Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 25, Issues 5, pp. 3876–3885, DOI 10.12694/scpe.v25i5.3026

# LEARNERS BEHAVIOUR PREDICTION AND ANALYSIS MODEL FOR SMART LEARNING PLATFORM USING DEEP LEARNING APPROACH

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**Abstract.** In the quickly changing field of instructional technology, intelligent educational systems are now essential for individualized and effective instruction. To forecast and understand learners' actions in intelligent educational settings, this research suggests an analytical framework that makes use of deep learning techniques. By offering real-time information on user activities, the goal is to improve these platforms' reactivity and flexibility. Using state-of-the-art deep learning designs, our technique examines large datasets that include interactions between users, interest trends, and efficiency measures. The proposed method classifies the e-learning based behaviour classification and then the e-learning performance prediction using CNN-LSTM. The suggested framework incorporates the temporal relationships and sequential patterns present in learners' actions on the platform by fusing convolutional neural networks (CNNs) and long short-term memory networks (LSTMs). Furthermore, using multimedia information like simulations that are interactive and video lectures, convolutional neural networks (CNNs) are used to gather spatial data. The present study advances smart learning technology by providing a stable and expandable structure for behavior analysis and prediction in students. Through proactive customization of learning events, instructors, content producers, and platform developers can create a setting that is both enjoyable and effective for students. This is made possible by the knowledge gained from this approach.

**Key words:** Learners Behaviour, prediction and analysis, smart learning platform, Deep Learning Approach, convolutional neural networks, e-learning

**1. Introduction.** The incorporation of electronic devices has made it possible for creative and customized educational experiences in the quickly changing field of learning. An example of this progress is the introduction of intelligent learning systems that use AI to improve the learning process. The subject of learner behavior has numerous applications, but one that requires significant attention is the forecasting and evaluation of behavior among learners. Customizing lessons to meet individual requirements requires an in-depth comprehension of how learners react to difficulties, respond to happiness, and interact with the educational setting.

Electronic learning is now a standard educational method [27] and has played a significant role in the growth of online learning. Because of the COVID-19 pandemic, e-learning has become increasingly popular due to its extensive learning materials, low knowledge intake threshold, and substantial temporal and spatial flexibility. Still, this style makes it difficult for teachers to assess the progress in learning of their students [28, 19], and concerns have been voiced over the caliber of e-learning. By forecasting how well pupils will do on upcoming tests, lowering the likelihood that students won't pass the course, and guaranteeing the quality of e-learning, the research of learning outcome predictions gives teachers a foundation on which to modify their teaching strategies for students who could have difficulties.

Students' e-learning behavior has a significant influence on their educational outcomes, according to a substantial body of studies examining the connection between e-learning behavior and learning performance. As a result, achievement in learning predictions using data from the learning process has attracted a lot of attention lately [32]. Teachers can adjust their instructional tactics in real time and begin employing the role of monitoring as well as early warning by using the measurement, collection, and evaluation of learning information to accomplish achievement predictions [8].

Studies point out that knowledge of e-learning processes depends on data on e-learning behavior [1, 2]. The term "e-learning behavior data" refers to the information created by students during a variety of behavioral activities carried out on e-learning systems or online educational companies. This information can be used to

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refer to the action documents of students during the learning process, with particular attention to the quantity of login systems, quantity of resource access, quantity of forum participants, quantity of resource access, and other behavioral data. As a result, scholars have studied e-learning behavior in detail and developed many educational outcome predictions according to e-learning behavior[3].

The main question on the research,

How does the BCEP prediction framework compare to traditional E-learning classification techniques in terms of prediction accuracy and efficiency?

What are the specific steps and methodologies used in the data cleansing process within the proposed CNN-LSTM prediction framework?

How does the combination of features in the BCEP framework contribute to the overall accuracy of behavior classification in E-learning settings?

What criteria are used for behavior categorization in the CNN-LSTM prediction framework, and how does this affect the system's predictive capabilities?

To lower the operational expenses of the model and deliver high-accuracy, low-time-consuming learning outcome prediction services for online platforms, choosing features can be utilized to preserve important learning behaviors [4, 5]. In addition, e-learning predictors must typically employ e-learning behavior data as input variables directly because of the single input technique for e-learning behavior data. Few models will employ training data that is integrated with learning behavior data (i.e., feature combination processes) on the exact same kind of learning behavior data. Lastly, there is a lack of standardization among crucial learning behavior indicators, with various researchers finding different ones. Important behavioral cues that can be utilized to accurately predict student achievement have not yet been found in this field of research [6, 7].

The main contribution of the proposed method is given below:

1. We offer the behavior classification-based E-learning prediction system (BCEP prediction framework) to address these issues, provide a summary of traditional E-learning classification techniques, and conduct a thorough analysis of the E-learning procedure.
2. Initially this study proposes a CNN-LSTM prediction framework based on BCEP, which consists of four steps: data cleansing, combination of features, behavior categorization, and training of the model.
3. Computing cost decreases throughout training, and the algorithm becomes more mobile and adaptable during use.

Remaining sections of this paper are structured as follows: Section 2 discusses about the related research works, Section 3 describes the Smart Learning, Behaviour classification and Deep Learning methods, Section 4 discusses about the experimented results and comparison and Section 6 concludes the proposed optimization method with future work.

**2. Related Works.** Tendency markers and behavioral indicators of performance [9, 10] are common summaries of e-learning success predictions. The propensity signals are characteristics that are inherent in itself; in general, propensity indicators are static data that are typically gathered prior to the commencement of a class or semester, such as gender [13], financial status [11], and past educational history [12]. The tendency indicators have been utilized by numerous academics to create learning early-warning systems that forecast students' learning across a course of study, an entire semester, and other phases. Despite exhibiting excellent results, the predictors identified by these investigations disregarded the significance of learning behavior data. For instance, a lot of research employed demographic or past student performance information unrelated to education.

Even while the characteristics of learners in this research can be used to predict learning achievement, this strategy neglected the fact that most tendency markers were outside of the control of both teachers and pupils, and it also disregarded the curricular modifications made by the students [14]. Preferences indicators also have privacy issues, because private information gathered by educational organizations is not permitted to be disclosed with the general population. In general, there was no issue with the behavioural performance indicator, which is the dynamic index that the learner reflects during the learning process [15, 16, 17]. The amount of time and effort that students devote to a particular course, as well as the regularity with which they access course materials and participate in online conversations, can be precisely described by e-learning behavior data.

The amount of time and effort that students devote to a particular course, as well as the regularity with which they access the content and participate in online conversations, can be precisely described by e-learning behavior data. Several researchers also attempted to finish learning prediction [18, 20, 21] by combining two signs, but they ran into issues with rising computational expenses. The basis for e-learning behavior study has been established by the growth in big educational data and the introduction of new means of communication and information exchange.

A study on the prediction of performance in learning based on learning behavior is encouraged by the importance of learning behavior information for students in analyzing shifts in behavior, tastes, and skill ranges [22]. Learning behavior is a major component influencing how well learners learn and a significant indicator for forecasting performance in learning, according to learning input theory, which also explains the connection among learning behavior and learning performance [23]. Simultaneously, several studies have established a strong link among student online activities and academic achievement [24, 25], and paying closer attention to individual learning activities might help students better understand the circumstances under which they study and encourage positive developing [26].

Researcher [29] discovered that cooperative interaction patterns in a virtual educational setting help students grasp material more deeply and push themselves to meet learning objectives. To forecast how well online learners would learn, author [30] employed learning interaction data. She discovered that learning outcomes can be strongly impacted by how students access and use books, forums, and course materials. A correlation between one or more behavioral actions and educational outcomes was the focus of certain investigations. A positive link has been observed by researcher [31] between the overall number of passwords and learners' final scores.

**3. Proposed Methodology.** This study suggests the behavior classification-based E-learning performance prediction framework (BCEP prediction framework) based CNN-LSTM, which creatively builds a learning performance predictor from the standpoint of behavior classes. As illustrated in Fig. 3.1, the BCEP prediction architecture explains the entire process of incorporating learning performance predictors via e-learning behavior categories. There are four main connections in the forecasting structure: (3.2) choosing features, which is carried out on pre-processed e-learning behavior data to get key e-learning behaviors; (3.1) data preprocessing, involving cleaning of data and the conversion from the initial e-learning behavior data collected through the e-learning system to obtain uniformed e-learning behavior data; (3.4) model development, which develops an e-learning achievement predictor using a range of deep learning computations; (3.3) feature merging, which creates an assortment of behavior categories, classifies fundamental learning behaviors in accordance with predetermined rules using CNN-LSTM, and then works feature fusion to get the group feature value for every kind of e-learning behavior. In figure 3.1 shows the architecture of the proposed method.

The use of sophisticated deep learning models serves as the core of this analytical methodology. Deep learning has shown its ability to handle complicated data and identify significant patterns, making it well-suited to the challenge of analyzing and predicting user behavior in e-learning settings. The framework starts with huge and diversified datasets that include a wide range of user interactions, trends in user interests, and numerous performance measures. These datasets are the main source of data for training and assessing the model.

The framework's first significant component is behavior categorization in the context of e-learning. The goal here is to identify and label various sorts of user activities. This categorization step is critical for later phases of performance prediction. Following behavior classification, the framework moves on to predicting e-learning performance. This requires predicting how users will do based on their past behavior and interactions with the educational platform. Prediction is critical for adapting educational experiences to specific students.

**3.1. Data Pre-processing.** Predictive model accuracy is directly impacted by the caliber of the e-learning behavior data. As a result, cleaning the e-learning behavioral information that was downloaded from the online learning system is the initial phase. While there isn't a single, effective strategy for cleansing information, the approach used to manage absent, replicated, and anomalous values should be chosen based on the actual state of the data. At the same time, it is frequently not possible to do feature selection, and e-learning behavior data spanning multiple dimensions is not numerically equivalent. Additionally, e-learning behavior data captured by e-learning systems is frequently not of one dimension at all. This issue is resolved by the suggested model,

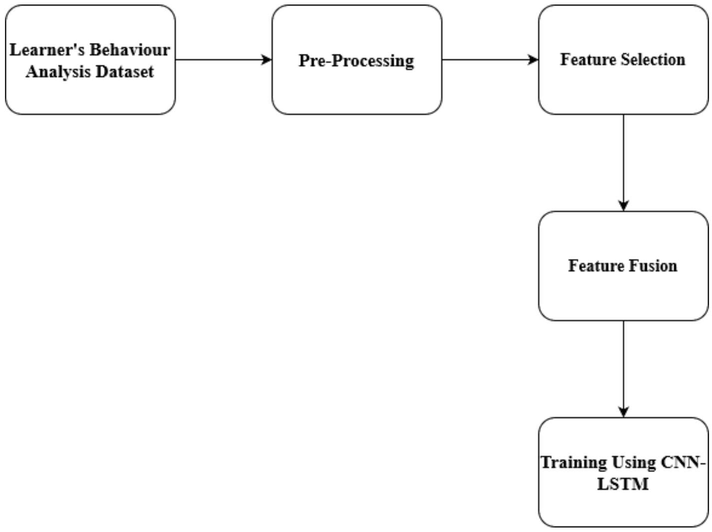


Fig. 3.1: Architecture of Proposed Methodology

which uses Z scores to standardize e-learning behavior data across several dimensions.

The standard e-learning behavior set B{b′, b′2,..., b′n} and the original e-learning behavior set B{b1, b2,...., bn} are defined. where b′n is the n-th online education behavior following standardization and bn is the n-th e-learning behavior as documented by the e-learning system. The initial and standard e-learning behavior data are specified simultaneously, with n denoting the n-th e-learning behavior and m denoting the m-th data of the present e-learning behavior. For instance, the equation for d′nm is as follows. Dnm is the second behavioral information of the first kind of e-learning behavior recorded by the platform for e-learning.

$$d^{'}_{nm} = \frac{d_{nm} - \mu b_m}{\sigma} \tag{3.1}$$

**3.2. Feature Selection.** By choosing pertinent features from among all features that are useful for training the model, one's selecting features can reduce the dimension of the feature and enhance its comprehension, generalization, and effectiveness in operation. This structure selects characteristics for standard e-learning behavior data using the variance filtering method. The variance filtration technique filters the characteristics by utilizing the variability of every single feature. The sample difference on this feature decreases with decreasing feature variance, and the feature's ability to differentiate the sample from other samples decreases as well. A crucial component of the variance filtering technique is the threshold, which denotes the variance threshold and determines which features are deleted if the variance of those features is smaller than the threshold.

$$V_n = \frac{\sum_{i=1}^{m} (d^{'}_{ni} - \mu\forall_m)}{n} \tag{3.2}$$

where the mean quantity of the n-th grade e-learning behavior data is represented by $\mu\forall_m$. The variance threshold is used to compare each component in iteration V. The appropriate e-learning behavior is included to the key e-learning behavior set if the present e-learning behavior feature value exceeds the threshold; alternatively, it is not included.

**3.3. Feature Fusion.** The primary e-learning behavior is separated into various e-learning behavior clusters based on the e-learning behavior classification model. It is assumed that there are n different types of e-learning behavior categories (i.e., M{C1, C2,..., Cn}) that make up the classification model M. Following the division of the e-learning behavior categories, n e-learning behavior clusters are produced, with each type of cluster containing a different number of e-learning behaviors, for example, C1{b1, b2,..., bn}, where bn is the n-th e-learning behavior that satisfies C1's norms.

$$V_{c_i} = \lambda.\max\left\{V_{b_1}, V_{b_2}, \ldots\ldots., V_{b_i}\right\} + (1-\lambda)\,.\frac{\sum_{i=1}^{m}\left(d^{`}_{ni} - \mu\forall_m\right)}{n} \tag{3.3}$$

**3.4. Training using CNN-LSTM for learners' behaviour Analysis..** The combination of long-short-term memory networks (LSTMs) and convolutional neural networks (CNNs) has become an effective model for behavioral analysis and forecasting in the context of smart educational systems in the ever-changing field of education technologies. This novel combination uses CNNs' spatial awareness and LSTMs' time ability to sequence to identify intricate trends in learners' behavior, providing previously unobtainable insights into how they engage with learning materials.

A CNN-LSTM-based prediction model successfully processes and analyzes sequential data with spatial information by combining Convolutional Neural Networks (CNNs) with Long Short-Term Memory networks (LSTMs). This hybrid model is widely utilized in a variety of applications, such as time series forecasting, picture captioning, and video analysis. The model starts with an input layer that receives sequential spatial data. This data can take the shape of time series, photos, videos, or any other data format that includes both temporal and geographic elements.

One or more CNN layers are used after the input layer to extract spatial information from the input data. CNNs recognize patterns and characteristics in data using convolutional filters. Each CNN layer generally has a number of convolutional and pooling processes. Convolutional operations use filters to discover local patterns in the input data, whereas pooling procedures downsample the spatial dimensions to minimize computing complexity and extract dominating features.

Following the CNN layers, the retrieved spatial characteristics are frequently flattened into a one-dimensional vector. This vector is used as the input for the next LSTM layers. LSTMs are recurrent neural networks (RNNs) that are designed to capture temporal relationships in sequential data. They are ideal for activities where the arrangement of data points is critical. LSTM layers accept flattened spatial characteristics as input and simulate the data's sequential patterns. They remain in a concealed state, allowing them to record long-term dependencies and recall relevant information from previous time steps.

The complete model is trained using labeled data, which includes input sequences and their associated target values. The model learns to minimize a loss function during training, modifying its internal parameters (weights and biases) to generate correct predictions. To update the model's parameters iteratively, optimization methods such as stochastic gradient descent (SGD) or Adam are typically utilized. The CNN-LSTM-based model may be used for sequence-to-sequence prediction in some instances, where it takes a series of input data and creates a corresponding sequence of output data. This is common in video captioning and language translation applications.

Thanks to advances in artificial intelligence, intelligent educational systems aim to go beyond the confines of conventional schooling by customizing the way that content is delivered to each pupil. In this quest, the incorporation of a CNN-LSTM-based prediction model is a significant advancement. Because the CNN component is so good at extracting spatial features, the algorithm can recognize patterns visually inside the learning surface. In addition, the LSTM part allows the model to understand how the learners' interest is changing over time by capturing the sequential relationships that are present in their conversations.

The power of this paradigm resides in its capacity to process both the dynamic development of learners' actions and static materials, including text and images. Through the examination of both the visual and sequence aspects of the data, the CNN-LSTM design enables the predictive algorithm to forecast future actions, identify possible problems, and suggest tailored remedies instantly.

The power of this paradigm resides in its capacity to process both the dynamic development of learners' actions and static materials, including text and images. Through the examination of both the visual and sequence aspects of the data, the CNN-LSTM design enables the predictive algorithm to forecast future actions, identify possible problems, and suggest tailored remedies instantly. Our goal as we investigate the CNN-LSTM model for learners' behavior prediction and analysis is to improve the adaptability and reactivity of intelligent learning environments. By providing an advanced awareness of how time and space clues might work together to provide a more individualized and holistic learning experience, this research aims to make a valuable contribution to the emerging field of schooling machine learning. We hope to create a revolutionary instructional environment where statistical analysis actively develops a dynamic and customized atmosphere for learning in addition to anticipating learners' requirements via the prism of the CNN-LSTM framework.

The completely connected layer's output data is received, and the next crucial step in determining the impact of behavior analysis is to do CNN on the information. Prior to implementing Behavior Analysis, it is important to comprehend how gradient optimization is used during the process. Gradient-based optimization is the most often used optimization technique in deep learning. The goal of this training procedure is to reduce the loss function as much as possible, which will guarantee behavioral analysis reliability.

$$J(\theta) = E_{a,b\sim pdata} L(a, b, \theta) = \frac{1}{m}\sum_{i=1}^{m} L\left(a^{(i)}, b^{(i)}, \theta\right) \tag{3.4}$$

L is the loss function for each sample:

$$L(a, b, \theta) = -\log p(b\,|a; \theta) \tag{3.5}$$

For these additive loss functions, gradient descent needs to be computed:

$$\Delta_\theta J(\theta) = \frac{1}{m}\sum_{i=1}^{m} L\left(a^{(i)}, b^{(i)}, \theta\right) \tag{3.6}$$

**3.4.1. Long-Short Term Memory (LSTM).** The term "neuron" refers to each component of deep learning; neurons are interconnected, and instruction is a way of altering a neuron's power. This modification makes a network made up of deep learning a multi-level neuron networks since each layer is tailored to the features of the neuron network [9].

Since behavior analysis can usually be expressed by a wide range of functions, a function like Formula 1 can be utilized to characterize this process.

$$f(a) = f^{(3)}\left(f^{(2)} f^{(1)}(a)\right) \tag{3.7}$$

A significant difficulty in the present-day network virtualization study is how to successfully anticipate the chance of network node and connection failure in a specific amount of time in the future using the parameters of the current network environment. This research suggests a long-short-term memory neural network (LSTM)-based behavior analysis technique [10] as a solution to this issue. Although the general neural network topology can theoretically address the issue of losing data due to parameter selection and distance, in actual use it is unable to produce the intended result [11]. Recurrent neural networks have certain drawbacks that LSTM can solve, allowing it to perform exceptionally well in a variety of applications. As seen in Figure 3.2, LSTM expands the original recurring neural network topology by including a memory storage structure.

**4. Result Analysis.** The study's findings, involving ACC, F1, Kappa, and each test group's prediction time as determined by the suggested CNN-LSTM deep learning techniques, are shown in this subsection.

In learner behavior evaluation, accuracy usually refers to how well the model can foresee or categorize various elements of learners' behavior. The tasks and objectives of the psychological analysis framework determine how accurate the assessment is. Classification accuracy is a key performance indicator for tasks that require grouping learner behavior into groups (such as engagement levels, learning preferences, or performance results). It calculates the proportion of correctly identified cases relative to all occurrences. In figure 4.1 shows the evaluation of Accuracy.

A popular metric for issues with classification is the F1-score, which offers a fair evaluation of an algorithm's recall and precision. F1-score is a useful measure for assessing how well prediction models recognize and classify different learner behaviors when it is used in learner behavior analysis.

Within the framework of learner behavior analysis, actions can be classified into many groups or categories, such as involvement, levels of engagement, or conceptual comprehension. The F1-score provides an equitable

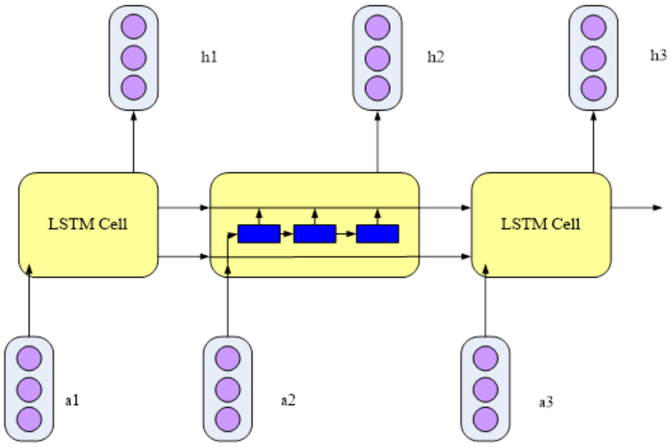


Fig. 3.2: LSTM Architecture

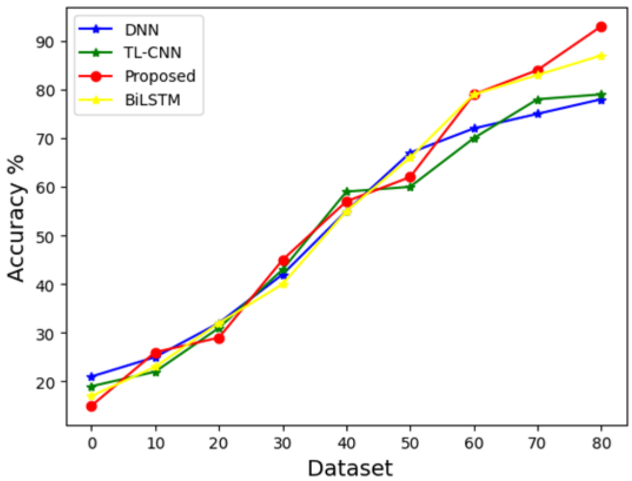


Fig. 4.1: Accuracy

assessment that is especially helpful in situations when the class distribution is unbalanced because it accounts for recall as well as precision. In figure 4.2 shows the evaluation of F1-score.

The Kappa statistic, sometimes referred to as Cohen's Kappa, is a way to gauge inter-rater concordance or, more specifically, how well projected, and actual categorized results coincide when it comes to automated training and predictive models. It comes in very handy when working with datasets that are unbalanced. The Kappa value can be utilized in learner behavior analysis to assess a predictive model's dependability. In circumstances where there are imbalances in the number of observable behaviors, Cohen's Kappa is especially appropriate. It evaluates the degree of coherence among anticipated results and actual actions in the setting of learner behavior analysis while considering the potential that agreement could have happened by coincidence only. In figure 4.3 shows the evaluation of Kappa Value.

In the domain of learner behavioral analysis, precision is an important parameter that evaluates how well a model predicts positive outcomes. The proportion of true positive forecasts to the total of actual positives and erroneous positives is known as precision. It offers insightful information about how well the model can recognize appropriate trends or behaviors across all the expected instances. When it comes to student behavior

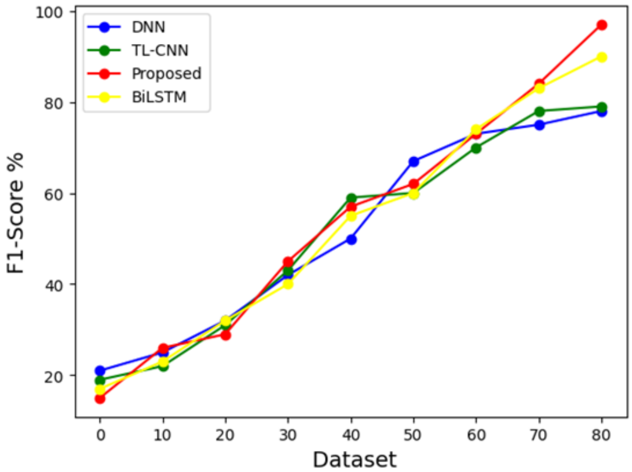


Fig. 4.2: F1-Score

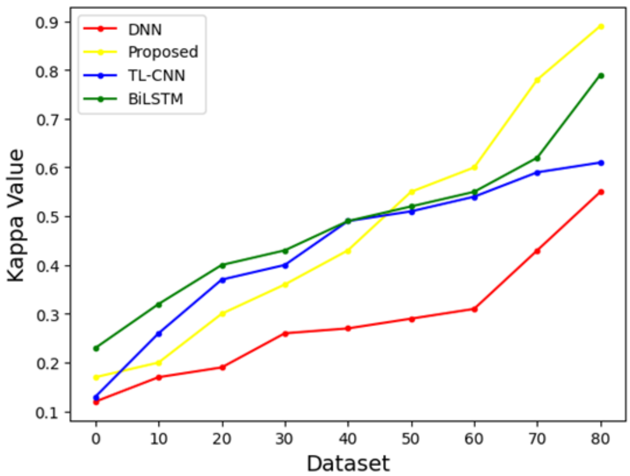


Fig. 4.3: Kappa Value

analysis, accuracy is especially important. A high precision number means that there are few false positives in the model's positive forecasts (e.g., correctly recognizing learning behaviors). Put practically, this means that there will be fewer false alarms because the model is more probable to be right when predicting a particular action.

To achieve high precision in learner behavior evaluation, sensitivity (recall) and specificity must frequently be carefully balanced. A comprehensive assessment considers recall (the model's capacity to catch all relevant occurrences) and other measures to offer a whole picture of the model's efficacy, whereas precision concentrates on the precision of its favorable forecasts. In figure 4.4 shows the evaluation of Precision.

**5. Conclusion.** Intelligent learning systems are currently necessary for tailored and efficient instruction in the rapidly evolving field of instructional technology. This paper proposes a framework for analysis that uses deep learning techniques to predict and explain learners' activities in intelligent educational situations. The objective is to increase the responsiveness and adaptability of these systems by providing current data

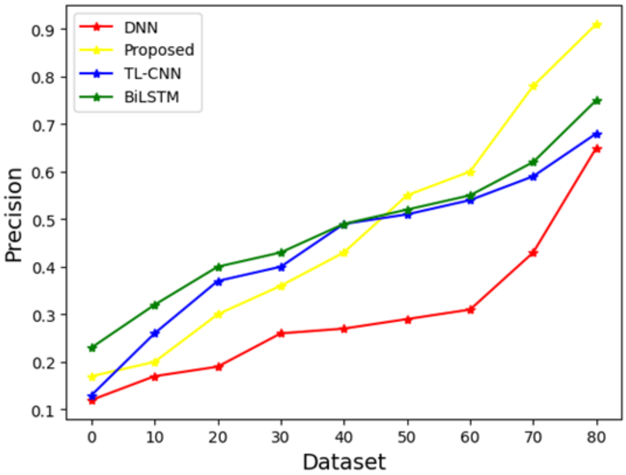


Fig. 4.4: Precision

on user behaviors. Our method analyzes big datasets containing interactions among users, attention patterns, and productivity metrics using cutting-edge deep learning designs. The suggested approach uses CNN-LSTM to classify behavior based on e-learning and then predicts e-learning performance. The proposed architecture combines convolutional neural networks (CNNs) and long short-term memory networks (LSTMs) to capture the temporal linkages and sequential patterns found in learners' behaviors on the platform. In addition, convolutional neural networks (CNNs) are utilized to collect spatial data utilizing multimedia content such as interactive simulations and video lectures. This work contributes to the field of smart learning technologies by offering a robust and scalable framework for pupil conduct monitoring and forecasting. Teachers, content creators, and platform developers may create an environment that is fun and productive for students by actively customizing learning experiences. The understanding obtained from this method makes this feasible.

**Acknowledgement.** [1]Research on the Construction of Vocational Education Evaluation System under the Threshold of Modern Governance "(No. D/2021/03/03)", Jiangsu Provincial Education Science "14th Five-Year Plan", Hosts: Feng Liyuan and Ji Yunfeng

[2]Research on Strategies and Paths for Universities to Serve Community Education under the Threshold of Lifelong Education "(No. WXSK21-JY-C30)", Wuxi Municipality Special Project for Social Education Development ,Host: Feng Liyuan

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*Edited by:* Rajanikanth Aluvalu
*Special issue on:* Evolutionary Computing for AI-Driven Security and Privacy: Advancing the state-of-the-art applications
*Received:* Dec 10, 2023
*Accepted:* Jan 4, 2024