if the data produces positive cases.	$SEN = \frac{W}{W + Z}$ W -True positive, Z -False negative.
MAE	The prediction error between predicted and actual outcomes is called MAE.	$MAE = \frac{\sum_{p=1}^{M} \left\| x_p - y_p \right\|}{M}$ x -Predicted value, y -Actual value M-Total samples
RMSE	RMSE designates the standard deviation of recommendation errors.	$RMSE = \sqrt{\frac{\sum_{p=1}^{M} \left(x_p - y_p\right)^2}{M}}$ x -Predicted value, y -Actual value M-Total samples

5.2 Performance metrics

The proposed recommendation model can be evaluated on considering diverse metrics like Accuracy, Sensitivity, Specificity, F1 score, Kappa, mean absolute error (MAE) and Root mean square error (RMSE). The performance metrics are described with its mathematical formulations for examining the proposed performance in Table 4.

5.3 Baseline model comparison analysis

The Proposed model is associated with several existing approaches to prove the superiority of the proposed approach. The existing methodologies like auto encoder (AE), deep convolutional neural network (DCNN), bidirectional gated recurrent unit (BiGRU) and BiLSTM are considered for comparison. The performance outcomes in terms of diverse evaluated metrics like Accuracy, Sensitivity,

Table 5. Performance comparison analysis

Performance outcomes (%)	Techniques				
	AE	DCNN	BiGRU	BiLSTM	Proposed
Accuracy	88.10	89.90	91.71	93.15	98.19
Sensitivity	78.75	87.14	89.00	90.63	97.41
Specificity	79.97	89.58	90.45	92.66	98.25
F1 score	68.14	72.48	74.49	76.52	91.28
Kappa	44.59	71.17	71.80	75.33	91.28
MAE	0.18	0.16	0.13	0.11	0.03
RMSE	0.42	0.43	0.37	0.37	0.21

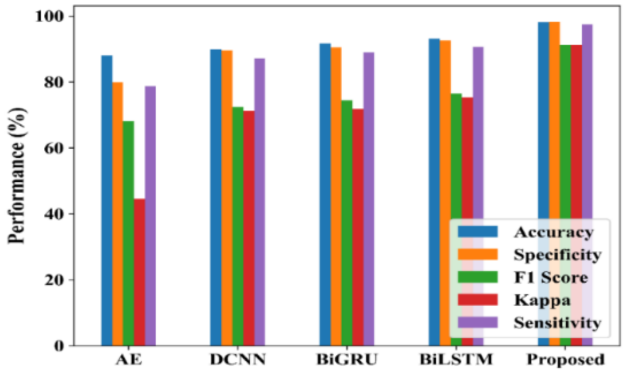


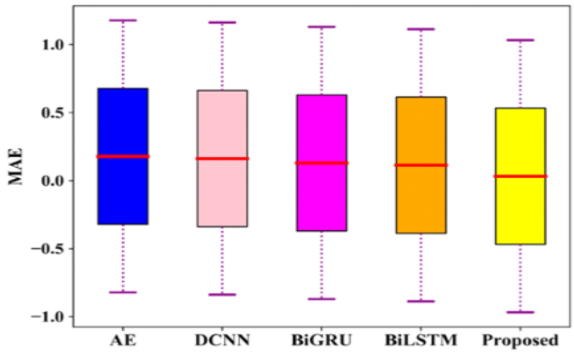
Figure. 5 Performance Comparison of recommendation models

Specificity, F1 score, kappa, MAE and RMSE are showed in Table 5.

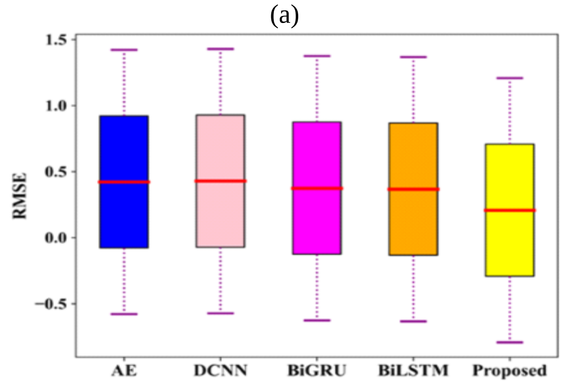
From the below table, it can be obviously analysed that the proposed model obtained better performance outcomes compared to the existing approaches. The performance of the proposed model is analyzed by comparing to the existing models like AE, DCNN, BiGRU and BiLSTM.

The above graphical represents clearly that the accuracy of proposed ChaBD-BiL model in solution recommendation based on the student review data is 98.19%, sensitivity as 97.41%, specificity as 98.25% and F1 score as 91.28%. Better accuracy rate can be obtained by focussing over the most appropriate features through effectual procedures for processing text data. Improved training ability and only slight errors are perceived by handling optimal features. The existing models like AE, DCNN, BiGRU and BiLSTM has accomplished less performance than the proposed model because of certain drawbacks like huge accumulation of features, high testing time, less convergence and less feature learning capability. Figure 6 (a)-(b) indicates the performance attained by the proposed and existing techniques in terms of MAE and RMSE.

For an enhanced recommendation model, the MAE and RMSE value must be less. The MAE and



(a)



(b)

Figure. 6 Error performance analysis: (a) MAE and (b) RMSE

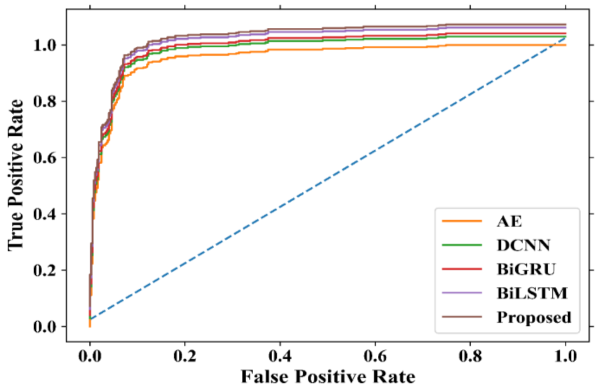


Figure. 7 ROC analysis of Existing & Proposed models

RMSE performance of proposed ChaBD-BiL model and existing models are analysed.

From the above graphical representation, the proposed RMSE is attained to be 0.21 and MAE as 0.03 respectively. When compared to the MAE and RMSE value of proposed model, existing models attained increased error rates. Because of the use of incapable features, the existing models are highly prone to increased error rate. Hence, it can be justified that the proposed model has obtained lesser rates of MAE and RMSE. Fig. 7 illustrates the ROC curve analysis of proposed and existing models.

The ROC curve is examined in terms of false positive rate (FPR) and True positive rate (TPR). The optimum cut-off depicts the supreme TPR or

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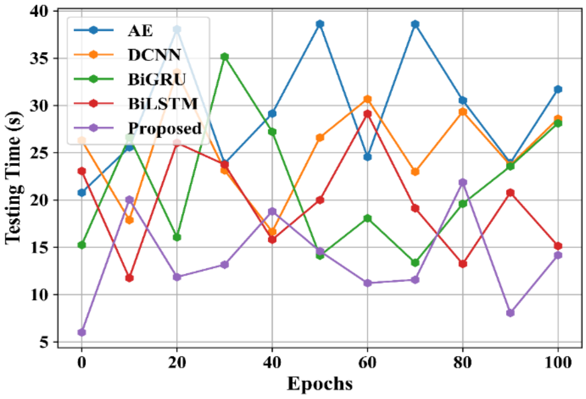


Figure. 8 Testing time analysis

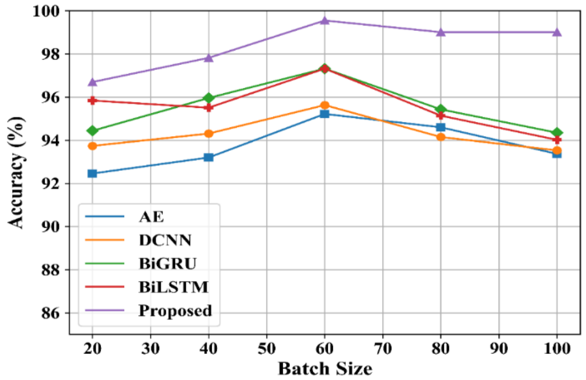


Figure. 9 Accuracy Vs Batch size performance analysis

sensitivity with least FPR or specificity. The ROC curves are often investigated to expose the trade-off between TPR and FPR for every probability. It designates the efficacy of recommendation model and it denotes the degree of ability in predicting the feedback performance. Higher the rate of ROC indicates better the performance of recommendation model. Fig. 8 depicts the testing time analysis of Proposed and Existing methods in terms of student feedback dataset.

When comparing the testing time of proposed ChaBD-BiL model with existing approaches, the proposed testing time is highly lesser than the existing methods like AE, DCNN, BiGRU and BiLSTM. The testing time performance is analysed by varying the epoch size from 0 to 100. The proposed recommendation model has attained 14.17 seconds for testing whereas the existing AE obtained 31.71 seconds,

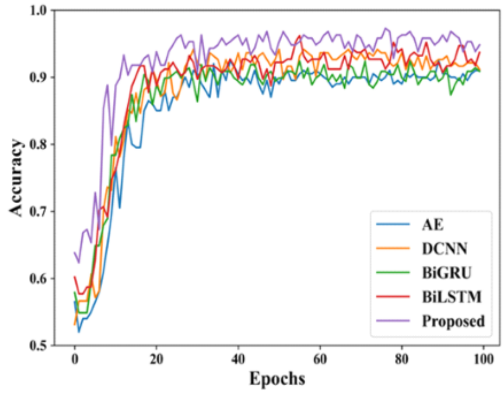
DCNN as 28.59 seconds, BiGRU as 28.11 seconds and BiLSTM as 15.14 seconds respectively. Because of huge accumulation of features, degraded learning ability and less convergence, existing approaches obtained enhanced testing time. Through this analysis, *It is clearly evident that the proposed algorithm offers a better performance.* Fig.9 indicates the accuracy performance by varying the training batch sizes.

The batch size is denoted as the amount of training data required for single iteration. The suggested model analyses the performance of accuracy under varying batch sizes and, the obtained outcome is compared with different existing techniques. The performance of proposed model is analysed by varying the batch size from 20 to 100 whereas higher accuracy is attained when the training batch size is set to be 60.

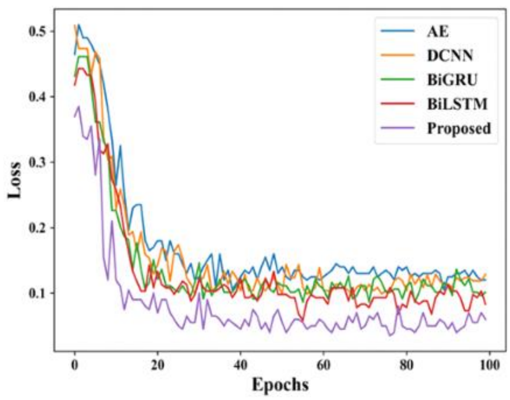
5.4 Accuracy and loss evaluation measures

The accuracy and loss of the proposed ChaBD-BiL model for solution recommendation are analysed with testing data. In the proposed research work, 80% of data is used for model training and 20% is utilized for model testing. The accuracy and loss performance obtained during testing stages in processing student review data are provided as follows. Figure 10 (a)-(b) indicates the testing performance analysis in terms of accuracy and loss.

To evaluate the learning performance of the commended ChaBD-BiL model, the Accuracy and loss curves are analysed. The accuracy and loss under testing phases are assessed by varying the epoch size from 1 to 100 consecutively.



(a)



(b)
Figure. 10 Testing curve analysis: (a) Accuracy and (b) Loss

Due to increased epoch size, increase in accuracy and decrease in loss may happen. The existing models like AE, DCNN, BiGRU and BiLSTM are analysed with respect to testing data. The testing phase of these existing methods were found to be slower than the proposed model and so reaching of greater accuracy is complicated. The existing models consumes more time for testing and so the computational time tends to be high. In the loss curve, the proposed testing loss gets diminished in case of increased epoch size. When compared with the existing architectures, the proposed recommendation model obtains higher accuracy with condensed loss. High losses are attained in the existing approaches because of increased time complexity, degraded training ability and convergence issues.

6. Conclusion

In the proposed research work, precise recommendation of solutions can be obtained based on the student feedback data to enhance the educational institution performance using novel approaches. Here, student feedback data was collected from Kaggle source and some of the attributes were added manually. The text data was pre-processed using Stemming, Tokenization, case - folding and stop - word - removal procedures. Effective features were extracted using ELexBert model and the most significant features were selected using ACoaT algorithm. The selected features were clustered using Uden_KMC model based on feature similarity. A novel hybrid DL based ChaBD-BiL model was employed for recommending better decisions. The drawbacks like degraded training ability, overfitting, time consumption and convergence issues were overcome through efficient learning of input data. The recommendation performances are analysed using PYTHON simulation platform whereas the overall accuracy of 98.19%, specificity of 98.25%, F1 score of 91.28%, sensitivity of 97.41% and Kappa score of 91.28% are obtained. Lesser rates of MAE as 0.03 and RMSE as 0.21 were obtained due to effective utilization of optimal features. Also, the testing time was less in recommending an appropriate solution for the input data. In future, the proposed work can be extended further with the utilization of larger datasets. Also, the consideration of features will be more optimal with the adoption of enhanced hybrid optimization strategies to enhance the recommendation accuracy.

Conflicts of Interest

The authors have no conflicts of interest to declare. All co-authors have seen and agreed with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

Author Contributions

Conceptualization, methodology, software, validation, formal analysis, writing-original paper draft, Naga Jyothi; writing-review and editing, Dr. Uma Dulhare; visualization, Naga Jyothi; supervision, Dr. Uma Dulhare.

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