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A DISTRIBUTED DEEP LEARNING FRAMEWORK FOR THE OPTIMIZATION OF ONLINE LEARNING UTILIZING ATTENTION-BASED BILSTM

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Abstract

Online learning has transformed education by making it more accessible and flexible—but it still faces key challenges, especially when it comes to understand- ing how well students are engaging and learning. In this work, we introduce a data-driven framework designed to optimize online course performance by look- ing beyond just grades. Our approach combines insights from student academic data and real-time visual feedback to build a more complete picture of learning effectiveness. First, we analyze students' academic performance data using an Attention-Based Bidirectional LSTM (ABi-LSTM) model, which helps identify patterns in learning progress and assigns an initial performance score. Next, we take video recordings of students during course sessions and examine their facial expressions to assess engagement levels. These visual features are extracted using a Vision Transformer and again processed with ABi-LSTM to generate a second score. By combining both scores, our system provides a deeper and more person- alized evaluation of student performance. Compared to conventional methods, this integrated framework shows improved accuracy and responsiveness, offering a smarter way to support and enhance online learning experiences.

Keywords: Online Course Optimization Framework; Education Data Driven; Statistical Features; Vision Transformer; Attention- based Bidirectional Long Short-Term Memory

1 Introduction

Online learning (OL) is the process of using various tools such as computers and mobile

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devices to engage in learning activities that can occur in real-time (synchronous) or at different times (asynchronous) [6]. Recently, online learning (OL) has gained pop- ularity due to its enhanced flexibility in terms of location and time. The pace of study on online platforms, as well as the variety of courses offered, is considered the most significant development [7]. In addition, the student can acquire knowledge and engage in communication with colleagues and students from any location by utilis- ing this online learning platform [8]. Furthermore, the acquisition of resilient digital platforms and infrastructure enables enhanced data collection interactivity and online course delivery. Furthermore, there is a requirement for a novel approach to engage in dynamic and autonomous learning for both students and teachers [9]. Therefore, a feasible evaluation method was employed to ensure the overall efficacy of online edu- cation [10]. Furthermore, colleges and universities have the capacity to fulfil learning objectives and enhance the process of measuring student satisfaction levels (SSL) [11]. Additionally, SSL is utilised to assess the elements influencing the perceived perfor- mance of educational services during the study period [12]. The promotion of OL tools has greatly expanded educational opportunities beyond traditional academic settings [13]. The constraint in effectively overseeing and involving students is in the online instructional program [14]. The student's utilisation of the Internet in instructional activities has been established by means of an e-learning software. In recent years, spe- cific standards have been established for the design of online classes. In addition, the researchers have developed a system in which student satisfaction is noticeably higher and is positively affected by the quality of online courses [15]. The implementation of several strategies to enhance the quality of online learning is of utmost importance in global standards. Some programs provide international criteria for detecting common- alities in online learning (OL), which are used to advise policymakers, academics, and government agencies on the key requirements for effective OL [16]. Machine learning and Artificial Intelligence (AI) are used efficiently to address several issues relating to the human environment, consumer behaviour, cyber security, and the health sector. These applications have had a significant impact on society[17]. Furthermore, in recent years, the educational system has relied on virtual blackboard teaching, smart class- rooms, online teaching, as well as machine learning and AI, which have significantly contributed to the delivery of high-quality education [18]. An intelligent tutoring sys- tem has the capability to effectively adjust to the learning style and preferences of the students [19]. Furthermore, the end-to-end video-dependent deep learning tech- niques are specifically developed to determine the extent of a student's engagement in online e-learning. In this approach, consecutive video frames are inputted into Convo- lutional Neural Networks (CNNs) [20]. One significant drawback of image-dependent approaches is their reliance on spatial information from a single frame or image. This research study implements an education data-driven online course optimisation framework employing ABi-LSTM. Below are some notable aspects of this research endeavour.

- The objective is to develop an education data- driven online course optimisa- tion framework employing ABi-LSTM to enhance students' learning potential and capabilities.
- The objective is to develop a vision transformer model that can extract face expression features from students learning in a video.

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- The ABi-LSTM is developed to validate the learning ability by integrating two projected scores. This is done to detect the teaching and learning efficiency and ultimately select the best e-learning system to enhance the efficiency of online courses.
- To assess the effectiveness of the provided education data-driven online course optimisation framework compared to alternative methods.

The subsequent section in the provided model is enumerated below. Part II of the work consists of a literature survey. Part III provides an architectural view of an education data-driven online course optimization framework, including a description of the dataset. Part IV focusses on feature extraction and the use of ABi-LSTM for selecting the learning platform. Part V presents the conclusion, and Part VI presents the results.

2 Literature Survey

2.1 Related Work

In 2022, Abdelkader et al. [1] utilised ”Feature Selection (FS)” to identify the most suitable subset of features. Additionally, a comprehensive analysis was conducted to examine the efficacy of SSL techniques in conjunction with FS approaches using the predictive satisfaction model. Furthermore, the quality of subsets with different cardinalities was assessed based on their prediction accuracy and the number of selected features. The performance of FS algorithms was used as the benchmark for comparison. Furthermore, the ideal dimensionality of the features enhances the prediction accuracy to its maximum potential In 2023, Nasser developed machine learning algorithms designed to assess student performance, thereby enhancing the quality of online training programs in accordance with the online learning criteria established by the Kingdom of Saudi Arabia (KSA).The primary objective of this model was to assess the performance of the academy by taking into account participation in an online learning environment. The Support Vector Machine (SVM) was utilised for the prediction process. Furthermore, the most relevant characteristics were identified through the application of optimization techniques, followed by subsequent classification processes. The sample assessment of the quality assurance of online training was validated to facilitate the detection and subsequent application of descriptive-analytical methodologies. In 2022, Al-Zawqari et al. [3] created a versatile methodology to identify and assess academic student performance. In addi- tion, the framework has been utilised in conjunction with multiple classifier models.

The selection of features was contingent upon the interpretability of the model. The anticipated outcomes of the adaptable feature selection model exceed expectations and are subsequently incorporated into the model. Furthermore, the prediction model exhibits a superior level of accuracy when it comes to forecasting students who are likely to drop out. In 2021, Bhardwaj et al. [4] developed a deep learning algorithm model that effectively tracks and analyses the emotions of students in real-time, including surprise, sadness, hap- piness, fear, rage, and other emotions. The ”Mean Engagement Score (MES)” is used to validate the proposed model by combining facial landmark detection with sur- vey weights to assess student behaviour. The

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implemented automated procedures will efficiently assist educational institutions in achieving a cutting-edge digital learning paradigm. In 2022, Selim et al.[5] introduced the ”Videos Recorded for Egyptian Stu- dents Engagement in E-learning (VRESEE)” as a method for detecting the amount of student participation in online e-learning. This model was developed to identify the progress of students in online e- learning videos using three innovative hybrid deep learning techniques. The three created models yield superior outcomes compared to the results of the already existing model.

Table 1 ADVANCEMENT AND LIMITATION OVER CLASSICAL ADVANCEMENT LEARNING-BASED ONLINE COURSE OPTIMIZATION MODEL

Author [citation]	**Methodology**	**Features**	**Challenges**
Abdelkader et al. (2022)	FS	It is highly useful in increasing the predic- tion accuracy	But it acquires more time for computation time, and it also needs high memory.
Nasser (2023)	ML	It is used to han- dle multi-dimensional data. It is used to iden- tify various patterns.	It needs more data to perform efficiently. The error rate is high.
Al-Zawqari et al. (2022)	RF and ANN	It can perform classi- fication and regression tasks. It can efficiently manage huge amounts of datasets.	It requires more train- ing. It acquires less accuracy.
Bhardwaj et al. (2021)	DL	It is used to retrieve high-level features. It is used to evaluate the mean engagement score.	It requires high com- putational costs. It is hard to train.

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Selim et al. (2022)	VRESEE	It is used to reduce vanishing gradient problems. It provides high classification accuracy.	It requires two sepa- rate models. It is slow and needs more train- ing.

2.2 Problem Specifications

The implementation of AI-based online learning platforms has a significant impact on the quality assurance of courses, often resulting in unfavourable rankings. E-learning systems may encounter issues related to quality assurance and accreditation. Consequently, it complicates the learning process. Table I presents the characteristics and difficulties of current online course optimisation strategies based on deep learning. Feature selection (FS) is extremely valuable in enhancing the accuracy of predictions. Nevertheless, the procedure necessitates an extended computational duration and requires a substantial amount of memory.Machine learning (ML) is employed to process data with several dimensions and to detect different patterns. However, in order to operate optimally, it requires additional data and exhibits a significant error rate. Random Forest (RF) and Artificial Neural Networks (ANN) are proficient in executing classification and regression tasks. Furthermore, they are capable of managing extensive datasets. However, these methods require additional training and tend to achieve lower accuracy levels. Deep Learning (DL) is utilized to extract high-level features and evaluate the average engagement score. Nonetheless, it requires substantial computational resources and presents challenges in the training process. VRESEE [5] helps solve the problem of vanishing gradients and makes classification more accurate. But it needs two different models, works slowly, and requires a lot of training.

3 Architectural View of Education Data-Driven Online Course Optimization Framework: Dataset Description

3.1 Proposed Model and Description

With the fast growth of the internet, online courses have greatly changed how colleges and universities teach.Furthermore, with the outbreak of COVID-19, the courses have transitioned from being conducted in person to being delivered online. While online courses have addressed the problem of students' atten- tiveness, the quality of learning remains a significant concern, and many challenges continue to arise. The primary constraint in the online course arises from the teacher's inability to adequately obtain input from students throughout course creation, leading to a lack of balanced information. Therefore, there is a deficiency in appropriate qual- ity assurance procedures for the online course, and the implementation of the mixed teaching reform is constrained in terms of its objectives and operational enhancement plan. The improvement of online education quality is a crucial matter that cannot be overlooked in the advancement of higher education. Furthermore, the consideration of both quantitative and qualitative analysis is significant. Hence, this study has created an

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education data-driven online course optimization framework utilizing ABi-LSTM. The graphical representation of this framework can be seen in Figure 1.

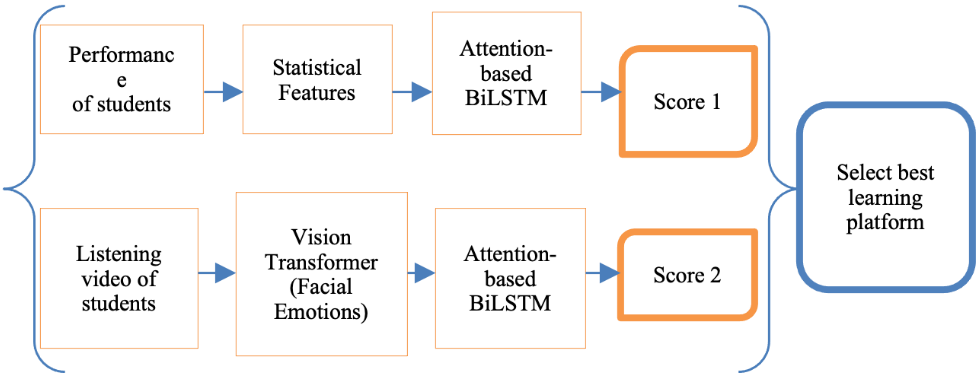

Fig. 1 Education data-driven online course optimization depiction

Consequently, an advanced machine learning-based model for online course optimization is employed to augment students' learning capacity.Initially, the performance of students is consol- idated from several web sources. The statistical features are efficiently derived from the aggregated student performance data to enhance the efficiency of the proposed model. Subsequently, the ABi-LSTM model was employed to assess the capacity of the learning mechanism, yielding a score of 1. In the second phase, the student's video of listening is collected and the facial emotions captured in the video are used as input to determine the student's learning ability. During this stage, the vision transformer is employed to acquire the features. In this context, ABi-LSTM is employed to assess the capacity for learning. The achieved value is designated as score 2. The optimal e-learning system is chosen based on the score values. The outcome of the advanced learning-based e-learning recommendation system is compared to standard approaches using several criteria.

3.2 Implemented Dataset Details

The proposed solution for optimizing online teaching is developed utilizing advanced learning methodologies. It utilizes two platforms and relies on two distinct datasets for its operation. In this model, the data in the datasets is generated by hand. Dataset 1 has information about how students perform. Dataset 2 has videos showing how students act in class and their facial expressions. Therefore, the aggregated raw data that are adequate to perform the sample video frames learning-based online course optimization models are indicated as dt^{st} and dt^{vi}, a=1,2.,A represent the total number of data that are being collected. Further, the sample images for dataset 2 are given in Fig.2.

Images	1	2	3	4
Sample images for dataset 2				

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Fig. 2 Depiction of sample video flames of student performance in online courses

4 Feature Extraction And Attention- Based Bidirectional LSTM For Selecting The Learning Platform

4.1 Statistical Features

A. Statistical Features An advanced learning-based online course optimization model is performed in two separate platforms. Here, by using the terms like mean, median, standard deviation, variance, minimum, maximum and Equinus to perform the statistical feature extraction. In one platform, the data relevant to student performance is given as the input to the feature extraction to attain the statistical features. Consequently, on the second platform, the facial expression that is attained from the data of the student listening to the class is subjected as the vision transformer model for retrieving the features. Thus, the two features attained through two platforms are indicated as ft^{st}_p and ft^{vi}_p, p= 1,2. ,p represent the total number of retrieved features.

4.2 Vision Transformer-based Features

In this phase, the raw data attained through facial expression is given as the input. Transformers (Wu Z. et al., 2019) have been effectively utilized in natural language for encoding a sequence of input words into the sequence of embeddings. Without loss of generality has fixed the hidden dimension as well as the number of heads. Further, they stack the various number of transformer blocks to construct multiple vision transformer models in accordance with diverse depths. In addition to that, the self-attention mechanism has acquired the key role in vision transformer that makes it effectively different from CNN. Then, to validate the attention maps over layers, the following cross-layer similarity among the attention maps through various layers and is equated in Eq. (1)

$$J^{m,l} I^{n} \quad I^{m,n} = \frac{k,l \quad k,l}{} \tag{1}$$

Here, to measure the similarity of attention for the head k as well as token l, Im,n is used, the similarity matrix for the map of layers m and n is shown.as Im,n. The O dimensional vector that depicting how the input token O attributes to every O output token are given as J∗ . To offer an appropriate measurement the attribution of one token different layer k l is given as Im,n. In the end, the outcomes attained using the vision transformer is indicated as ftvi.

1.1 Attention-based BiLSTM for Score Computation

In this phase, the features attained from two platforms ftst and ftvi are given as the

p p

input to the ABi-LSTM (Zhou D. et al., 2021). More commonly, the LSTM model

has been regarded as the variant of the Recurrent Neural Networks (RNNs) as well as it has been utilized to tackle the gradient losses that are being caused by the RNN dependence model. The goal of this Bi-LSTM model is to get context information from the input

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sequence by using two hidden layers of Long Short-Term Memory (LSTM) networks.Through concatenating the two hidden vectors of LSTM, the context vector is designed as

hvb

→ ←

vb; vb

. Further, the basic LSTM functionality is expressed as in Eq. (2).

h

The equations in the image are as follows:

 z˜b   σ (J 1

  =   BΓ + d

(2)

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$$\square x_b \square \square \sigma \square \qquad hv_{b-1}$$
$$w_b \qquad \tanh$$

$$z_b = w_b \bullet \tilde{z}_b + y_b \bullet z_{b-1} \tag{3}$$

$$hv_b = x_b \bullet \tanh(z_b) \tag{4}$$

Here, the input vector is denoted as c_b, the dot product function is termed as • *output, andf orgetgatesaredepictedas* w_b, x_b and y_b accordingly, the sigmoid function is represented as σ, and the trainable parameters are given as B^r and d.

Then the attention mechanism over the Bi-LSTM is employed in this model. It is then summarized as follows the weights as well as the value matrix $c \in \Re^{ex2fg}$ are weighted summation to attain the final attention, then, the weight of each word is attained through determining the similarity among matrix $D \in \Re^{ex2fg}$ and each key matrix $E \in \Re^{ex2fg}$, where the dimension of hidden units of the Bi-LSTM is depicted as f_g and here, the perceptron and concatenation and dot products are utilized as the similarity function in general and normalize the similarity score as well as determine the weights through utilizing the SoftMax function. In the end, the attention is derived in Eq. (5). Thus, in the end, the outcomes attained from the ABi- LSTM model are considered as score 1 and score 2. Among, these two predicted scores, the best e- learning system is selected and then the better performance of the given model is achieved, and it is given in Fig.3.

5 Results And Discussion

5.1 Simulation Setup

The developed advanced learning-based online course optimization model was implemented using python. Some of the classical classifiers like RNN, LSTM, and RNN+LSTM were used for comparison in this model.

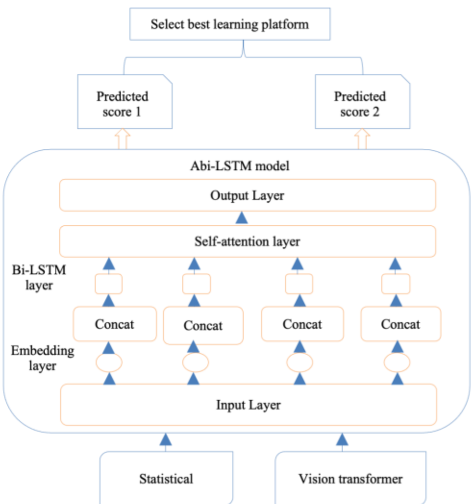

Fig. 3 Depiction of education data-driven online course optimization framework using ABi-LSTM for a score prediction

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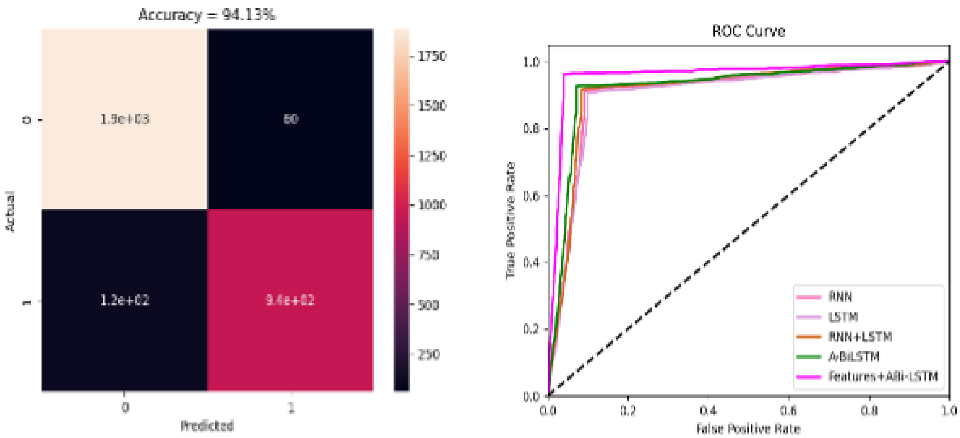
5.2 Confusion metrics and ROC validation over the given model

Figure 4 shows the ROC validation and confusion metrics for the model. From the graphical depiction, it is proved that the proposed Feature+ABi- LSTM are better than the other classifier model.

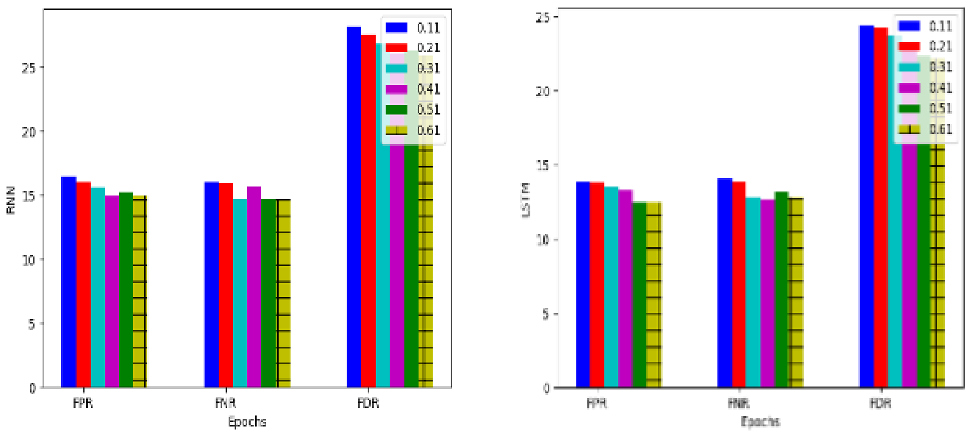


(a) Confusion Matrix (b) ROC Curve

Fig. 4 Analysis of the advanced learning-based online course optimization model.

5.3 Determination over negative and positive measures for the proposed model in terms of learning rate

Figure 5 and 6 illustrate the calculation of the negative and positive metrics for the advanced learning-based online course optimisation model. The y-axis represents the values of different epochs, while the x-axis represents different metrics. The FPR value at a learning rate of 0.11 for the suggested Feature+ABi-LSTM model is 63LSTM, RNN+LSTM, and ABi-LSTM models, respectively. This demonstrates the superior performance of the produced model.



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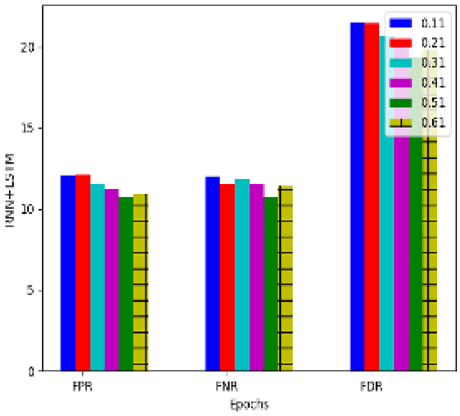
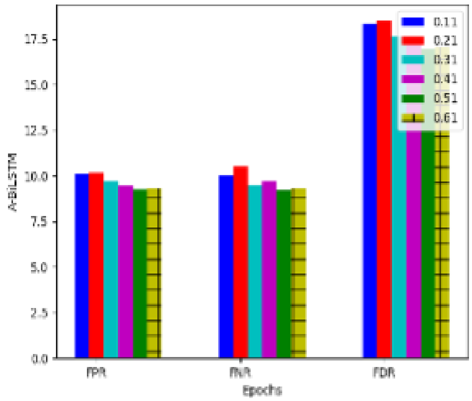
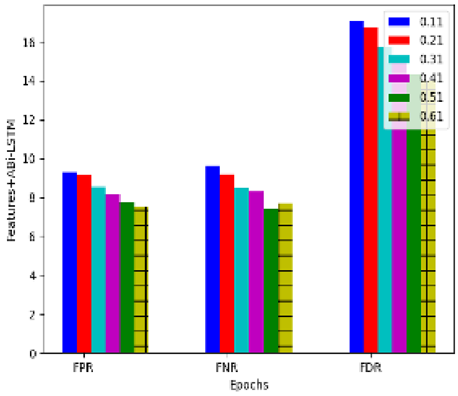
(a) epoch= 50 (b) epoch= 100



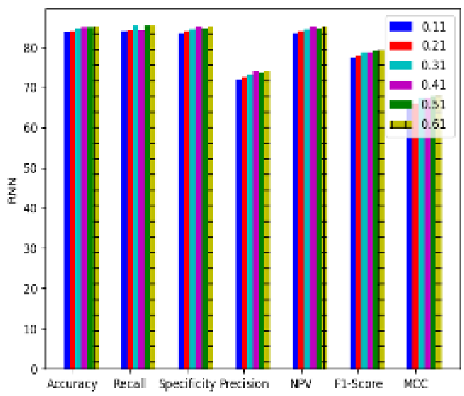


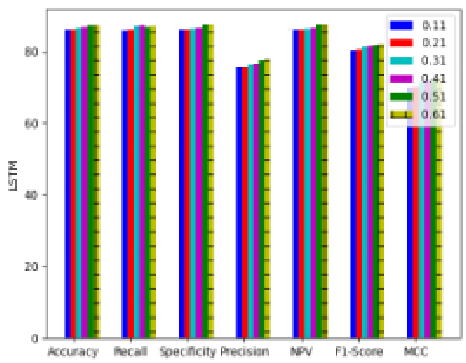
(c) epoch= 150 (d)epoch= 200



(e) epoch= 250

Fig. 5 Validating the advanced learning-based online course optimization models when compared to classifiers by varying the epochs in terms of negative measures for dataset 1





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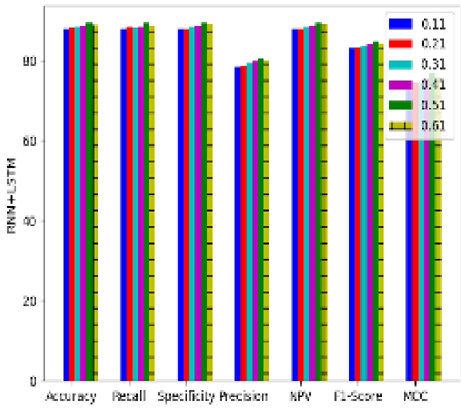
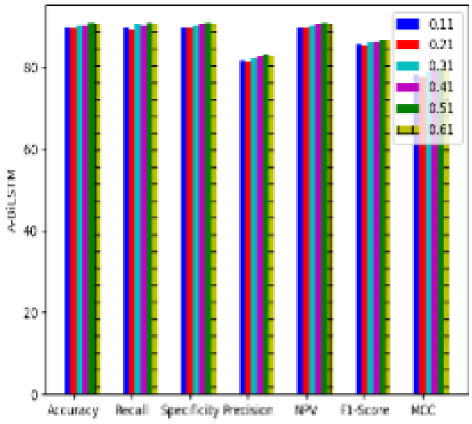
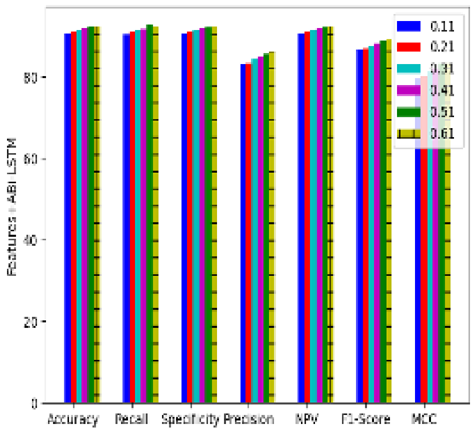


(c) epoch= 150



(d)epoch= 200



(e) epoch= 250

Fig. 6 Validating the advanced learning-based online course optimization models when compared to classifiers by varying the epochs in terms of positive measures for dataset 1

5.4 Performance Measures

Table 2 depicts the performance determination over various traditional classifiers has been compared with the newly designed online course optimization model. When as- simulated over classifiers like RNN, LSTM, RNN+LSTM and ABi-LSTM model the value of specificity is 10. The table outlines a comprehensive comparison of the perfor- mance metrics for several distinct machine learning models applied to a particular task. These models encompass various techniques and configurations, each contributing to a range of predictive abilities. In the first model, labeled as RNN [21], an accuracy

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of 84.93333% is achieved, with a sensitivity of 85.3% and specificity of 84.75%. The precision stands at 73.66149%, accompanied by a false positive rate (FPR) of 84.75% and a false negative rate (FNR) of 79.05468%.

Table 2 Performance validation over various classical classifiers for the designed advanced learning-based online course optimization model.

Terms	RNN	LSTM	RNN+LSTM	A-BiLSTM	Features+A-BiLSTM
Accuracy	84.93333	87.26667	89.3	90.76667	94.13333
Sensitivity	85.3	86.8	89.3	90.8	94.9
Specificity	84.75	87.73334	89.3	90.75	94.2
Precision	73.66149	77.63864	80.66847	83.07411	89.01515
FPR	84.75	87.5	89.3	90.75	94.2
FNR	79.05468	81.96412	84.76507	86.76541	91.43969
NPV	67.83035	72.43911	76.78713	79.88285	87.05696
FDR	15.25	12.5	10.7	9.25	5.8
F1-Score	14.7	13.2	12.7	11.2	7.5
MCC	26.33851	22.36136	19.33153	16.92589	10.98485

The negative predictive value (NPV) is calculated as 67.83035%, while the false discovery rate (FDR) is noted at 15.25%. The F1-Score and Matthews correlation coefficient (MCC) for this model are 14.7 and 26.33851, respectively. Moving on to the LSTM [22] model, it showcases an accuracy of 87.26667%, sensitivity of 86.8%, and specificity of 87.5%. Precision reaches 77.63864%, whereas the FPR is found to be 87.5%, and the FNR amounts to 81.96412%. NPV is computed at 72.43911%, and FDR at 12.5%. The F1- Score and MCC for this model are 13.2 and 22.36136, respectively. A combination of RNN [21] and LSTM [22] constitutes the third model, achieving an accuracy, sensitivity, and specificity all at 89.3%. Precision is recorded as 80.66847%, and the FPR as 89.3%. The FNR for this model is 84.76507%, while the NPV reaches 76.78713%. The FDR is calculated at 10.7%, and both the F1-Score and MCC stand at 10.7 and 19.33153, respectively.The fourth model, termed A- BiLSTM [23], achieves notable results with an accuracy of 90.76667%, sensitivity of 90.8%, and specificity of 90.75%. Precision is measured at 83.07411%, and the FPR at 90.75%. The FNR is observed to be 86.76541%, while the NPV is computed as 79.88285%. The FDR is notably low at 9.25%. The F1-Score and MCC for this model are 9.2 and 16.92589, respectively. Lastly, the model denoted as Features + A-BiLSTM emerges with an impressive accuracy of 94.13333%, sensitivity of 94%, and specificity of 94.2%. Preci- sion attains a high value of 89.01515%, while the FPR is noted at 94.2%. The FNR reaches 91.43969%, and the

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NPV is calculated as 87.05696%. Remarkably, the FDR for this model is merely 5.8%. The F1-Score and MCC are recorded as 6 and 10.98485, respectively. In essence, the table comprehensively contrasts the performance of these machine learning models using a diverse range of performance metrics, providing valu- able insights into their individual strengths and weaknesses in addressing the specified task.

6 Conclusion

This study presented an innovative framework to optimize online course performance by combining student academic data and real-time visual engagement analysis. By extracting meaningful features from diverse online sources and applying an AttentionBased Bidirectional LSTM (ABi-LSTM) model, we were able to effectively evaluate students' learning abilities in two stages: first through performance data, then through facial expression analysis captured in video recordings. The integration of these two scores allowed our system to select the most effective e-learning strate- gies tailored to individual students. Our framework demonstrated improved accuracy compared to traditional classifiers like RNN and LSTM, highlighting the power of combining attention mechanisms with bidirectional processing. While the results are promising, this approach still faces challenges, such as the reliance on one-way eval- uation metrics and the need for more dynamic feedback mechanisms. Future work will focus on enhancing the model's ability to adapt to different learning contexts, including language proficiency and course length, to create even more personalized and effective online learning experiences.

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