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OPTIMIZATION

An efficient e-learning recommendation system for user preferences using hybrid optimization algorithm

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Abstract

The expanding approval of e-learning structure has made the need for the customized suggestion prototype which can be utilized to advance the successful learning condition for the learners. Customized suggestion model is a particular sort of data separating framework used to recognize a lot of articles that are applicable to a e-learners. In this paper, we mainly propose the efficient e-learning recommendation (EELR) system for user preferences using hybrid optimization algorithm (HOA). EELR system constructs a HOA with deep recurrent neural network (DRNN) and improved whale optimization (IWO) algorithm. First, DRNN is utilized to order the e-learner types dependent on these e-learner gatherings, clients can acquire course proposal from the gathering's persuasion. Thereafter, the conduct and the inclinations of the learners are examined via completing the mining of the arrangements watched every now and again by the IWO calculation. Rather than a learner effectively looking for data, recommender frameworks give counsel to students about articles they may wish to analyze. At last, the proposal of the e-learning depends on the appraisals comparing to these arrangements watched often. This proposed system is going to implement and validate in numerous e-learning entries against the client inclinations over some undefined time frame and demonstrated to be more proficiency and exactness contrasted with the customary recommender framework. This strategy can help learners to grasp the knowledge system and learning direction, and improve their learning efficiency. Observation results show that the proposed methodology empowers the asset suggestion to singular clients, which is started from different sources.

Keywords Efficient e-learning recommendation · Hybrid optimization algorithm · Deep recurrent neural network · Improved whale optimization

1 Introduction

Over the latest couple of years, recommender systems have been commonly used as an answer towards watching out for the information over-trouble issue (Klašnja-Milićević et al. 2011; Cuéllar et al. 2011a). Basically, e-learning recommender structures deal with this issue through subsequently endorsing fitting learning materials to understudies reliant on their modified understudy tendency and profile. A critical informational activity in supporting on the web understudies in e-learning conditions by giving altered proposition of learning materials for better achievement of the learning targets (Cuéllar et al. 2011b). When in doubt, to empower personalization, existing frameworks use in any occasion one kind of learning and personalization in e-learning structures concern flexible association, adaptable course movement, content disclosure and social occasion, and adaptable composed exertion support (Salehi and Kmalabadi 2012; Othman et al. 2012). The class of flexible course movement shows the most outstanding and extensively used assembling of change systems applied in e-learning structures today. Thusly, personalization accepts a colossal activity in an adaptable e-learning structure. This needs understudy profile in perspective on various propensities, learning rehearses among understudies (Aher and Lobo 2013). Considering the gigantic extent of learning assets on the web, it is

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dubious learning assets identified with understudy demand. The proposition structure is an application prepared for displaying a customer a proposition for a thing, procured dependent on his past tendencies and the tendencies of a system. Henceforth, recommendation structures help understudies to diminish the over-weight of data that they experience these days, giving, simultaneously, changed access to data for a particular region (Salehi 2013).

From the presence of the World Wide Web, we investigate in e-learning and online transport clearly material has gotten thought (Dascalu et al. 2014). Regardless, again, very few course the administrators structures solidify insightful pros that would allow tweaking the course transport system or individualizing the prescribed learning material. Near applications in business have succeeded (Garrido and Morales 2014). The personalization of online records and virtual stores to improve the electronic acquiring information, limit blending, appeal purchase and attract new customers has been the point of convergence of many research contemplates in enrolling science, business, correspondence and mind science. Today, various such applications are advertised and are getting the opportunity to be unmistakable (Tian et al. 2014). For example, a few destinations may present changed thing files that would contain generally things that resemble the customer's past likings or with high probability to be acquired reliant on the customer's profile declining aggravating the customer with long and silly records (Parkes et al. 2015; Ficapal-Cusí and Boada-Grau 2015). Different business goals may give customized proposals to things subject to the present purchase and the likings and 'tastes' of the customer and the total choices.

Ontology web language (OWL) is used to grasp the semantics of the data base. The course.owl and user.owl are used to store learning materials and to execute the Felder-Silverman learning style model independently (Rani et al. 2015). E-slanting structure licenses motorized and quantifiable computations open the opportunity to beat burdens of the ordinary area strategy that uses essentially survey (Truong 2016). An e-learning structures accomplishment model joins a social form, autonomy/network (Aparicio et al. 2016). An electronic examination coursed to cutting edge instruction understudies having a spot with various taking in levels and from various schools. A definite-based strategy is coordinated to explore how teachers partner with an e-learning condition reliant on a predefined task model depicting low-level interchanges (Tan et al. 2008). Online e-learning structure is used to improve the limit of endoscopists to examine gastric malady at a starting period was made and was surveyed for its feasibility (Yao et al. 2015). A proposition system model (Duwairi and Ammari 2016) is executed for on the customer's navigational history without mentioning express commitment from her. Edu-AREA is genuinely open in comprehension to the UNESCO definition considering the way that any customer can copy, use, change and re-share any information record available in the system (Caeiro-Rodríguez et al. 2015). An e-learning organization model (Tan et al. 2017) is used for the life-cycle process the administrators subject to the understudy's works on through e-learning organizations, the booking procedures, and the checking arrangement of instruction works out.

This paper is structured into six segments. First, we establish about e-learning techniques in Sect. 1. Segment 2 describes relevant previous works of e-learning. In Segment 3, we provide the problem methodology and system architecture of our proposed model. Segment 4 is the technique path of our approach. The experimental results of the proposed approach are presented in Segment 5. Finally, we conclude the paper in Segment 6.

2 Related works

Truong et al. (2016) have proposed revelations uncover a bewildering image of the examination field with promising outcomes and extending applications, yet many open issues. It is discovered that Felder–Silverman is by a wide edge, the most observable theory that has been applied in e-learning structure. While the theory can be commensurate, there are a few factors utilized for estimation that have been seen. In any case, the outcomes in addition raise an issue which is that none of the past assessments give data on the power of various qualities in sorting out learning styles. What's more, however, different strategy considers have been investigated as a part of which Bayesian network and rules based are the most broadly utilizes, just a little level of papers considers depiction techniques evaluation or methodologies blend.

Tarus et al. (2017) have approach the circuits extra data from power space learning and SPM into the recommendation system. Introspective philosophy is utilized to address information about the understudy and learning assets while SPM estimation to find understudy's chronicled successive learning models. From the exploratory outcomes, it may be seen that the proposed half and half calculation can get favored execution and precision over other related tallies.

Tarus et al. (2018a) have structured recommender frameworks in e-learning space acknowledge a basic action in helping the understudies to discover noteworthy and fitting learning information that meet their modifying needs. Changed sharp specialists and suggest frameworks have been widely perceived as plans towards beating data recovery opposition by understudies ascending out of data over-inconvenience. Utilization of thinking for information portrayal in learning-based recommender frameworks for e-learning has changed into an intriguing examination district.

Benhamdi et al. (2017) have planned a proposition approach subject to network masterminded and content-based sifting is shown: NPR_eL (new multi-personalized recommender for e-learning). This methodology was participated in a learning space so as to pass on changed learning material. We show the abundancy of our strategy through the structure, use, assessment and assessment of an individual learning condition.

Ouadoud et al. (2017) have displayed a stage decision, assurance of accomplishment and sensibility for insightful contraption that in like way appears in plentifulness with the free stages' point of view and their region dynamic. It emitted an impression of being intriguing to apply considering the way that a proposal strategy of the free e-learning stages dependent on a careful and fundamental way of thinking energized by the thing wanting to help the decision of the most reasonable e-learning stage to the goals and institutional nuances.

Tarus et al. (2018b) have displayed a cream proposal strategy joining setting care, dynamic a model mining (SPM) and CF means underwriting learning points of interest for the understudies. In our recommendation approach, setting care is utilized to consolidate appropriate data about the understudy, for example, information recollected objectives; SPM count is used to mine the internet logs then discover the understudy's dynamic access models; and CF figures guesses and makes proposition for the objective understudy subject to contextualized information and understudy's consecutive access structures.

Bourkoukou et al. (2016) have proposed an issues concerning personalization in learning framework have been generally investigated in the prior decades and remain the purpose of combination of thought of different stars to a day. Adjusted e-learning dependent on recommender framework is viewed as one of the most dazzling appraisal field in the planning and instructing in this last decade, since, the learning style is unequivocal with each understudy.

Dorça et al. (2016) have proposed a content personalization in instructive frameworks is a developing investigation area. Studies show that understudies will generally speaking have better shows when the substance is balanced by his/her propensities. One basic bit of understudy's particularities is the techniques by which they like to learn. In this specific condition, understudies learning styles ought to be considered, because of the vitality of this fragment to the adaptively approach in such structures.

Klašnja-Milićević et al. (2017) have displayed the recommender frameworks ardently rely on the unprecedented circumstance or zone they work in, and it is routinely outlandish to take a proposition technique starting with one setting and move it then onto the accompanying setting or space. Revamped proposal can help understudies with vanquishing the data over-inconvenience issue, by supporting learning assets as exhibited by understudies' propensities and level of information.

Harrati et al. (2016) have introduced a positive client experience and better convenience is of prime importance for edifying based learning structures tolerating key occupation for the assertion, fulfillment and benefit of astute establishments. Clear-based appraisal is coordinated to investigate how speakers collaborate with an e-learning condition structure subject to a predefined undertaking model delineating low-level knowledge rehearses for moving showing assets for understudies. The summary of research gap is given in Table 1.

3 Problem methodology

Perumal et al. (2019) have proposed proposal structure which gives sensible substance by refining the last perpetual thing models progressing from nonstop model mining framework and subsequently requesting the last substance using feathery method of reasoning into three levels. This is practiced by creating progressive thing structures in the wake of combining the customer interest changes with a comprehensive screw up edge leftover portion. Furthermore, soft rules are utilized in this work to empower the standard burrowing prerequisites for satisfying a wide scope of understudies while applying rules on the model tables. E-Learning goals are getting pervasiveness bit by bit and related to programming designing and information advancement field. This structure implements a model various tables subjects that are exceedamid the customer tendencies, and the customer updates from interest rank are kept up additionally. The exact appropriate things, a satisfactory security cushion is permitted in most of the ceaseless model mining counts. This structure also evacuates customer tendencies as progressive cutoff in the log record using a ceaseless model mining method. Recommender structures in e-learning zone expect a noteworthy activity in helping the understudies to find significant and appropriate learning materials that meet their changing needs. Adjusted sharp chairmen and recommender structures have been completely perceived as courses of action towards defeating data recovery challenges by understudies ascending out of data over-inconvenience. It is difficult for the individual understudies to pick overhauled practices for their specific requirements, since there exists no tweaked organization that has a spot with that specific customer.

Table 1 Summary of research gap

Refs.	Recommendation learning	Proposed methodology	Parameter improved	Remarks
Truong (2016)	Computerized and statistical algorithms	To overcome drawbacks of the traditional detection method that uses mainly questionnaire	Accuracy and precession	Difficulty in choosing relevant and useful learning resources
Tarus et al. (2017)	Hybrid knowledge-based approach	Ontology and sequential pattern mining used to incorporate additional learner data	Accuracy and precession	Learning system is closed learning environments
Tarus et al. (2018)	Ontology-based recommenders	Broad survey	Accuracy and precession	Information retrieval challenges by learners arising from information overload
Benhamdi et al. (2017)	New multi-personalized recommender	Provides to students the best learning materials according to their preferences, interests, background knowledge, and their memory capacity	Accuracy and precession	Not able to respond to each learner's needs
Ouadoud et al. (2017)	Functional architecture	Depending on the objects and pedagogical tools related to the recommended teaching and learning device	Accuracy and precession	Not suitable all learns
Tarus et al. (2018b)	SPM and CF algorithms	Context awareness is used to incorporate contextual information about the learner	Quality and accuracy	Difficulties in retrieval of suitable online learning resources due to information overload
Bourkoukou et al. (2016)	Personalized e-learning	Personalize learning scenario by selecting the most appropriate learning objects	Accuracy and precession	Not suitable all learns
Dorça et al. (2016)	Automatic and dynamic approach	Expert system that implements a set of rules which classifies learning objects	Quality and accuracy	Information overload
Klašnja-Milićević et al. (2017)	Context or domain-based system	Learners to overcome the information overload problem	Accuracy and precession	Not able to respond to each learner's needs
Harrati et al. (2016)	Empirical-based system	Explore lecturers interact with an e-learning environment based on a predefined task model describing low-level interactions	Quality and accuracy	Information overload

To overcome these issues, we implemented EELR system using following techniques

Deep recurrent neural network was used to analyze the e-learner types with its group. It used to classify with deep multi-layers.

Secondly, improved whale optimization algorithm is used for order the e-learner ratings in sequence.

Finally, the recommendation of the e-learning is based on the ratings corresponding to these sequences observed frequently.

3.1 System model

The proposed structure for a customized web content framework begins with overview of content, user visitor count, proof read, open source accessibility, online compiler, etc. Furthermore, these logs comprise of all relative data with the use of web substance by the e-learners. From our database, profound intermittent neural system used to arrange the e-students types dependent on e-student gatherings. After grouping, the improved whale advancement is utilized to arrange the appraisals in succession. At that point, different advances happen during the mining forms, for example, information cleaning, information reconciliation, information change and example revelation. Then, we analysis the performance of e-learner ratings and recommending e-learner based on high ratings. Above figure shows the system model of our proposed work shown in Fig. 1.

4 Classifying E-learner models using DRNN

The deep recurrent neural network (DRNN) with a solitary unidirectional shrouded layer. In the particular utilitarian type of how idle factors and perceptions interface was somewhat subjective. This is definitely not a major issue as

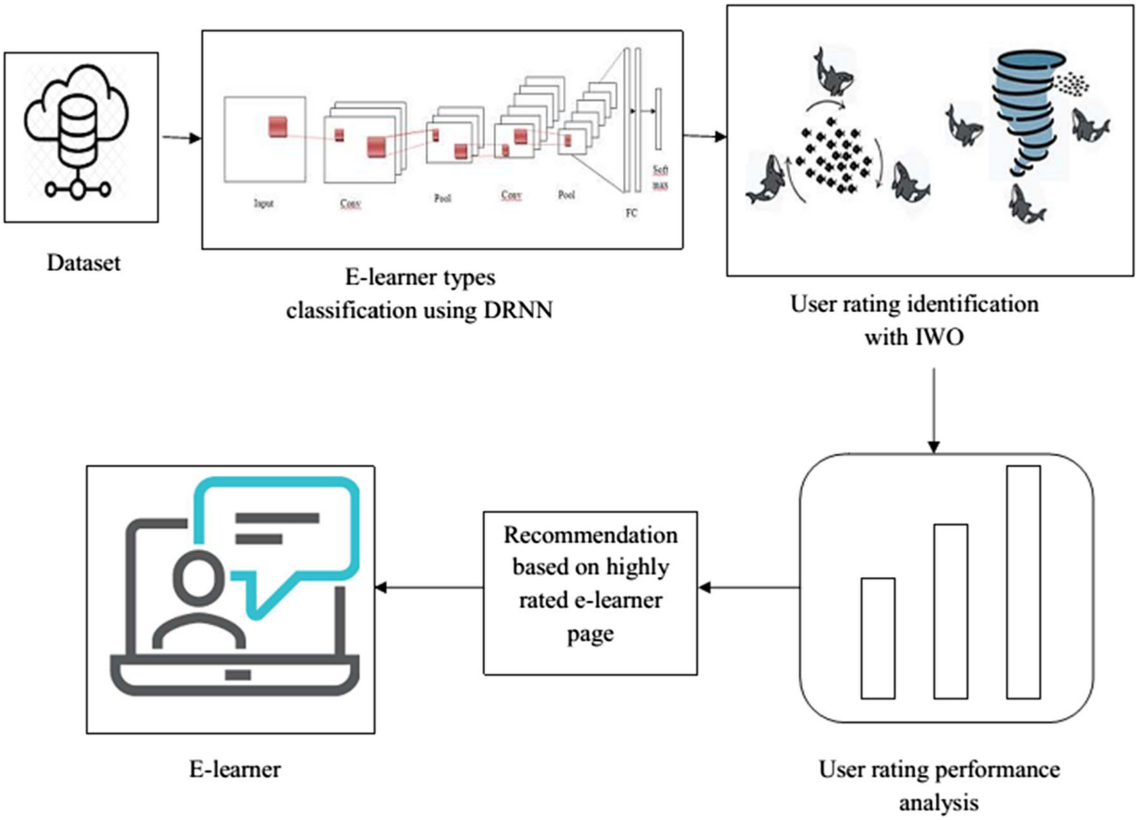


Fig. 1 E-learner recommendation using our proposed EELR system

long as we have enough adaptability to demonstrate various sorts of connections. With a solitary layer, be that as it may, this can be very testing. On account of the recognition, we confirm this issue by including many layers. Inside DRNNs, this is more dubious, first we, required to choose where and how to include additional irregularity. Our exchange underneath centers basically around long short-term memory (LSTM) yet it applies to other arrangement models, as well. We could add additional irregularity to the gating components. That is, rather than utilizing a solitary perceptron we could utilize different layers. This leaves the instrument of the LSTM unaltered. Rather it makes it increasingly modern. This would bode well on the off chance that we were persuaded that the LSTM instrument portrays some type of generally accepted fact of how idle variable autoregressive models work. We could stack various layers of LSTMs more than each other. This outcomes in a system that is progressively adaptable, because of the blend of a few straightforward layers. Specifically, information may be significant at various degrees of the stack. For example, we should keep elevated level information about money-related economic situations (bear or positively trending business sector) accessible at a significant level, while at a lower level we just record shorter-term fleeting elements shown in Fig. 2.

4.1 Mathematical dependencies

At time step t, we expect that we have a small bunch $X_t \in R^{n \times d}$ (number of models: n, number of information sources: d). The shrouded condition of concealed layer (l = 1,….T) is $H_t^{(l)} \in R^{n \times h}$ (number of concealed units: h), the yield layer variable $O_t \in R^{n \times q}$ (number of yields: q) and a concealed layer actuation work f_l for layer l. We register the shrouded condition of layer l as in the past, utilizing X_t as info. For every single consequent layer, the concealed condition of the past layer is utilized in its place.

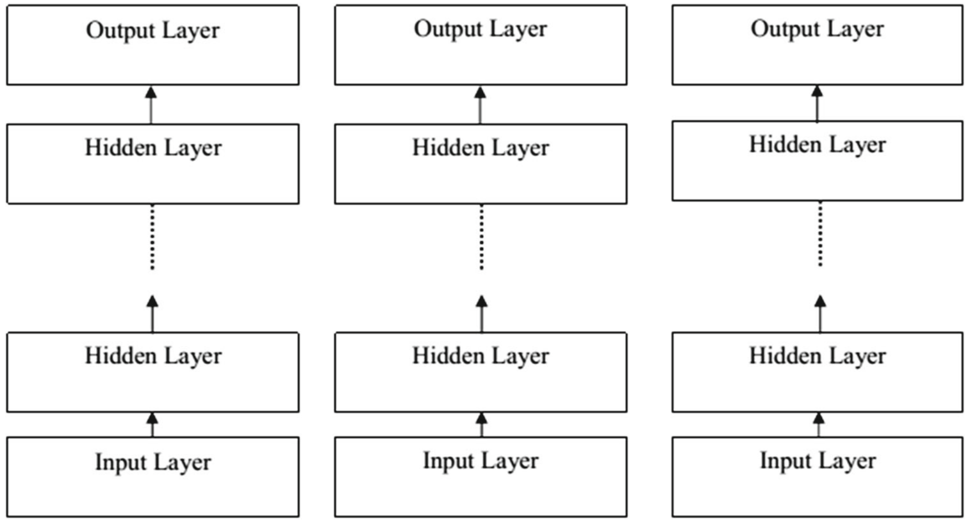
$$H_t^{(1)} = f_1(X_t, H_{t-1}^{(1)}) \tag{1}$$

At last, the yield of the yield layer is just founded on the concealed condition of shrouded layer L. We utilize the yield work g to address this:

$$O_t = g\left(H_t^{(L)}\right) \tag{2}$$

Similarly as with many layers examination, the quantity of shrouded number of concealed units h and layers L is hyper framework. Specifically, we can pick a standard DRNN, the LSTM to actualize the model. A DRNN is a class of fake neural system that broadens the customary feed forward neural system with circles in associations. In

Fig. 2 Design of deep recurrent neural network formulation



contrast to a feed forward neural system, a RNN can process the consecutive contributions by having an intermittent concealed express whose initiation at each progression relies upon that of the past advance. Thusly, the system can show dynamic fleeting conduct. Given a succession information, $x = \left(x_{1,}x_2, \ldots, x_i\right)$ where x_i is the information at ith step time, the RNN refreshes its intermittent concealed state h_t by

$$h_t = \begin{cases} 0, & \text{if } t = 0 \\ \phi(h_{t-1}, x_t), & \text{otherwise} \end{cases} \tag{3}$$

where ϕ is irregular capacity, for example, a calculated transverse capacity or enlarged digression work. Alternatively, this may have yield $y = \left(y_{1,}y_2, \ldots, y_i\right)$. For certain errands, for example, hyper otherworldly picture arrangement, this required just one yield. In the customary RNN term, the standard update of the repetitive concealed state is typically executed as pursues:

$$h_t = \phi(Wx_t + Uh_{t-1}) \tag{4}$$

where U and W are factor grids for present contribution at advance and the enactment of intermittent shrouded past advance units, individually. Indeed, a RNN can demonstrate a likelihood appropriation throughout the following component of the grouping information, given its current state h_t, by catching a circulation over arrangement information of changeable length. Let $p\left(x_{1,}x_2, \ldots, x_T\right)$ be the grouping likelihood, it can be deteriorated into

$$p\left(x_{1,}x_2, \ldots, x_T\right) = p(x_1)\ldots.p(x_T|x_1, \ldots, x_{T-1}) \tag{5}$$

At that point, each restrictive likelihood conveyance can be demonstrated with a repetitive system

$$p(x_t|x_1, \ldots, x_{t-1}) = \phi(h_t) \tag{6}$$

where h_t is acquired from (5) and (6). A hyper ghastly pixel goes about as consecutive information rather than an element vector, thus a repetitive system can be embraced to display the unearthly grouping. As a significant part of the profound adapting family, DRNNs have as of late demonstrated promising outcomes in many AI and PC vision assignments. Notwithstanding, it has been seen that it is hard to prepare the DRNNs to manage long haul consecutive information, as the angles will in general evaporate. To address this issue, one normal methodology is to plan a progressively refined repetitive unit. An intermittent layer with conventional repetitive shrouded units is appeared in (7), which just computes a weighted direct total of sources of info and afterward applies a nonlinear capacity. Interestingly, based on LSTM, layer repetitive makes a storage cell c_t at point t. The initiation of the designed LSTM units is

$$h_t = o_t \tanh(c_t) \tag{7}$$

where $\tanh(\cdot)$ is the hyperbolic digression capacity and o_t is the yield door that decides the piece of the memory content that will be uncovered. The yield door is refreshed by

$$o_t = \sigma(W_{oi}x_t + W_{oh}h_{t-1} + W_{oc}c_t) \tag{8}$$

where σ (•) is a calculated sigmoid capacity and W terms mean weight grids, e.g., W_{oi} is the info yield weight network and W_{oc} speaks to the memory-yield weight framework. The memory cell c_t is refreshed by including new substance of memory cell $\tilde{c}_t$ and disposing of part of the present memory content

$$c_t = i_t\Theta\,\tilde{c}_t + f_t\Theta c_{t-1} \tag{9}$$

where c_t is a component insightful augmentation and the new substance of memory cell $\tilde{c}_t$ is gotten by

$$\tilde{c}_t = \tanh(W_{ci}x_t + W_{oh}h_{t-1}) \tag{10}$$

Info door it tweaks the degree to which the new memory data are added to the memory cell. How much substance of the current memory cell is overlooked is chosen by the overlook entryway f_t. The conditions that ascertain these two entryways are as per the following:

$$i_t = \sigma(W_i ix_t + W_{ih}h_{t-1} + W_{ic}c_{t-1}) \tag{11}$$

$$f_t = \sigma(W_f ix_t + W_{fh}h_{t-1} + W_{fc}c_{t-1}) \tag{12}$$

4.2 Sequence mining by improved WOA

Improved whale enhancement calculation (IWOA) is a nature enlivened meta-heuristic advancement calculation presented. IWOA depends on the chasing conduct of humpback whales. Moreover, WOA mimics the chasing conduct with arbitrary or the ideal inquiry operator to chase the prey (investigation) and the utilization of a winding air pocket net assaulting instrument of humpback whales to reproduce the getting of prey (abuse). The pursuit procedure of most meta heuristic offers a typical component. It includes two stages: misuse and investigation. Whale optimization algorithm (WOA) is roused by the endurance and chasing conduct of humpback whales. Whales can endure alone or in gatherings and can be up to 30 m long. Additionally, humpback whales have a one of a kind chasing technique called air pocket net nourishing strategy which generally includes making rises along a hover around the prey while floating around the prey.

4.2.1 Searching for prey

The investigation stage depends on the variety of vector An and it is to activate the inquiry operators looking for better arrangements like a worldwide pursuit. The estimation of |A| is set to more noteworthy than 1 which powers the hunt specialist to wander far away in the pursuit space. As a conspicuous difference to the misuse stage, the pursuit operators update their situation concerning haphazardly picked inquiry specialist as opposed to alluding to the best search specialist. Humpback whales scan for prey arbitrarily as far as the situation of one another. The scientific model can be portrayed as pursues:

The numerical model can be depicted as pursues

$$D = |C.X_{\text{rand}} - X_i| \tag{13}$$

$$X(t+1) = X_{\text{rand}} - A \cdot D \tag{14}$$

$$A = 2a \cdot r - a \tag{15}$$

$$C = 2 \cdot r \tag{16}$$

$$D = |C.\omega X * (t) - X(t)| \tag{17}$$

$$K(t+1) = X * (t) - A \cdot D \tag{18}$$

where A signifies coefficient vector, t is the present emphasis, X is the position vector, C is coefficient vectors, an is straight diminishing from 2 to 0, r is the arbitrary number between [0,1], X* is the best estimation of the position vector. Conditions (13) and (14) present looking through prey on the off chance that $A \geq 1$, while in some other case conditions (18) and (19) are utilized which speak to encompassing the prey by contracting system. X is situation of separate, and Xrand is arbitrarily chosen from present age and speaks to a vector position, t shows the present cycle, the image || is the supreme worth, An and C are vectors coefficient. |

$$X(t+1) = \begin{cases} \omega X^*(t) - A \cdot D & \text{if } p < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + \omega X^{*(t)} & \text{if } p \geq 0.5 \end{cases} \tag{19}$$

$A| \geq 1$ powers search administrator to move far away from a reference whale.

4.2.2 Bubble-net attacking

Whales update their positions emulating the circling conduct during the enhancement, around the situation of the ebb and flow best search specialist. The best up-and-comer arrangement acquired so far is considered as the objective prey and the other pursuit operators target refreshing their situations towards the best arrangement. So as to reenact the air pocket net searching conduct of humpback whales, two methodologies are proposed: contracting enclosing system: This method is accomplished by diminishing the estimation of a directly and A will be an arbitrary vector in the range [$-$ an, a] as indicated by (19); winding refreshing position: A winding condition is utilized to copy the helix-formed move of humpback whales as in (20)

$$\vec{D} = |\vec{C}.\omega\vec{X} * (t) - \vec{X}(t)| \tag{20}$$

$$\vec{X}(t+1) = \omega\vec{X} * (t) - \vec{A}.\vec{D} \tag{21}$$

where t is the current iteration, $\vec{A}$ and $\vec{C}$ is coefficient vectors and $\vec{X}$ is the position vector. The position vector of the best solution that has been obtained so far is given by (21). The value of X is updated after each iteration if a better solution exists. The coefficient vectors $\vec{A}$ and $\vec{C}$ are calculated by Eqs. (22) and (23):

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{22}$$

$$\vec{C} = 2.r \tag{23}$$

where vector $\vec{a}$ linearly decreases from 2 to 0 over the course of iterations and r is a random vector that varies between [0, 1]. In IWOA, there is half likelihood that search specialists pick either the encompassing system or the winding way through an irregular variable p.

Improved Whale Optimization Algorithm.

1. Create the initial community Y_j $(j = 1, 2, \ldots, NP)$
2. Calculate the capability for each discrete in Xi
3. Best discrete is X*
4. While the stopping model isn't fulfilled do
5. For every person, map the wellness to the quantity of species
6. For $j = 1 \rightarrow NP$ do
7. Choose static arbitrary $r1 \neq r2 \neq r3 \neq j$
8. Modernize $A = 2a.r.a$, $a = 2\text{-}t.(2/t_{max})$, $C = 2.r$
9. When $i = 1$ to n do
10. Whether $p \leq \lambda$ next
11. $j = \, = jrand$or if $rndrealj\ [0, 1) \leq CR$ then
12. $U_i(j) = X*(j) + F \times (X_{r2}(j) - X_{r3}(j))$
13. Else
14. Choose aarbitrary discrete Xrand
15. $D = |C.X_{\text{rand}} - X_i|$
16. $U_i(j) = X_{\text{rand}}(j) - A \cdot D$
17. End for

4.2.3 Attacking of Prey

The assaulting conduct is demonstrated regarding the air pocket net assaulting methodology. Two fundamental methodologies are taken so as to demonstrate the air pocket net conduct of humpback whales. The two strategies are contracting enclosing instrument and winding refreshing position system. Humpback whales can execute any of this two system to get the prey and along these lines, every one of this component can occur with a likelihood of half. An irregular variable p is presented where p fluctuates between [0, 1]. In contracting encompassing instrument the estimation of a is diminished in Eq. 23. The estimation of A will be an arbitrary incentive between $[-a, a]$ where a is diminished from two to zero over the all out number of cycles. The winding refreshing position component is done in such a manner in order to impersonate the helix organized move of humpback whale. The assaulting of prey is the abuse period of this enhancement calculation. Misuse comprises of looking through a confined (yet encouraging) locale of the hunt space with the desire for improving the inside the area of arrangement 'S'. This activity sums then to strengthening (refining) the inquiry in the region of that arrangement 'S'. The estimation of A is between $[-1, 1]$ and subsequently when $|A| < 1$, at that point abuse is incited and all the hunt specialists merge to acquire the best arrangement. The refreshing model can be given by Eq. 24.

$$X(t+1) = \begin{cases} \omega X^*(t) - A \cdot D & \text{if } p < 0.5 \\ D' \cdot e^{bl} \cdot \cos(2\pi l) + \omega X^{*(t)} & \text{if } p \geq 0.5 \end{cases} \tag{25}$$

where p is a random number in [0,1]. In addition to the bubble-net method, the humpback whales search for prey randomly.

The center of our proposed strategy, IWOA, is hybridized the WOA's administrators with DE's transformation administrator to improve WOA's investigation abuse tradeoff. The primary administrator of IWOA is a half breed administrator (see lines 10–28 of which joins DE's change and the segments of WOA, to be specific, encompassing prey, look for ask and winding refreshing position. IWOA has two fundamental parts: the investigation part (see lines 11–18 of Algorithm 2 and misuse one. As indicated by Algorithm 2, when rand $< \lambda$ the investigation part changes the people. λ is balanced by Eq. (25)

The center of our implemented strategy IWOA is interbreed the WOA's administrators with DE's change administrator to develop WOA's investigation abuse contract. The primary administrator of IWOA is a half and half administrator consolidates DE's change and the parts of WOA, in particular, enclosing prey, scan for ask and winding refreshing location. IWOA has two fundamental parts: the investigation part. As per Algorithm 2, if rand $< \lambda$ the investigation part changes the people. λ is balanced by Eq. (25)

$$\lambda = 1 - \frac{t}{t_{\max}} \tag{25}$$

where t represents age of $t_{\max}$ provide the greatest digits of ages. We register λ to command the investigation and the misuse capacity of IWOA. As indicated by Eq. (25), the estimation of λ is diminished after some time from 1 to 0. Along these lines, the people are permitted to investigate in the underlying age.

Investigation domain requires DE's change and quest for ask of the WOA. IWOA incorporates DE's change on account of its prevalence in investigating the pursuit space. The misuse some portion of IWOA is like WOA. As opposed to WOA, IWOA is an strategy. Specifically, the new position for ith individual in the bleeding edge is the fitter one between parent X_i and children U_i. It is critical to take note of that, arrangements ought to think about limit limitations. On the off chance that these requirements are abused, the fixing standard is applied by Eq. (26).

$$X_i(j) = \begin{cases} \delta_j + \text{rndreal}(0, 1) \times (\mu_j - \delta_j) & if\ X_i(j) < \delta_j \\ \mu_j - \text{rndreal}(0, 1) \times (\mu_j - \delta_j) & if\ X_i(j) < \mu_j \end{cases} \tag{26}$$

5 Result and discussion

The proposed EELR technique is used to detect the highly recommended page like tutorial point, fresher world and w3school etc.…. It will recommend based on highly rated by multi e-learners. Here, we analyzed three types of performance using deep recurrent neural network and improved whale optimization algorithm. From our datasets, we found total number of instances 25, from that, correctly classified instances was 24 and incorrectly classified instances was 1. The proposed technique Performance is evaluated based on the basis of 3 performance metrics, namely precision, recall and harmonic mean. The proposed technique is tested using weka tool and the obtained results are given below.

5.1 Experimental dataset and setup

Sets of tests were led so as to assess the exhibition of the proposed efficient e-learning recommendation approach (EELR). The dataset was made dependent on our own model with multi e-learning pages. The all out number of e-students utilizing our own datasets to help their picking up during the time of examination. This enables the students to rate the learning assets on a size of 1–5 (1–extremely immaterial, 2–genuinely unimportant, 3–unessential, 4–applicable, 5–exceptionally pertinent). The recommender framework can propose learning assets to the students by coordinating their inclinations and relevant data. The underlying setting data (information level) was gathered during enlistment of students to our datasets and is in this manner refreshed occasionally as the students utilize our datasets to get to web-based learning assets. The logical data of the students, specifically information level continue changing with time and circumstances as the student's information regarding a matter improves. Student's information level can change to tenderfoot, middle of the road or progressed as circumstances change. During the dataset assortment periods, the student appraisals and student's logical data were removed from the recommender framework database and consecutive access designs got by mining the web logs utilizing the improved whale enhancement calculation. The dataset was then part into preparing subset (80%) and test subset (20%) for motivations behind exploratory assessment. The dataset depiction is appeared in Table.1

The suggestion models are put away in this database which supplies diverse proposal administrations. This database is administrated by "Datasets" module, and it fabricates numerous proposal models to produce various types of suggestion. Proposal framework database stores suggestion procedures. It sets up a balanced comparing association with suggestion motor, and it is overseen by proposal the board module. Proposal motor burden various methodologies arrangement in the suggestion framework database and create proposals. For motivations behind assessing the adequacy of the proposed productive e-learning suggestion approach, two calculations were assessed over the equivalent dataset depicted in Table 1 and their outcomes are contrasted and existing condition of-workmanship. The calculations that were assessed are implemented deep recurrent neural network and improved whale optimization algorithm.

5.2 Experimental results

The fundamental objective of this work was to propose an effective e-learning suggestion approach dependent on DRNN and IWO calculations for prescribing e-learning assets to students in e-learning situations. In this subsection, we investigate and present the exploratory outcomes and assessment measurements to test the presentation and adequacy of the proposed suggestion approach EELR and shown in Table 2.

A progression of trials was directed while differing the spans of neighborhoods in order to set up the ideal size of neighborhood for best outcomes to use in consequent tests. The size of closest neighbors in recommender frameworks affects both expectation precision and nature of suggestions. Correspondingly, tests were done to quantify the forecast exactness for the four proposal calculations under various sizes of neighborhood. The precision of expectations is registered utilizing the deep recurrent neural network and improved whale optimization algorithm. The highly rated e-learners page is predicted for accuracy. The exactness of expectation for the proposed effective e-learning suggestion approach just as the other two proposal calculations increments consistently as we increment the quantity of cases from 0 to 25 accomplishing the ideal forecast precision when the quantity of closest neighbors in 25. After 25, the bend for the two calculations starts to

Table 2 Performance metrics

Correctly classified instances	24	96%
Incorrectly classified instances	1	4%
Mean absolute error	0.072	
Root mean squared error	0.1833	
Relative absolute error	–	31.80%
Root relative squared error	–	56.30%
Total number of instances	25	100%

ascend at littler interims. Based on our all out number of examples, our expectation precision may increments.

5.3 Performance metrics

The assignment of a recommender framework in e-learning is to prescribe helpful learning assets to the students. To quantify the exhibition of the proposed suggestion technique EELR, we use review, accuracy, symphonious mean, TP rate, FP rate, MCC, ROC region and PRC region measurements. We assess and think about the presentation of the proposed EELR suggestion approach against fluffy rationale proposal calculations, as far as review, exactness and consonant mean. Review and accuracy can without much of a stretch be processed with the guide of disarray framework appear in Table 3. In utilizing accuracy and review assessment measurements, learning assets are evaluated on a size of 1–5. Learning assets appraised 1–3 are considered "not applicable," while those evaluated 4–5 are considered "significant." Precision is the proportion of prescribed learning assets to the quantity of learning assets chose.

$$\text{Precession} = \frac{\text{Recommended } e - \text{learning resources}}{\text{Total } e - \text{learning resources}} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{27}$$

Review then again is the proportion of accurately prescribed e-learning assets to the significant learning assets.

$$\text{Recall} = \frac{\text{Correctly recommended } e - \text{learning resources}}{\text{Relevant } e - \text{learning resources}} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{28}$$

where TP is true positive rate, FP is false positive rate, TN is true negative rate and FN is false negative rate.

Accuracy is determined as the quantity of every single right expectation partitioned by the complete number of the dataset. Precision is a evaluation that reveals to us what extent of recommendation that we analyzed as having highly rated page, really have high ratings. The anticipated positives (people ratings are denoted as TP and FP) and the individuals really having recommended resources are TP.

Table 3 Confusion matrix of proposed EELR

a	b	Classes
3	0	Absent
1	21	Present

5.4 Confusion matrix

A perplexity lattice is a table that is regularly used to portray the exhibition of a characterization model (or "classifier") on a lot of test information for which the genuine qualities are known. Numerous measures for assessing the presentation of data recovery frameworks have been proposed, among which review and exactness are the most mainstream ones. Review and accuracy can be additionally utilized in uncommon objective location issues. The biggest scores are delegated class missing and the rest of the things are named class present. The arrangement result is normally exhibited in a disarray lattice displayed in Table 3.

Table 4 shows the exhibition of the proposed productive e-learning suggestion approach utilizing DRNN and IWO calculation in examination with past condition of-workmanship model, as far as exactness, review and consonant mean for 25 proposal occasions. It is obvious from Table 4 that the proposed suggestion calculation EELR beats the current condition of-workmanship proposal calculations as far as both accuracy and review measurements for any number of proposals. It can likewise be seen that expansion in number of proposals brings about lessening in exactness for existing method. Conversely, as the quantity of proposals expands, review increments also for past model. Symphonious mean measurement joins both accuracy and review into a solitary incentive for simplicity of examination just as to get a fair perspective on execution. The symphonious mean gives equivalent load to exactness and review.

$$\text{Harmonic mean} = \frac{2 * p * r}{p + r} \tag{29}$$

-P denotes precision and r denotes recall. The exhibition as far as consonant mean of the proposed EELR suggestion approach in examination with the current system proposal strategies to be specific, fluffy rationale. Toward the finish of the analyses, students were assessed on their fulfillment with suggestions from the proposed EELR strategy and shown in Table 4.

To complete this assessment, a shut finished survey was controlled to the students which tried to see if the student was fulfilled or not happy with the proposals. Recognized "client fulfillment" as one of the significant assessment measures for e-learning recommender frameworks. Figure 3 shows the reactions of the respondents on whether they were fulfilled or not happy with the proposals from the proposed EELR technique. From Fig. 3, lion's share of the students (96%) were fulfilled, while just 4% were not happy with the proposals.

Table 4 Performance analysis of proposed technique

TP rate	FP rate	Precision	Recall	Harmonic mean	MCC	ROC area	PRC area	Class
1.000	0.045	0.750	1.000	0.857	0.846	0.977	0.750	Absent
0.955	0.000	1.000	0.955	0.977	0.846	0.977	0.995	Present
0.960	0.005	0.970	0.960	0.962	0.846	0.977	0.965	Average

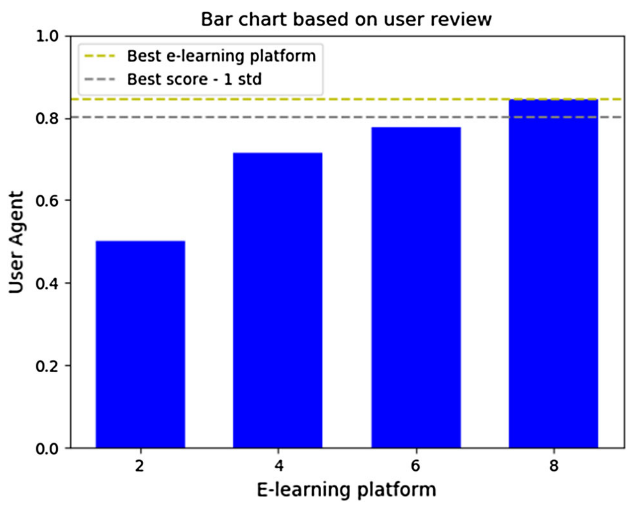


Fig. 3 Shows graphical representation of user agent versus e-learning platform

6 Conclusion

In this paper, we have proposed an EELR system for user preferences using hybrid optimization algorithm. To create the effective and exact suggestions, we plan an e-learning proposal framework. Suggestion framework is a helpful device for e-learning reason. We actualized a novel technique for archive suggestion with subject investigation for e-learning frameworks. With our proposed framework, it used to arrange and dissect e-student model. We demonstrated by our examination that through subject displaying and comparability measure, we can prescribe profoundly applicable reports to the concerned client and significantly beat the issue of confined substance investigation and substance over-specialization. This coordinated model demonstrates to be a fundamental part for the e-learning frameworks since it will advance the viable connection between the student and the framework by fulfilling the student's data needs. In addition, the proposed principles likewise enable different ways to deal with be fused and high practicability in e-learning areas. Contrast with customary recommender framework, proficiency and precision were expanded utilizing our proposed technique.

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Declarations

Conflict of interest The authors declare that we have no conflict of interest.

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