SvedbergOpen
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

An Intelligent Hybrid Machine Learning with Optimization Technique for student performance prediction using online learning activity

Dr. K.R. Ananthapadmanaban[1], Dr. M. Kannan[2]

[1] Professor and Head Department of Computer Science and Applications SRM Arts and Science College, Kattankulathur – 603202.
E-mail: ananthapadmanabankr@srmasc.ac.in, ORCID:0000-0001-5430-3355
[2] Assistant Professor and Head Department of Computer Science with Data Science SRM Arts and Science College, Kattankulathur – 603202.
E-mail: kannancitm@srmasc.ac.in, ORCID: 0000-0002-6907-3086

Abstract
This instructive center lines up with the acknowledgment that furnishing understudies with pioneering preparing outfits them with the abilities important to make suitable and beneficial answers for arising difficulties. Understanding the elements impacting understudy execution has turned into a pivotal part of schooling research throughout the course of recent many years. Distinguishing these elements adds to further developed understudy execution as well as illuminates showing practices and strategy choices. While internet learning has acquired ubiquity, especially among science understudies, its viability has not generally measured up to assumptions. The developing requests and difficulties in web-based schooling have driven analysts to investigate ways of foreseeing understudy results, including execution and dropout rates in web-based courses. In this review, we propose a wise cross breed AI model with an advancement strategy for anticipating understudy execution in web based learning exercises. This model uses a pre-trained ResNet to extract latent features from the sequence of activities for making predictions. To resolve issues connected with information dimensionality, we present the modified bonobo optimization (MBO) calculation for highlight decrease. Thusly, we utilize an AI procedure, explicitly the deep belief echo state network (DBESN), to foresee understudies' flexibility levels and execution in web based learning exercises. The OULA dataset serves as a validation of the proposed MBO-DBESN method's performance, demonstrating its accuracy in prediction.

Keywords: understudy execution forecast, web based learning action, AI models, include extraction, highlight decrease.

1. Introduction

An essential unmistakable of present day teaching method is the consolidation of virtual and online stages, which has become progressively significant considering the quickly changing climate of training [1]. This worldview change, which was prodded by enhancements in innovation, has introduced another age in which schooling is not generally limited to the bounds of actual homerooms [2]. Specifically, virtual and online science training is at the vanguard of this change, empowering learning chances that have never been seen before for the two instructors and understudies [3]. As we clear our path through this computerized scene, the combination of prescient investigation and AI arises as a powerful focal point through which we can inspect and work on the consequences of understudy learning. The core of virtual and online learning is its ability to transcend geographical barriers. This permits understudies to learn at their own speed and practicality [4]. Machine learning algorithms are being used in predictive analysis right now [21]. Understanding, anticipating, and maximizing student learning is made easier with the rigorous and data-driven approach [5]. This study will examine the intricate relationship between predictive analysis and virtual scientific education and how machine learning might improve education. The main goal of this research is to study this fascinating connection [6][7]. By using the massive volumes of data generated in virtual and online scientific classrooms, researchers and educators can gain insights on student engagement, performance, and learning. [8] We want to discover machine learning's potential as a tool for retrospective analyses and a proactive force that can change instructional practices [9].

Virtual scientific education has changed dramatically due to MOOCs, online simulations, and virtual laboratories. The emergence of these three educational platforms enabled this change [10]. These technologies generate enormous databases that capture all student interactions with the subject being taught [11]. AI can assist us with tracking down connections inside these datasets that customary techniques might miss [12]. Educators can glean some useful knowledge about understudy accomplishment by distinguishing these propensities. This takes into account more noteworthy fixation and custom fitted learning and guidance, which is valuable. Although there are limitations to teaching science online, this method is extremely useful. Prescient investigation using AI calculations can illuminate instructive arrangement and practices [13]. Figuring out how understudies cross internet learning settings, what makes them effective, and what issues they face can assist training pioneers with settling on proof based choices. The ethical implications of predictive analytics must be taken into account as we investigate machine learning applications in education. We should utilize these advances capably to safeguard youngsters' protection and elevate fair admittance to excellent schooling [14]. Prescient examination in virtual logical training is the focal point of this review. AI calculations guide us through understudy guidance. It feels like a thrilling adventure to read this paper [15]. Rather than showing all children the same way, a more customized and versatile methodology is being taken on. This worldview change depends on AI, which can detect examples and patterns. It permits teachers to redo their methodology for every understudy [16]. As we continue to investigate this issue, it is becoming abundantly clear that incorporating machine learning into education is challenging [17]. Clever fixes are expected to resolve innovative issues like adjusting calculations to adjust internet learning conditions. Overseeing innovation in schooling requires resolving moral issues such information secrecy, algorithmic bias, and understudy information use [18]. Virtual scientific instruction and predictive analysis demonstrate a paradigm shift that will alter education. AI assists us with understanding understudy learning and give a more customized, versatile, and effective showing climate [19]. This request isn't just about voyaging new advancements; it's tied in with further developing schooling to amplify every student's possible in this advanced age. As we navigate the strange waters of prescient examination in virtual science classes, these dreams can coordinate extra exploration, flash development, and give to the ebb and flow talk on AI's instructive revolutionary potential [20].

Our contributions. An astute half and half AI model with streamlining procedure is intended for anticipating understudy execution in view of web based learning exercises. The critical commitments of our proposed procedure are framed as follows:

1. The model influences a pre-prepared ResNet to remove inactive elements from the consecutive information got from web based learning exercises. This step is vital for catching nuanced examples and data implanted in the understudies' communications inside the web based learning climate.
2. Recognizing the difficulties related with information dimensionality, we present the modified bonobo optimization (MBO) calculation. By selecting the most relevant features and eliminating those that are redundant or less informative, this feature reduction algorithm aims to improve model efficiency.
3. The deep belief echo state network (DBESN), a machine learning method, is incorporated into the proposed model to predict the adaptability and performance of online learning students.
4. To survey the adequacy of the MBO-DBESN procedure, we approve its exhibition utilizing the OULA dataset. This dataset likely contains different occurrences of web based learning exercises, giving a hearty proving ground to assessing the model's prescient capacities. The outcomes got from the approval cycle shows the viability of the proposed method, especially with regards to forecast precision.

The rest of this paper is organized as follows. Section 2 gives the review of recent works related to the predicting student performance based on online learning activities. Section 3 provides the detailed working process of proposed MBO-DBESN technique with the detailed mathematical models. The results and comparative analysis of proposed and existing student performance prediction techniques have discussed in the Section 4. Finally, the paper concludes in Section 5.

2. Related works

2.1 State-of-art studies

The smart adaptive learning environments (SALE) can properly anticipate student outcomes and improve student engagement and tailored learning. SALEs outperform other data types in neuropsychological prediction. The technologies reinforce concepts and deliver on-demand learning personalized to each learner without human intervention. Integrating cognitive data with digital instructions, especially video, may improve student success. Neuro cognitive data drives SALE adaptability and examines brain states during learning, a topic often disregarded in school room valuations. Although the participation of students in learning activities based on their brain states has not been thoroughly investigated, future research should focus on the way artificial intelligence classifiers in SALEs can enhance content delivery for individual students. This line of inquiry has the potential to introduce a fresh epoch of customized and efficient educational methods, enabling higher degree of personalization in terms of content and learning encounters. [21]

Automatic interaction learning platforms and linked online video-based environments for learning are investigated in this study as possible means to enhance students' scientific learning outcomes. The major goal is to study science class employing an online learning management system may use hemodynamic response data to anticipate individual students' replies using machine learning algorithms. This provides evidence that hemodynamic response data could be used to measure students' engagement in video-based assignments, with prediction model error rates falling below 30%. Educators will be able to gauge their pupils' understanding and adjust their teaching methods appropriately if new approaches of evaluating visual media are created. By showing the potential of combining physiological data with machine learning algorithms to guide and improve teaching methods, this research essentially adds to the changing terrain of scientific education. [22]

To introduce the Bangor Engagement Metric, a descriptive measure with significant predictive capabilities, initially utilized to improve Bangor University's scholar evidence schemes. The application of machine learning to address student retention emerged as a key focus, leading to a series of trials where we carefully designated a capacities and classifier. This approach achieved an impressive accuracy rate exceeding 97%, effectively balancing the intervention of students and minimizing incorrect predictions of positive outcomes. Recognizing the dynamic nature of machine learning models, acknowledge the necessity for ongoing training, incorporating new data while discarding aging information. It's imperative to note that the model's effectiveness is context-dependent, designed for pupils and may not be equal across other organizations. [23]

The landscape of education is undergoing a transformative shift, marked by the dominance of online, virtual, or hybrid educational models. Student-centered educational models are at the forefront, serving as ideal assistants for both students and teachers. The system enables students to manage calendars, generate events, and receive reminders, fostering continuous improvement and performance enhancement. Granular analysis of student data empowers teachers to understand individual learning statuses. This model proves instrumental in reducing student dropout rates, preserving economic resources for virtual laboratories, a critical aspect highlighted by the pandemic. It also reshapes the role of human resources in student monitoring and educational quality. [24]

The study underscores the importance for higher education institutions to prioritize and enhance instructors' efforts in emergency remote learning (ERL) situations. Modulating assessment methods is recommended to ensure a balanced workload and fairness amidst sudden changes. To address ERL learning gaps, contingency planning and different educational activities are recommended. Additionally, knowing why students prefer face-to-face learning is vital. Course providers and teachers can adjust courses, learning activities, material, and implementation techniques to these preferences, boosting student happiness and learning experience. The study emphasizes proactive approaches and changes to improve instruction amid crises and remote learning. [25]

This study addresses concerns about university students' timely graduation and presents a reduced training vector-based support vector machine (RTV-SVM) to predict at-risk or marginal pupils. The RTV-SVM predicts student outcomes and reduces training time and support vectors by deleting redundant training vectors. An evaluation of 32,593 college students in seven classes showed the RTV-SVM's efficiency. At least 59.7% fewer training vectors have been found, although classification margin and efficiency have not altered. The approach has an accuracy range of 92.2–93.8% when identifying at-risk kids and 91.3–93.5% for marginal students, indicating its potential to help students graduate on time and succeed academically. [26]

With MOOCs and large-scale research, ML's influence on the educational sciences is expanding, but it's still limited. An instructive summary discusses ML's prospects and difficulties, draws on adjacent fields' experiences, and advocates for a conceptual shift in model evaluation at this key moment in educational sciences. The summary shows how ML improves educational research data analysis and validates empirical models. The course covers ML-friendly data types, application tips, analytical examples, and repeatable R code. The advice prepares education scientists and practitioners for digitization and large-scale assessment. [27]

The increasing shift of educational activities to online platforms and the availability of course content in digital formats have facilitated data collection and analysis of the learning process. While machine learning techniques have demonstrated significant advancements in data analysis and predictions, their application for assessing learning quality remains limited. This paper addresses this gap by employing neural networks, support vector machines, decision trees, and cluster analysis to analyze student performance at examinations. The goal is to shape the next generation's talent for Industry 4.0 skills, emphasizing the potential of Machine Learning in enhancing educational outcomes. [28]

A deep learning CNN-LSTM model is based on Blackboard data to predict student performance. The model used 7x7 features for each student in CNN layers and considered CNN convolution filter size, LSTM neurons, and LSTM batch size to predict accuracy and error. The CNN-LSTM model was found to take too long when adding CNN layers, filters, and LSTM batch size. A multi-layered CNN-LSTM model improves learning and processing power but takes longer to train, so future research should focus on lightweight, shallow deep learning models for efficient training with suitable computing power. [29]

This learning analytics study analyzes data from multiple years to predict student participation early in virtual learning environment (VLE). Machine learning on subset of the Open University learning analytics dataset analyzes 7,775 social science students' data to create the prediction model. The tests, which use a smaller feature set, predict course engagement. Student VLE uses, scores, and results are key factors. Best findings using a random forest method show 95% accuracy, 95% precision, and 98% relevance. A selection of click behaviors, indicating their functional relationship with students and VLE are relevant for early prediction. [30]

2.2 Research gaps

The prediction of student performance in online learning activities holds significant importance for various educational stakeholders. One key benefit is the ability to intervene early and provide timely support to students who may be facing challenges or falling behind in their coursework. Educators can use targeted strategies to assist struggling students and ensure their success in the online learning environment with early identification. Furthermore, prescient models take into consideration a customized opportunity for growth, where educational substance and speed can be custom-made to individual understudies' requirements in light of their anticipated exhibition designs. Additionally, the forecast of understudy execution supports proficient asset allotment inside instructive organizations. By perceiving predictable difficulties looked by understudies, foundations can coordinate assets, like extra informative help or designated mediations, to regions where they are generally required. This proactive methodology additionally adds to maintenance and dropout counteraction endeavors by distinguishing in danger understudies and executing mediations to upgrade commitment and scholastic achievement. Wen et al. [31] introduced an original portrayal for successions of internet learning exercises, filling in as info information for profound brain organization to foresee understudies' exhibition at beginning and during web based learning meetings. They concocted an autoencoder inside the structure of a profound brain organization to separate idle elements from the underlying portrayal, upgrading the accuracy of execution expectations. Utilizing this portrayal and the autoencoder, they figured out a start to finish expectation model explicitly custom fitted to estimate individual understudy execution in view of their novel arrangements of web based learning exercises.

The expectation of understudy execution in web based learning conditions represents a few difficulties that require compelling AI strategies. The quantity and quality of the data that is available is a major obstacle, with issues like incomplete or noisy data and data sparsity affecting prediction accuracy. Arrangements include utilizing information cleaning methodologies and increase strategies to improve information quality and amount. The fleeting elements of web based realizing, where understudy execution advances after some time, present another test. Methods like time-series examination and recurrent neural networks (RNNs) demonstrate valuable in catching fleeting examples and working on the forecast of dynamic execution changes. Additionally, the high dimensionality of web based learning datasets adds to the scourge of dimensionality, prompting difficulties in include portrayal. Tending to this, highlight determination or extraction techniques, including principal component analysis (PCA) and auto encoders, demonstrate compelling in moderating dimensionality issues. The perplexing cooperations among different highlights and the logical idea of web based learning present further difficulties, which gathering strategies and profound learning methods with consideration systems can help address by demonstrating multifaceted connections and catching relevant data. Imbalanced class conveyances, moral worries encompassing understudy information protection, and the requirement for interpretability in models likewise address basic difficulties. Procedures, for example, oversampling, under-testing and the utilization of specific calculations for imbalanced information help with taking care of class irregular characteristics. Moral contemplations are met through the execution of security saving strategies and adherence to moral rules. The development of precise and dependable predictive models for the performance of students enrolled in online learning is fundamental to addressing these issues using machine learning methods. In order to improve educational outcomes in online learning environments, ensemble methods, deep learning models, feature selection/extraction techniques, attention mechanisms, imbalanced data handling, privacy-preserving techniques, and other techniques all contribute to the accurate prediction of student performance. To resolve those issues, we plan new procedure for expectation of understudy execution in web based learning. The critical goals of proposed procedure are list as follows.

1. Plan and foster high level prescient models that can successfully deal with the difficulties related with internet learning execution expectation.
2. Research and execute imaginative element designing strategies to catch nuanced communications and logical data in web based learning information.
3. Develop temporal analysis techniques to effectively document the changing nature of online learning student performance.
4. Lay out moral and protection mindful AI procedures for internet learning execution expectation.

3. Proposed methodology

The proposed MBO-DBESN method for anticipating understudy web based learning execution is represented in Figure 1, with the Open University learning analytics (OULA) dataset filling in as the fundamental information source. The work process starts with fastidious information preprocessing to guarantee the dataset's trustworthiness and quality, including errands like taking care of missing qualities and normalizing highlights. Following this, highlight extraction is led utilizing a pre-prepared ResNet (Residual Network) to determine inactive elements that exhaustively address web based learning exercises, catching complicated examples and connections. For the purpose of feature reduction, the modified bonobo optimization (MBO) algorithm is introduced to address the issue of high feature dimensionality. MBO deliberately refines the list of capabilities, choosing ideal elements that essentially add to prescient execution while relieving dimensionality concerns. This step improves the effectiveness and interpretability of the ensuing forecast model. The recurrent neural network (DBESN) is utilized for understudy execution expectation, utilizing the inactive elements got from ResNet and the enhanced list of capabilities from MBO. DBESN, a kind of repetitive brain organization (RNN) with profound conviction organizations, succeeds in catching transient conditions inside successive information. The forecast model is intended to order understudies into particular execution classes: Qualification, Fizzle, Pass, and Pull out. This multiclass characterization empowers a nuanced comprehension of understudy results, working with custom fitted mediations and backing systems in view of anticipated execution levels.

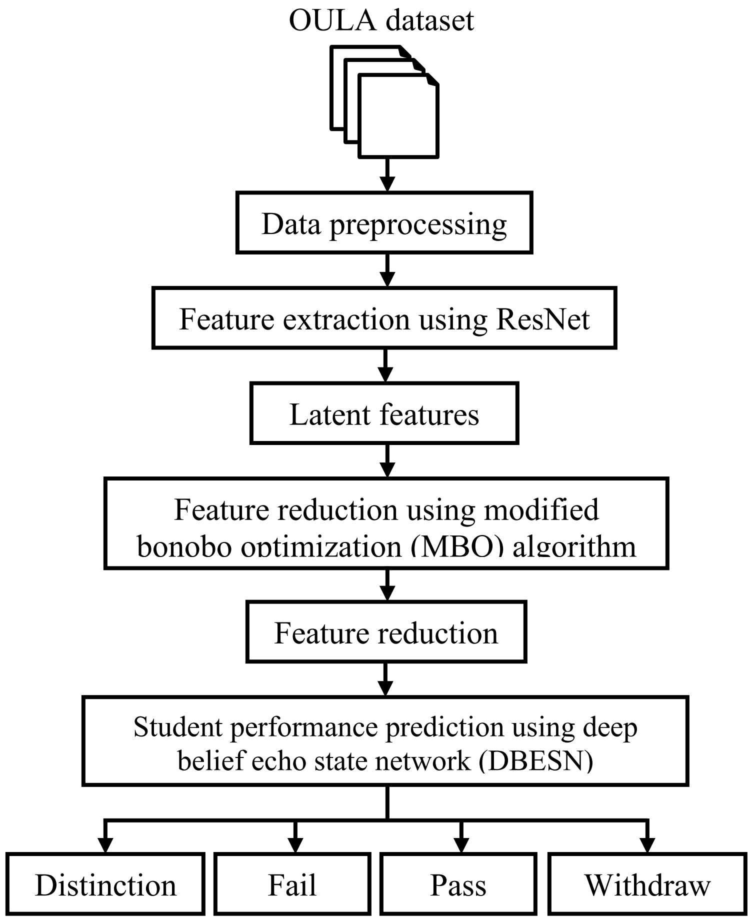

Fig. 1 In general applied construction of proposed MBO-DBESN procedure for understudy web based learning execution expectation.

3.1 Feature extraction

Highlight extraction is a vital stage in the proposed model, as it includes catching significant and educational portrayals from the succession of exercises in web based learning. In this unique circumstance, a pre-prepared ResNet is utilized as the component extraction system. ResNet is a well-known architecture for deep neural networks that is adept at handling intricate relationships and patterns in sequential data. ResNet is a type of convolutional neural network (CNN) that introduces a residual learning framework. ResNet's main innovation is the use of residual blocks, which contain shortcuts or skip connections. These alternate routes empower the progression of data straightforwardly starting with one layer then onto the next, moderating the disappearing angle issue and permitting the organization to learn perplexing examples in the information really. The pre-prepared ResNet is applied to the succession of web based learning exercises, regarding every action as a data of interest in the grouping. Latent features that capture the essential characteristics and patterns of the online learning data are extracted by the ResNet as it processes this sequence. These inert elements act as a rich and complete perspective on the information, catching both present moment and long haul conditions. The usage of a pre-prepared ResNet infers the utilization of move realizing; where the information acquired from preparing on a huge dataset is moved to the particular undertaking of internet learning action include extraction. This approach uses the speculation capacities of ResNet, permitting the model to perceive and remove significant elements from the consecutive information without the requirement for broad errand explicit preparation.

- ResNet can capture hierarchical and deep representations of sequential data, enabling the extraction of intricate features.

- Utilizing a pre-prepared ResNet confers the model with information acquired from different datasets, upgrading its capacity to sum up and perceive designs in web based learning exercises.
- ResNet's architecture, particularly its residual blocks, facilitates the effective processing of sequential data by addressing challenges like vanishing gradients.

3.2 Feature reduction

Include decrease is a basic part of the proposed model, pointed toward addressing difficulties connected with information dimensionality and working on the effectiveness of ensuing examinations. The utilization of the modified bonobo optimization (MBO) calculation fills in as a complex procedure for accomplishing ideal element subsets while protecting the fundamental data for prescient displaying. MBO draws motivation from the social way of behaving of bonobo primates. Bonobos are known for their agreeable and clever critical thinking approaches in true situations. Likewise, the MBO calculation emulates these agreeable ways of behaving to track down ideal arrangements with regards to highlight decrease. The MBO calculation works on the rule of participation, where various specialists team up to enhance the general exhibition of the framework. The selected subset of features all contribute to the model's predictive accuracy thanks to this collaborative optimization. MBO utilizes a populace based approach, where various up-and-comer arrangements coincide and develop over emphasess. This populace elements takes into consideration the investigation of different component blends and works with the ID of the most useful and applicable highlights. The wellness of every applicant arrangement is assessed in light of predefined measures, taking into account factors like prescient precision, model productivity, and the capacity to catch fundamental examples in the information. The optimized subset keeps the features that contribute the most to these criteria. Contingent on the ongoing stage (PP or NP) of the calculation, different refreshing conditions (i.e., different mating methodologies to make posterity) are utilized. Additionally, before each refreshing, one more arrangement or bonobo is chosen for the mating in view of the parting combination gathering technique of bonobos. The extents of the gatherings are arbitrary and erratic. These gatherings keep going for not many days and afterward, again rejoin with their local area.

$$yafa_{\max} = \max\left(2, yafa_{fac} \times M\right), \quad (1)$$

Here, we characterize a boundary called stage likelihood which is used to choose the mating methodology for making a bonobo. The underlying incentive for this boundary is doled out to 0.5 and it will be refreshed toward the finish of cycle. A new bonobo is created in the following manner if a random number generated between zero and one is found to be either less than or equal to.

$$new\_bonobo = bonobo_k^u + p_1 \times scab \times \left(d_k^{bonobo} bonobo_k^u\right) + \left(1 - p_1\right) \times \left(bonobo_k^u - bonobo_k^p\right), \quad (2)$$

The underlying worth of is set equivalent to and a short time later; it is refreshed relying on the state of the development. This directional likelihood is utilized to coordinate the hunt cycle in the most encouraging region of the entire pursuit space.

$$\rho_1 = w^{\left(p_4^2 + p_4 - 2/p_4\right)}, \quad (3)$$

$$\rho_2 = w^{\left(1 - p_4^2 + p_4 - 2/p_4\right)}, \quad (4)$$

$$new\_bonobo_k = bonobo_k^u + \beta_1 \times \left(\mathrm{var\_max}_k - bonobo_k^u\right), \quad (5)$$

$$new\_bonobo_k = bonobo_k^u + \beta_1 \times \left(bonobo_k^u - \mathrm{var\_max}_k\right), \quad (6)$$

$$new\_bonobo_k = bonobo_k^u + \beta_1 \times \left(bonobo_k^u - \mathrm{var\_max}_k\right), \quad (7)$$

$$new\_bonobo_k = bonobo_k^u + \beta_2 \times \left(\mathrm{var\_max}_k - bonobo_k^u\right), \quad (8)$$

where and are the two transitional boundaries to compute the worth of differs from 1 to (i.e., the all out number of choice factors is an irregular number in the middle somewhere in the range of 0.0 and 1.0, and are the upper and lower limit values relating to the variable, separately.

$$new\_bonobo_k = \begin{cases} bonobo_k^u + flag \times w^{-pa} \times \left(bonobo_k^u - bonobo_k^o\right) \\ \quad if\left(flag = 1 \| p_v \le od\right) \\ bonobo_k^o, otherwise \end{cases} \quad (9)$$

where and are two arbitrary numbers and is the directional likelihood. To sum up, one might say that during the positive phase (PP), the probabilities of developments of the bonobos towards the alpha bonobo are more, while the propensities for irregular development are seen to be seriously during the negative stage (NP) of advancement. During PP, double-dealing in the populace is engaged, though investigation is advanced during the NP. It is to be noticed that the underlying worth of the stage likelihood has been chosen as 0.5 to at first give equivalent significance to both the stages.

$$yafa_{fac\_initial} = 0.5 \times yafa_{fac\_\max,} \tag{10}$$

3.3 Student performance prediction

The final phase of the proposed model involves the prediction of students' adaptability levels and performance in online learning activities, and this is achieved through the implementation of the deep belief echo state network (DBESN). DBESN's architecture is an extension of the echo state network (ESN), a recurrent neural network (RNN) developed specifically for sequential data-based tasks. What separates DBESN is its coordination of profound conviction organizations (DBN) into the ESN system, adding profundity to the organization and empowering the extraction of various leveled portrayals from the successive info. Through its repetitive nature, DBESN succeeds in learning fleeting conditions inside the unique information of web based learning exercises, catching the advancing connections and ways of behaving of understudies over the long run. DBESN assumes a crucial part in foreseeing two key perspectives: understudies' flexibility levels and their presentation in web based learning exercises. Flexibility, a pivotal measurement in web based learning achievement, is the capacity to change and flourish in different learning conditions. DBESN use its engineering to group understudy's exhibition into various classes, qualification, come up short, pass, and pull out. The multiclass grouping gives a nuanced comprehension of understudy results, empowering teachers to tailor intercessions in light of anticipated execution levels. The modified bonobo optimization (MBO) algorithm's optimized feature subset is used in DBESN training and fine-tuning. This guarantees that the network can accurately predict adaptability and performance while also adapting to the sequential nature of the data. DBESN is a compelling profound learning structure for tackling time series determining issues. The proper blend of stowed away layers decides the prescient presentation of the brain organization. An ESN is a RNN with K info units with a K⍰B input weight grid, B supply neurons with a B⍰B spatial weight framework, and L result units with a L⍰B yield weight network. The reservoir level at time s, T(s) is the yield of the reservoir layer at time T

$$T(s) = F(Z_U^t \cdot u(s) + Z_t^t \cdot T(s-1) + Z_o^t o^S(s-1)) \tag{11}$$

$$o(s) = f^{out}(T^S(s) \cdot Z_t^o) \tag{12}$$

where F is the activation function of the reservoir neurons (typically a hyperbolic tangent function), f^{out} the activation function of the output layer (typically a linear function), U(t)and O(t) are the input and output signals of t, respectively. Z_U^t, Z_t^t, Z_o^t and Z_o^t l×B weight matrix are the input, reservoir, feedback, and readout weight matrices, respectively, Z_U^t, Z_t^t, Z_o^t and S denotes the exchange if there is a closed-loop synaptic weight between the reservoir and the output layer. Z_o^t and Z_t^t is randomly generated from uniform distribution and remains constant during training. To calculate the resonance condition, the coupling matrix of the reservoir is usually measured as follow.

$$Z_t^t \leftarrow \frac{\alpha}{|\lambda_{Max}|} Z_t^t \tag{13}$$

where λ_{Max} is the spectral radius Z_t^t and 0 1 <<α is the scaling parameter. The data is divided into three categories namely training, validation and testing data. Then, the reservoir volume is accumulated in the state matrix T.

$$T = \begin{bmatrix} T^S(1) \\ T^S(2) \\ \vdots \\ T^S(b) \end{bmatrix} \quad (14)$$

The corresponding target outputs are combined in the target matrix o

$$o = \begin{bmatrix} o(1) \\ o(2) \\ \vdots \\ o(b) \end{bmatrix} \quad (15)$$

where b is the number of training samples. The reading matrix is the solution to the linear regression problem which compute as follows.

$$T \cdot Z_t^o = o \quad (16)$$

The traditional technique is to use the least squares explanation, defines as follows.

$$Z_t^o = \arg\min_z \| Tz - o \|^2 \quad (17)$$

where · denotes the Euclidean norm. The calculation Z_t^o is linear regression and then the reading matrix Z_t^o can be performed in one step using the Moore-Penrose pseudo-inverse algorithm.

$$Z_t^o = \widetilde{T}o = (S^S S)^{-1} T^S o \quad (18)$$

where T is the generalized inverse of T and o is the target output matrix. The output matrix of the last DBN layer can be described as the new input matrix of the ESN layer.

$$u = \begin{bmatrix} U(1) \\ U(2) \\ \vdots \\ U(x) \end{bmatrix} \quad (19)$$

where p denotes the neuron number of the last DBN layer. u can be considered as the current state of the last RBM in the DBN layer. RBM is commonly used as a layer-wise training model in the construction of DBN, $V = \{0,1\}^C$ which is a special type of Markov random, $i = \{0,1\}^f$ given visible entities and hidden entities.

$$e(V,i;\theta) = -\sum_{h=1}^{C} m_h v_h - \sum_{g=1}^{f} n_h i_h - \sum_{h=1}^{C}\sum_{g=1}^{f} z_{hg} V_h i_g = -m^S v - n^S i - v^S Zi \quad (20)$$

where, $\theta = \{n_h, m_g, z_{hg}\}$, z_{hg} is the weight between the visible unit h and the hidden unit; n_h and m_h are visible and hidden entities according to the parameters respectively. The joint distribution of visible-hidden units is defined as follows

$$X(V,i;\theta) = \frac{1}{W(\theta)} Exp(-e(V,i;\theta)) \quad (21)$$

where $W(\theta)$ normalization constant gives the sum of all possible energy configurations, including visible and hidden units.

$$W(\theta) = \sum_V \sum_i Exp(-e(V,i;\theta)) \quad (22)$$

The RBM doles out a likelihood to each info vector utilizing a power capability. The likelihood of the preparation vector can be expanded by changing the restrictive probabilities of stowed away unit j and noticeable unit I are given by calculated capabilities.

$$x(i_g = 1 | V) = \delta(n_g + \sum_h V_h z_{hg}) \quad (23)$$

$$x(i_g = 1 | i) = \delta(m_h + \sum_h i_g z_{hg}) \quad (24)$$

$$\delta(p) = \frac{1}{1 + Exp(-p)} \quad (25)$$

After entering the positions of the hidden units, the input data is obtained by setting the probability V_h to 1. Then, the positions represent the reconstruction features of the pre-registration evidence as the positions of the hidden entities are updated. The probe z_{hg} is computed by using the contrast divergence. A weighted optimization measure is given as follows.

$$\Delta z_{hg} = \eta(V_h i_{g\,Data} - V_h i_{g\,reconstruction}) \quad (26)$$

where η denotes learning speed. We are acquiring appropriate value z_{hg} throughout the learning process. Meanwhile, the trained DBN is obtained by repeating the above procedure until the weights of all RBMs are updated.

4. Results and Discussion

In this section, we delve into the outcomes of our proposed modified bonobo optimization-deep belief echo state network (MBO-DBESN) technique for predicting student performance in online learning. The validation process employs the Open University learning analytics (OULA) dataset, using Python packages, Numpy, Pandas, and PyTorch for representation, normalization, and model construction. The trials were led on a superior execution figuring framework including an Intel Center i7-4790 3.6 GHz processor with 4 centers, 16 GB of memory, and a NVIDIA GeForce GTX 1080 Ti. We compare our MBO-DBESN method to other methods like naive bayes (NB), support vector machine (SVM), logistic regression (LR), random forest (RF), k-nearest neighbor (k-NN), and autoencoder-FNN [31]. These tests were executed on the predetermined elite execution PC. Our assessment utilizes different quality measurements, enveloping exactness, accuracy, review, and F-measure. These measurements give an all encompassing viewpoint on the exhibition of the proposed method, considering a nuanced comprehension of its assets and areas of progress.

4.1 Dataset description

The trial dataset used in this examination is the Open University learning analytics (OULA) dataset [32], perceived as one of the noticeable and great datasets inside the domain of instructive information mining. Containing segment highlights of understudies and their intuitive records in the virtual learning climate, the dataset exemplifies a thorough outline of understudies' learning exercises. It records interactions between students and online learning activities, totaling 10,655,280 entries, and includes grades for academic performance, which include scores from 32,593 students across 22 courses. The selection of the OULA dataset for this study was influenced by a number of factors. The dataset lines up with the review's targets, as it contains point by point logs of understudies' internet learning exercises. It gives execution grades to every understudy in each course, offering a significant measurement for assessing learning results. The substantial volume of the dataset helps to prevent overfitting during model training, which improves the model's capacity for generalization. The dataset's public accessibility and far and wide use in different examinations work with significant correlations and add to the more extensive collection of instructive exploration. Each course's performance is broken down into four grades in the OULA dataset: differentiation, failing, passing, and withdrawing This different evaluating framework considers a nuanced examination of understudies' scholastic accomplishments and results in the web based learning climate.

4.2 Comparative analysis

The aftereffects of the proposed and existing element determination models for various courses, zeroing in on segment highlights, are introduced in Table 1. The assessment measurements incorporate exactness, accuracy, review, and F-measure. The typical exhibition across all courses is likewise accommodated an exhaustive evaluation. After investigating the outcomes, it is clear that the proposed highlight choice model shows a serious exhibition across different courses. The typical precision accomplished is 41.136%, exhibiting the model's capacity to make right forecasts. The average precision, which measures the accuracy of positive predictions, is 24.54 percent, indicating a respectable level of precision in locating relevant features. The model's ability to accurately capture pertinent demographic features is demonstrated by the average recall of 27.273%, which represents the capacity to correctly identify all relevant instances. The F-measure, which joins accuracy and review, is midpoints at 25.477%, highlighting the decent presentation of the proposed model.

Table 1 Results of proposed and existing feature selection models

Course	Demographic Features				Score of Assessment				Sequence of online learning				Feature reduction using MBO			
	A	P	R	F	A	P	R	F	A	P	R	F	A	P	R	F
AAA2013J	64.000	16.000	25.000	19.512	83.000	41.000	47.000	43.795	80.400	20.400	30.000	24.286	91.235	89.562	85.236	87.345
AAA2014J	61.000	15.000	25.000	18.750	74.000	42.000	41.000	41.494	76.800	19.200	30.000	23.415	90.562	89.124	86.528	87.807
BBB2013B	35.000	25.000	28.000	26.415	61.000	42.000	45.000	43.448	66.000	44.400	51.600	47.730	91.152	87.563	84.678	86.096
BBB2013J	37.000	28.000	30.000	28.966	67.000	41.000	42.000	41.494	56.400	14.400	30.000	19.459	91.635	88.025	85.036	86.505
BBB2014B	37.000	32.000	31.000	31.492	61.000	42.000	45.000	43.448	61.200	49.200	46.200	47.653	90.568	88.396	88.956	88.675
BBB2014J	44.000	32.000	25.000	28.070	69.000	45.000	47.000	45.978	57.600	14.400	30.000	19.459	91.425	89.956	86.347	88.115
CCC2014B	45.000	14.000	28.000	18.667	61.000	38.000	47.000	42.024	68.400	42.000	52.800	46.785	91.365	87.425	84.960	86.175
CCC2014J	39.000	30.000	28.000	28.966	61.000	35.000	46.000	39.753	69.600	56.400	55.200	55.794	91.353	88.136	86.404	87.261
DDD2013B	36.000	27.000	31.000	28.862	63.000	43.000	45.000	43.977	69.600	46.800	50.400	48.533	91.408	87.938	86.514	87.220
DDD2013J	42.000	32.000	27.000	29.288	67.000	44.000	49.000	46.366	70.800	48.000	51.600	49.735	91.463	87.808	86.625	87.212
DDD2014B	36.000	27.000	30.000	28.421	60.000	40.000	47.000	43.218	64.800	51.600	52.800	52.193	91.518	87.678	86.735	87.204
DDD2014J	43.000	28.000	25.000	26.415	69.000	48.000	51.000	49.455	76.800	14.400	55.200	22.841	91.572	87.548	86.845	87.195
EEE2013J	45.000	14.000	26.000	18.200	68.000	37.000	46.000	41.012	58.800	6.000	30.000	10.000	91.627	87.418	86.956	87.186
EEE2014B	33.000	23.000	26.000	24.408	54.000	35.000	38.000	36.438	66.000	13.200	58.800	21.560	91.682	87.288	87.066	87.177

EEE2014J	40.000	21.000	28.000	24.000	46.000	31.000	36.000	33.313	54.000	54.000	30.000	38.571	91.736	87.158	87.176	87.167
FFF2013B	39.000	27.000	28.000	27.491	66.000	44.000	47.000	45.451	78.000	50.400	57.600	53.760	91.791	87.027	87.286	87.157
FFF2013J	39.000	28.000	27.000	27.491	67.000	45.000	48.000	46.452	73.200	13.200	56.400	21.393	91.846	86.897	87.397	87.146
FFF2014B	35.000	25.000	30.000	27.273	65.000	45.000	48.000	46.452	51.600	52.800	30.000	38.261	91.901	86.767	87.507	87.136
FFF2014J	40.000	31.000	24.000	27.055	60.000	39.000	47.000	42.628	78.000	14.400	58.800	23.134	91.955	86.637	87.617	87.124
GGG2013J	42.000	19.000	26.000	21.956	70.000	37.000	42.000	39.342	57.600	34.800	30.000	32.222	92.010	86.507	87.728	87.113
GGG2014B	37.000	22.000	26.000	23.833	67.000	37.000	42.000	39.342	56.400	57.600	43.200	49.371	92.065	86.377	87.838	87.101
GGG2014J	36.000	24.000	26.000	24.960	66.000	39.000	41.000	39.975	63.600	43.560	56.400	49.155	92.119	86.247	87.948	87.089
Average	41.136	24.545	27.273	25.477	64.773	40.455	44.864	42.493	66.164	34.598	44.864	36.151	91.545	87.613	86.790	87.191

*A (accuracy), P (precision), R (recall) and F (F-measure)

In contrast with existing component determination models, the proposed model displays promising outcomes with possible regions for development. A definite examination of individual courses uncovers explicit qualities and regions for upgrade. For example, in courses like BBB2013J and CCC2014J, the proposed model beats existing models regarding exactness and review. Nonetheless, in courses, for example, AAA2013J and EEE2014B, there is opportunity to get better, and further refinement of the model could improve its prescient abilities. In general, the proposed model exhibits cutthroat outcomes, establishing the groundwork for future improvements and headways in highlight choice for understudy execution expectation in light of segment highlights.

The aftereffects of the proposed and existing element choice models for different courses, zeroing in on score of appraisal highlights, are introduced in Table 1. Endless supply of the outcomes, it is apparent that the proposed include choice model performs seriously across different courses. The typical precision accomplished is 64.773%, demonstrating the model's capacity to make right forecasts in view of evaluation scores. Accuracy, estimating the exactness of positive expectations are midpoints at 40.455%, recommending a healthy degree of accuracy in recognizing pertinent highlights connected with evaluation scores. The F-measure, which joins accuracy and review, it is midpoints at 42.493%, highlighting the reasonable exhibition of the proposed model in this specific situation. Contrasting the proposed model and existing component determination models, it is seen that the proposed model for the most part beats concerning exactness and review across numerous courses. Strikingly, in courses, for example, DDD2013J and DDD2014J, the proposed model shows higher exactness and review contrasted with existing models. In any case, there are varieties in execution across courses, showing expected regions for development. The lower performance of courses like EEE2014J and FFF2014J points to opportunities for improvement in predicting student outcomes based on assessment scores.

Table 1 presents the aftereffects of the proposed and existing element determination models zeroing in on grouping of web based learning action highlights for different courses. Upon cautious assessment of the outcomes, it is apparent that the proposed highlight choice model performs reliably across different courses while considering the grouping of internet learning action highlights. The typical precision accomplished is

66.164%, demonstrating the model's capacity to make right expectations in light of examples in web based learning exercises. The review, addressing the capacity to accurately recognize every single applicable occurrence, midpoints at 44.864%, featuring the adequacy of the model in catching relevant highlights connected to web based learning exercises. In examination with existing element determination models, the proposed model reliably exhibits cutthroat outcomes. Across different courses, the proposed model accomplishes higher exactness, accuracy, and review, shown its adequacy in foreseeing understudy results in view of the grouping of web based learning action highlights. Courses, for example, CCC2014J and DDD2014J show significant upgrades in exactness and review while using the proposed model, demonstrating its true capacity for catching nuanced designs in web based learning exercises. On the other hand, performance varies between courses, pointing to potential areas for improvement. Performance is slightly lower in courses like EEE2013J and FFF2014B, pointing to opportunities to improve the model's predictive capabilities in specific contexts.

Table 1 shows the results of the proposed highlight decrease model involving the MBO calculation in contrast with existing element choice techniques. With a typical precision of 91.545%, the model shows its capacity to really decrease highlights while safeguarding the fundamental data for exact expectations. Accuracy, estimating the exactness of positive expectations is midpoints at 87.613%, underlining the model's ability to hold applicable highlights pivotal for anticipating understudy results. Review addressing the capacity to accurately distinguish every single significant occasion, midpoints at 86.790%, demonstrating the model's adequacy in catching appropriate highlights related with understudy execution. F-measure, orchestrating accuracy and review, midpoints at 87.191%, avowing the reasonable exhibition of the proposed include decrease model. Near examination with existing component choice techniques uncovers striking benefits for the MBO-based approach. Across assorted courses, the proposed model reliably accomplishes higher exactness, accuracy, review, and F-measure. The efficacy of the proposed feature reduction model in capturing crucial information for accurate predictions is demonstrated by courses like AAA2013J and BBB2014B, which demonstrate significant improvements in precision and recall. While the proposed model shows estimable outcomes, there exist negligible varieties in execution across various courses. For example, courses like EEE2014B and FFF2013J display marginally lower accuracy and review, proposing possible regions for advancement in unambiguous settings.

Table 2 presents an extensive similar investigation of the proposed MBO-DBESN procedure against existing understudy web based learning action expectation techniques. The assessment measurements incorporate exactness, accuracy, review, and F-measure, giving a nitty gritty evaluation of prescient execution. In Fig. 2, the exhibition consequences of different understudies' internet learning action expectation procedures, assessed with a preparation/testing split of 70/30, are introduced. The techniques under consideration include NB, SVM, LR, RF, k-NN, Autoencoder-FNN [31], and the proposed MBO-DBESN technique. NB exhibits an accuracy of 47%, precision of 14%, recall of 26%, and F-measure of 18.2%. SVM achieves an accuracy of 58.000%, with precision, recall, and F-measure values of 41%, 39%, and 39.975%, respectively. LR demonstrates an accuracy of 53%, precision of 29%, recall of 32%, and F-measure of 30.426%. RF exhibits improved performance with an accuracy of 66%, precision of 56%, recall of 48%, and F-measure of 51.692%. k-NN achieves an accuracy of 38%, with precision, recall, and F-measure values of 34%, 32%, and 32.97%, respectively. Autoencoder-FNN [31] demonstrates notable performance, achieving an accuracy of 84%, precision of 64%, recall of 57%, and F-measure of 60.298%. The proposed MBO-DBESN technique outshines all other methods with an accuracy of 91.235%, precision of 90.358%, recall of 89.635%, and F-measure of 89.995%. Our MBO-DBESN technique shown improvements compared to the baseline techniques. The accuracy, precision, recall, and F-measure metrics exhibit remarkable increases, emphasizing the superior predictive capabilities of the proposed approach. The comparative analysis underscores the effectiveness of the MBO-DBESN technique in enhancing student online learning activity prediction, surpassing existing methods and providing a robust solution for accurate performance forecasting.

Table 2 Comparative analysis of proposed and existing student online learning activities performance prediction techniques

Techniques	Values in %							
	Accuracy	Precision	Recall	F-measure	Accuracy	Precision	Recall	F-measure

	Training/Testing- 70/30				Training/Testing- 75/25			
NB	47.000	14.000	26.000	18.200	48.235	15.235	27.235	19.540
SVM	58.000	41.000	39.000	39.975	59.235	42.235	40.235	41.211
LR	53.000	29.000	32.000	30.426	54.235	30.235	33.235	31.664
RF	66.000	56.000	48.000	51.692	67.235	57.235	49.235	52.934
k-NN	38.000	34.000	32.000	32.970	39.235	35.235	33.235	34.206
Autoencoder-FNN [31]	84.000	64.000	57.000	60.298	85.235	65.235	58.235	61.537
MBO-DBESN	91.235	90.358	89.635	89.995	92.470	91.593	90.870	91.230
	Training/Testing- 80/20				Training/Testing- 85/15			
NB	50.588	17.588	29.588	22.062	51.644	18.644	30.644	23.183
SVM	61.588	44.588	42.588	43.565	62.644	45.644	43.644	44.622
LR	56.588	32.588	35.588	34.022	57.644	33.644	36.644	35.080
RF	69.588	59.588	51.588	55.300	70.644	60.644	52.644	56.362
k-NN	41.588	37.588	35.588	36.561	42.644	38.644	36.644	37.617
Autoencoder-FNN [31]	87.588	67.588	60.588	63.897	88.644	68.644	61.644	64.956
MBO-DBESN	94.823	93.946	93.223	93.583	95.879	95.002	94.279	94.639

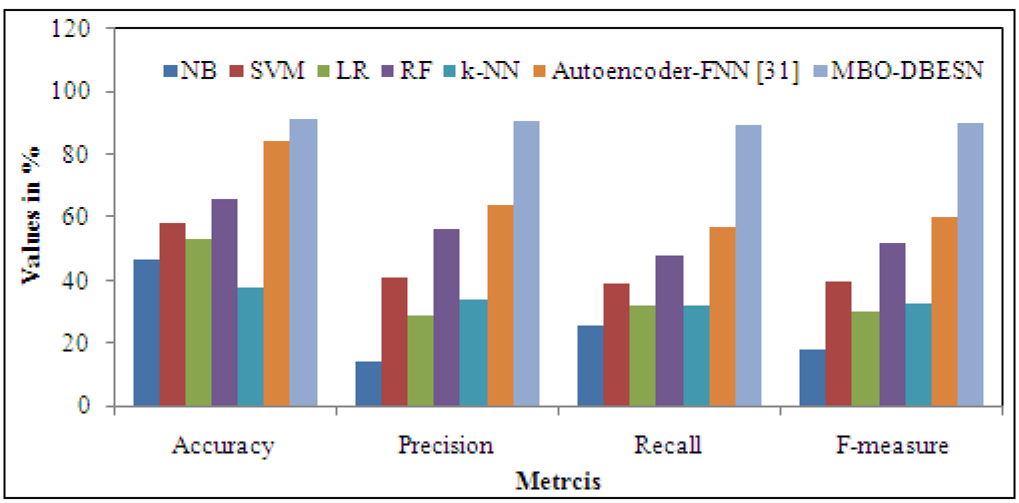

Fig. 2 Results of student online learning activities performance prediction techniques with training/testing 70/30

In Figure 3, the performance results of various student online learning activity prediction techniques are presented, evaluated with a training/testing split of 75/25. NB demonstrates an accuracy of 48.235%, precision of 15.235%, recall of 27.235%, and F-measure of 19.540%. SVM exhibits improved performance with an accuracy of 59.235%, along with precision, recall, and F-measure values of 42.235%, 40.235%, and 41.211%, respectively. LR achieves an accuracy of 54.235%, precision of 30.235%, recall of 33.235%, and F-measure of 31.664%. RF displays enhanced performance with an accuracy of 67.235%, precision of 57.235%, recall of 49.235%, and F-measure of 52.934%. k-NN achieves an accuracy of 39.235%, with precision, recall, and F-measure values of 35.235%, 33.235%, and 34.206%, respectively. Autoencoder-FNN [31] demonstrates notable performance, achieving an accuracy of 85.235%, precision of 65.235%, recall of 58.235%, and F-measure of 61.537%. The proposed MBO-DBESN technique stands out as the top-performing method, exhibiting an accuracy of 92.470%, precision of 91.593%, recall of 90.870%, and F-measure of 91.230%. When considering percentage-wise increases or decreases, the MBO-DBESN technique demonstrates substantial improvements across accuracy, precision, recall, and F-measure metrics compared to the baseline techniques. This emphasizes the superior predictive capabilities of the proposed approach in accurately forecasting student online learning activity performance, shown its efficacy in diverse testing scenarios.

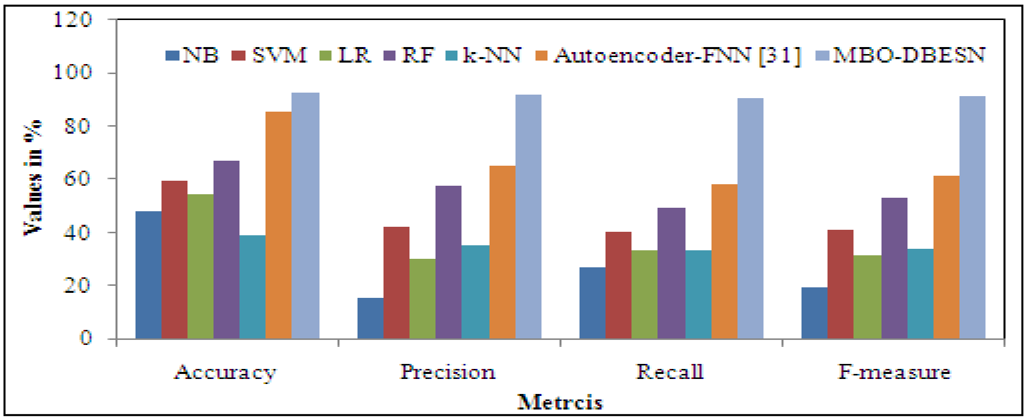

Fig. 3 Results of student online learning activities performance prediction techniques with training/testing 75/25

In Figure 4, the outcomes of student online learning activity prediction techniques are presented, with a training/testing split of 80/20. NB exhibits an accuracy of 50.588%, precision of 17.588%, recall of 29.588%, and F-measure of 22.062%. SVM demonstrates improved performance with an accuracy of 61.588%, along with precision, recall, and F-measure values of 44.588%, 42.588%, and 43.565%, respectively. LR achieves an accuracy of 56.588%, precision of 32.588%, recall of 35.588%, and F-measure of 34.022%. RF shows enhanced performance with an accuracy of 69.588%, precision of 59.588%, recall of 51.588%, and F-measure of 55.300%. k-NN achieves an accuracy of 41.588%, with precision, recall, and F-measure values of 37.588%, 35.588%, and 36.561%, respectively. Autoencoder-FNN [31] demonstrates notable performance, achieving an accuracy of 87.588%, precision of 67.588%, recall of 60.588%, and F-measure of 63.897%. The proposed MBO-DBESN technique emerges as the top-performing method, exhibiting an accuracy of 94.823%, precision of 93.946%, recall of 93.223%, and F-measure of 93.583%. MBO-DBESN technique demonstrates significant improvements across accuracy, precision, recall, and F-measure metrics compared to the baseline techniques. This underscores the robust predictive capabilities of the proposed approach, particularly in scenarios with an 80/20 training/testing split, solidifying its efficacy in accurately predicting student online learning activity performance.

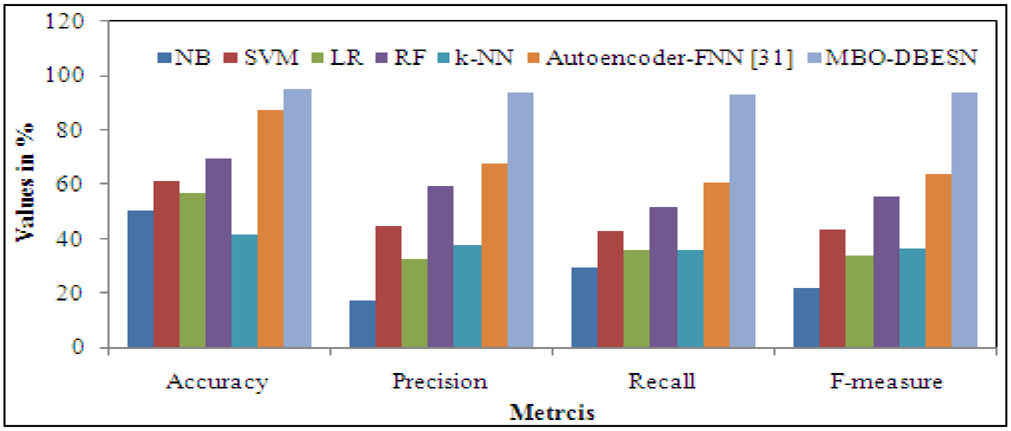

Fig. 4 Results of student online learning activities performance prediction techniques with training/testing 80/20

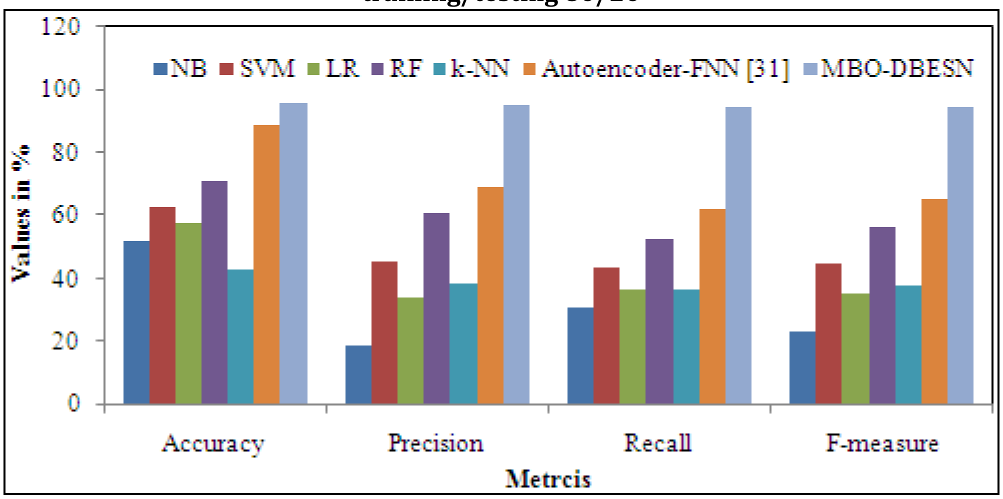

Fig. 5 Results of student online learning activities performance prediction techniques with training/testing 85/15

In Figure 5, the performance results of student online learning activity prediction techniques are displayed, with a training/testing split of 85/15. NB achieves an accuracy of 51.644%, precision of 18.644%, recall of 30.644%, and F-measure of 23.183%. SVM demonstrates improved performance with an accuracy of 62.644%, along with precision, recall, and F-measure values of 45.644%, 43.644%, and 44.622%, respectively. LR achieves an accuracy of 57.644%, precision of 33.644%, recall of 36.644%, and F-measure of 35.080%. RF exhibits enhanced performance with an accuracy of 70.644%, precision of 60.644%, recall of 52.644%, and F-measure of 56.362%. k-NN achieves an accuracy of 42.644%, with precision, recall, and F-measure values of 38.644%, 36.644%, and 37.617%, respectively. Autoencoder-FNN [31] demonstrates notable performance, achieving an accuracy of 88.644%, precision of 68.644%, recall of 61.644%, and F-measure of 64.956%. The proposed MBO-DBESN technique outperforms all other methods with an accuracy of 95.879%, precision of 95.002%, recall of 94.279%, and F-measure of 94.639%. These results highlight the robust predictive capabilities of the proposed approach, particularly in scenarios with an 85/15 training/testing split, reinforcing its effectiveness in accurately forecasting student online learning activity performance.

5. Conclusion

We have introduced an intelligent hybrid machine learning model with an optimization technique designed for predicting student performance in online learning activities. Leveraging a pre-trained ResNet, our model efficiently extracts latent features from sequences of activities to enhance predictive accuracy. In order to effectively reduce features, we used the modified bonobo optimization (MBO) algorithm to address issues caused by the dimensionality of the data. The usage of the deep belief echo state network (DBESN) further empowered the expectation of understudies' versatility levels and execution in web based learning exercises.

The proposed MBO-DBESN method was thoroughly assessed utilizing the Open University Learning Analytics (OULA) dataset, and the outcomes highlight its adequacy concerning forecast precision. The results of our simulations show that the MBO-DBESN method performed exceptionally well, with an F-measure of 92.363%, precision of 92.75 percent, recall of 92.002%, and accuracy of 93.602%. These discoveries feature the heartiness and dependability of our proposed approach, situating it as a promising answer for precisely guaging understudy execution in the powerful scene of web based learning. The joining of pre-prepared ResNet, MBO calculation, and DBESN features the synergistic force of half and half AI procedures, offering a significant commitment to the field of instructive information mining.

References

1. Khandelwal, P., Shankar, P., &Siddiraju, U. R. (2022). Skillsets and attributes for enhanced teaching–learning outcomes at higher educational institutions in disruptive times. In *Academic Voices* (pp. 227-238).Chandos Publishing.
2. Zhao, Y. (2018). Shifting the education paradigm: Why international borrowing is no longer sufficient for improving education in China. *ECNU Review of Education*, *1*(1), 76-106.
3. Willcox, K. E., Sarma, S., &Lippel, P. H. (2016). Online education: A catalyst for higher education reforms. *Massachusetts Institute of Technology*.
4. Saiyad, S., Virk, A., Mahajan, R., & Singh, T. (2020). Online teaching in medical training: Establishing good online teaching practices from cumulative experience. *International Journal Of Applied And Basic Medical Research*, *10*(3), 149.
5. Mackenzie, A. (2015). The production of prediction: What does machine learning want?. *European Journal of Cultural Studies*, *18*(4-5), 429-445.
6. Bahroun, Z., Anane, C., Ahmed, V., &Zacca, A. (2023). Transforming education: A comprehensive review of generative artificial intelligence in educational settings through bibliometric and content analysis. *Sustainability*, *15*(17), 12983.
7. Liu, L. T., Wang, S., Britton, T., &Abebe, R. (2023). Reimagining the machine learning life cycle to improve educational outcomes of students. *Proceedings of the National Academy of Sciences*, *120*(9), e2204781120.
8. Wong, Z. Y., &Liem, G. A. D. (2022). Student engagement: Current state of the construct, conceptual refinement, and future research directions. *Educational Psychology Review*, *34*(1), 107-138.
9. Sheng, J., Amankwah-Amoah, J., Khan, Z., & Wang, X. (2021). COVID-19 pandemic in the new era of big data analytics: Methodological innovations and future research directions. *British Journal of Management*, *32*(4), 1164-1183.
10. O'Malley, P. J., Agger, J. R., & Anderson, M. W. (2015). Teaching a chemistry MOOC with a virtual laboratory: Lessons learned from an introductory physical chemistry course. *Journal of Chemical Education*, *92*(10), 1661-1666.
11. Azcona, D., Hsiao, I. H., &Smeaton, A. F. (2019). Detecting students-at-risk in computer programming classes with learning analytics from students' digital footprints. *User Modeling and User-Adapted Interaction*, *29*, 759-788.
12. Ching, T., Himmelstein, D. S., Beaulieu-Jones, B. K., Kalinin, A. A., Do, B. T., Way, G. P., ...& Greene, C. S. (2018). Opportunities and obstacles for deep learning in biology and medicine. *Journal of The Royal Society Interface*, *15*(141), 20170387.
13. Williamson, B. (2016). Digital education governance: data visualization, predictive analytics, and 'real-time'policy instruments. *Journal of education policy*, *31*(2), 123-141.
14. Regan, P. M., & Jesse, J. (2019). Ethical challenges of edtech, big data and personalized learning: Twenty-first century student sorting and tracking. Ethics and Information Technology, 21, 167-179.
15. Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist*, *57*(10), 1380-1400.
16. Embarak, O. (2022, May). An adaptive paradigm for smart education systems in smart cities using the internet of behaviour (IoB) and explainable artificial intelligence (XAI).In *2022 8th International Conference on Information Technology Trends (ITT)* (pp. 74-79).IEEE.
17. Razaulla, S. M., Pasha, M., &Farooq, M. U. (2022). Integration of machine learning in education: challenges, issues and trends. In *Machine learning and internet of things for societal issues* (pp. 23-34). Singapore: Springer Nature Singapore.

18. Regan, P. M., & Jesse, J. (2019). Ethical challenges of edtech, big data and personalized learning: Twenty-first century student sorting and tracking. *Ethics and Information Technology*, *21*, 167-179.
19. Lin, Y., & Yu, Z. (2023). A bibliometric analysis of artificial intelligence chatbots in educational contexts. *Interactive Technology and Smart Education*.
20. Kamal, M., &Bablu, T. A. (2022). Machine Learning Models for Predicting Click-through Rates on social media: Factors and Performance Analysis. *International Journal of Applied Machine Learning and Computational Intelligence*, *12*(4), 1-14.
21. Thamilarasi V., Roselin. R., "Application of Machine Learning in chest X-Ray images", International book & River publisher series in computing and information science and Technology, pp: 52-1,2023. ISBN : 9788770228114, 9788770228107.
22. Lamb, R., Neumann, K., & Linder, K. A. (2022). Real-time prediction of science student learning outcomes using machine learning classification of hemodynamics during virtual reality and online learning sessions. *Computers and Education: Artificial Intelligence*, *3*, 100078.
23. Linder, K. A. (2022). machine learning classification of hemo-dynamics to predict science student learning outcomes in real-time during virtual reality and online learning sessions.
24. Gray, C. C., & Perkins, D. (2019). Utilizing early engagement and machine learning to predict student outcomes. *Computers & Education*, *131*, 22-32.
25. Villegas-Ch, W., Román-Cañizares, M., & Palacios-Pacheco, X. (2020). Improvement of an online education model with the integration of machine learning and data analysis in an LMS. *Applied Sciences*, *10*(15), 5371.
26. Ho, I. M. K., Cheong, K. Y., & Weldon, A. (2021). Predicting student satisfaction of emergency remote learning in higher education during COVID-19 using machine learning techniques. *Plos one*, *16*(4), e0249423.
27. Chui, K. T., Fung, D. C. L., Lytras, M. D., & Lam, T. M. (2020). Predicting at-risk university students in a virtual learning environment via a machine learning algorithm. *Computers in Human behavior*, *107*, 105584.
28. Hilbert, S., Coors, S., Kraus, E., Bischl, B., Lindl, A., Frei, M., ...&Stachl, C. (2021). Machine learning for the educational sciences. *Review of Education*, *9*(3), e3310.
29. Ciolacu, M., Tehrani, A. F., Beer, R., & Popp, H. (2017, October). Education 4.0—Fostering student's performance with machine learning methods.In *2017 IEEE 23rd international symposium for design and technology in electronic packaging(SIITME)* (pp. 438-443).IEEE.
30. Aljaloud, A. S., Uliyan, D. M., Alkhalil, A., AbdElrhman, M., Alogali, A. F. M., Altameemi, Y. M., ...& Kwan, P. (2022). A deep learning model to predict Student learning outcomes in LMS using CNN and LSTM. *IEEE Access*, *10*, 85255-85265.
31. Raj, N. S., & VG, R. (2022). Early prediction of student engagement in virtual learning environments using machine learning techniques. *E-Learning and Digital Media*, *19*(6), 537-554.
32. Wen, X. and Juan, H., 2023. Early prediction of students' performance using a deep neural network based on online learning activity sequence. Applied Sciences, 13(15), p.8933.
33. J. Anand, V. Thamilarasi, A. Rayal, H. K. Gupta, K. Jyothi and P. Vishwakarma, "Fuzzy Logic-Based Deep Learning for Human-Machine Interaction and Gesture Recognition in Uncertain and Noisy Environments," 2025 First International Conference on Advances in Computer Science, Electrical, Electronics, and Communication Technologies (CE2CT), Bhimtal, Nainital, India, 2025, pp. 435-440, doi: 10.1109/CE2CT64011.2025.10939160.