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Development Of Learning Path Recommendation System Using The Deep Learning Based O-Recurrent Learnernet

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Abstract

Recent focus has been directed on programming education due to the rising need for programming and information technology competencies. Nonetheless, an insufficiency of instructional materials and personnel is a significant obstacle to fulfilling the increasing demand for programming education. One method to mitigate the deficit of qualified educators is to use deep learning approaches to support students. We present a learning route recommendation system using a student's ability chart via an optimised recurrent learner network. The learning route index dataset was first acquired via Kaggle. The data may thereafter be processed via the error splash quartz filter. The various course-related characteristics are grouped using the wrapper-k-doc technique. Finally, the path recommendation system was developed using the O-recurrent learner net algorithm. Here the classifier parameters are hypertuned using the greywolf optimizer algorithm. The overall experimentation was carried out in a Python environment. From the analysis, the suggested methodology overcomes the existing methodology by obtaining a high range of accuracy(99.9%).

Index Terms**—** Deep learning, O-recurrent learner net, learning path recommendation

1. Introduction

As information retrieval technology becomes more widespread and advanced, more learners are opting for self-directed learning over the Internet, a well-established method of e-learning [1]. Unlike the traditional teacher-centered pedagogical method, e-learning has advantages: learners may independently seek and access learning goals from any place, not alone inside the classroom. However, the fragmentation of online learning resources has always presented a difficulty for e-learning in systematically and efficiently obtaining diverse knowledge components within a singular topic. Researchers have acknowledged that the arrangement of educational materials substantially affects the quality of learning [2,3]. Methods for organising fragmented learning material via learning pathways to guide learners have become more accepted. This might substantially reduce the time required to collect instructional materials and improve learning efficiency. An effective learning pathway improves learners' understanding of the instructional content. Thus, the creation of high-quality learning pathways is of significant importance to the scientific community. Recent research [1–9] has focused on developing high-quality personalised learning trajectories to address the demands of e-learners. Clustering-based learning route-generating methods often generate redundant or superfluous learning items owing to their neglect of potential links among these entities. Subsequent research [10–20] used knowledge graphs to include these dependencies in the learning route recommendation model, producing significant outcomes. However, they formed only the most basic connections between learning objects and did not advance the formation of more complex meanings in these interactions. This study inadequately used the interconnectedness of the knowledge network to correlate learning elements via various semantic relationships. As a result, they are restricted to creating unique learning pathways that do not meet the varied educational needs of modern e-learning. This work introduces a technique for selecting learning routes according to user knowledge in order to meet diverse learning needs. Improve the learning pathway recommendation model using the O-recurrent learner network. We establish a multidimensional framework by classifying the learning object into the hierarchical categories of "basic knowledge," "algorithm," and "task."

The aim of this inquiry is to resolve these issues and provide the ensuing contributions.

A new optimization-based O-recurrent learner network strategy for recommending appropriate learning paths is provided, with a specific focus on the multi-class issue.

This research examines the usefulness of the wrapper-k-doc algorithm's feature removal technique for the given challenge.

This document is structured as follows. Section 2 presents pertinent literature on learning route suggestions. Section 3 delineates the specifics of the algorithms used in the learning route recommendation model. Section 4 assesses the learning route recommendation model. Section 5 delineates the findings and prospective research.

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2. Related Works

A prominent field of study aimed at enhancing learning efficiency is the development of systems [13–15] that propose educational resources to online students. Durand et al. [9] emphasised the significance of learning object sequences for learners and proposed a graph-theory-based system capable of generating unidirectional learning pathways. This approach depends on the interconnections among all fundamental learning components. Chen's study [16] substantiates the notion that learning items should be organised into learning pathways since comprehension of the present learning object is enhanced by acquiring prior and subsequent information. Individuals must engage with educational materials in a systematic sequence to attain their learning objectives efficiently when studying online. Scholars have examined the extent to which e-learning systems depend on course content. Chen et al. [17] suggested an efficient data-driven categorisation of prerequisites, highlighting the significance of prerequisite linkages across concepts in e-learning. To evaluate the thoughts according to the representations of acquired course concepts, Pan et al. [18] devised a graph-based propagation method. Simultaneously, other academics [19–21] tried to use innovative methodologies, such as directed graphs, to deduce critical connections between concepts grounded on course dependencies. The investigation of reliance on learning materials in an online environment has significant opportunities for future study. However, they continue to overlook the significance of categorising the interdependencies and connections among various kinds of learning materials to effectively manage data for online students. Researchers extensively used data mining to structure educational materials into learning pathways. Chen [22] developed a genetically-informed, personalised e-learning system capable of analysing individual learners' pretest and performance data to construct suitable learning trajectories. Dwivedi et al. [23] enhanced Chen's approaches and devised learning routes by integrating the learning path records from predecessors into a variable-length genetic algorithm (VLGA). Chen et al. [24] introduced an enhanced ant colony optimisation algorithm (ACO) that uses a coordinate system to choose learning trajectories. Bendahmane et al. [25] presented a competency-based approach (CBA) based on data gathered from students' actual learning and their expected goals. The grouping and monitoring of pupils resulted in the creation of individualised learning plans under this methodology. An efficient learning trajectory was produced by an e-learning system created by Hsieh and Wang [26] using data mining techniques to establish hierarchical relationships among learning materials. Students may circumvent the laborious task of organising course materials by the use of these data-mining techniques; yet, the following issues persist: The learning system's lack of autonomous adaptability necessitates the creation of a new learning route with each data update, rendering data updates a formidable challenge. Utilising identical educational resources, both ways may provide equivalent outcomes. Knowledge graphs, a prominent field of research, have lately been used in the creation of learning paths due to their ability to eliminate ambiguities in the descriptions of educational content. Motivated by this attribute, some researchers [27–29] attempted to address issues (1) and (2) by developing learning systems capable of selecting learning routes informed by knowledge graphs. In their proposal for a learner-centric learning recommendation technique, Wan et al. [30] represent knowledge units as nodes and the connections among them as demonstrating the interrelations between these units, aiming to construct knowledge-based learning pathways. Ouf et al. [31] established the foundation for an intelligent online classroom by integrating a knowledge graph with SWRL. Shmelev et al. [32] developed a system that integrates knowledge graph technology with evolutionary algorithms to sequence learning components. Utilising the relationships shown in concept maps, Chu et al. [33] developed an online learning system that enables users to design their own educational pathways. Zhu et al. [10] acknowledged that learners need individualised learning pathways in diverse contexts and therefore proposed a system for selecting learning routes tailored to certain learning situations. They provided a mechanism for generating learning pathways that require the specification of beginning and ending nodes. All the abovestated research concentrates on knowledge graphs and their potential use in developing effective learning pathways. The educational components and relationships in this study resemble nodes and pathways in a learning trajectory, respectively. Nevertheless, the linkages of the knowledge graph were inadequately leveraged by these knowledge-network-based methodologies. The links among learning items should be labelled with names that logically convey specific meanings, rather than just shown as a connecting line. Simultaneously, these studies indicate that online learners may need distinct learning pathways for identical educational content; hence, an effective learning route recommendation model must have adaptable routes that cater to varying circumstances and individual student requirements. We will establish a specialised knowledge network for the learning route recommendation model using the previously described research. Our objective is to provide people with structured learning pathways that address their diverse educational requirements. Graph theory provides mathematical representations of entities and their interactions. It has been shown to be an effective instrument in addressing several educational challenges. To demonstrate the relationships among learning items, which are founded on information and media space, Alian et al. constructed a directed acyclic graph [20]. Alshalabi et al. [21] used a weighted directed network in their online education model, with each node symbolising a unit of study. Developing a concept map that accurately depicts a domain's knowledge structure while preserving essential ideas and their interrelations is another significant application [22]. Nonetheless, previous research has often encountered the issue of domain-specific, predetermined concept mappings [3, 9]. No one values the basis of public knowledge. Fundamental principles may be unintelligible to certain pupils. This underscores the essential need for using graph theory in the dynamic development of learner-centered idea maps. Adaptive learning route recommendations are regarded as a combinatorial optimisation problem, and evolutionary algorithms serve as an effective method for addressing this issue [3]. Chen suggested an algorithm that employs genetic principles to develop a personalised learning pathway for each individual's distinct requirements [10].

Table 1 Existing methodology analysis Citation	Recommendation Approach	Method/Algorithm/Tools	Evaluation approaches	Personalization parameters
Nabizadeh et al. (2018)	The learning route is suggested by taking into account the time constraint of pupils.	Learning time and score probability of error, median, item response theory (IRT), data-driven sampling (DFS), and mean	Offline	Style of learning, amount of knowledge, amount of time required
Segal et al. (2019)	Using the users' answers to rank a series of questions from easiest to most difficult	Collaborative filtering approaches, EduRank, and the voting method	online	Performance-based on score

Cun-Ling et al. (2019)	Because they take into account the student's learning style, learning needs, and past knowledge, they propose a way that enhances the student's learning outcomes.	Graph Theory, Felder-Silverman Learning Style Index, and Improved Immune Algorithm	Performance of the System, Online, User Research	Learning style/knowledge level
Vanitha et al. (2019)	Making a route recommendation depending on the user's mood and mental abilities	Genetic algorithm for optimising ant colonies	online	Performance-based on score
Li and Zhang (2019)	Recommending high-scoring, previously ignored courses to a user based on their profile traits and the impact of their previous users' learning	Structure of the network, the impact of learning, and Three types of searches: breadth-first, depth-first, and random traversal.	Offline	Learning style
Cai et al. (2019)	While studying, recommend the most appropriate course of action according to the requirements of each knowledge unit.	Markov decision process, neural network, knowledge tracing model, and reinforcement learning process	Offline	Performance-based on score
Nabizadeh et al. (2020)	Recommending a path that improves a user's score in the the least amount of Time	Topic Response Theory (IRT), Two-Layer Graph for Courses, Depth First Search, Learning Time, and Error Probability	Offline/ online/	Time taken/performance-based on score/knowledge level

Niknam and Thulasiraman (2020)	Students are sorted into several groups and assigned a route based on what they already know.	Ant colony optimisation methodology, Clustering methods, and Fuzzy C-Mean	Online	Learning style/knowledge level
Shi et al. (2020)	Considering the students' requirements and learning goals, making all potential pathways, and then suggesting the one with the highest score	Finding high-quality educational resources using a network traversal method, a knowledge graph, and a Cohen kappa coefficient	Online	Time Taken/Performance-based on score
Benmesbah et al. (2021a)	Create learning outcomes (LO) sequences that take into account learner preferences, course relationships, and LO characteristics.	Modified Genetic Algorithm	Offline/simulated data	Performance
Benmesbah et al. (2021b)	Adapting Learning Paths with the Use of Concept Graphs	Modified Genetic Algorithm	Offline	Performance
Ramos et al. (2021)	Creating a visual depiction of the learning route and offering suggestions to a group of learners who are working together	Methods for clustering K-means and learning-path-based clustering	Online	Performance-based on score
Son et al. (2021)	For specific skill sets, design massive open online course (MOOC)-based learning routes.	In the world of algorithms, you may find ant colony optimisation algorithms, genetic algorithms, and metaheuristics.	Offline	Time required, score-based performance, preferred method of learning

Wang et al. (2021)	Recommending a learning path and assessing learner satisfaction. That being the case, choose a different way.	Knowledge network and differential evolution (DE) algorithm	Offline	Performance-based on score

3. PROBLEM STATEMENT

Our analysis of the survey data shows that adaptive learning routes should include several factors, such as the learner's attitude, motivation, ability, and so on [See Table 1]. We chose learning goals, knowledge base, and learning style traits to provide a more representative trial, however, more details usually lead to more accurate findings. It will not be much changed by adding a few pertinent characteristics to the model. To choose which concepts to convey, the system must be aware of the learner's prior knowledge as well as their current learning goals, in accordance with the principles of instructional design. At the same time, there is substantial evidence that a student's chosen learning style is significantly related to their overall academic performance. Adapting course materials to fit the learning styles of individual students. While several research covered feature selection approaches, optimization-based classifiers for learning system route identification were under-represented. Consequently, this research involves creating a new classifier using an optimisation method.

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4. PROPOSED WORK

This study introduces a new framework method for efficiently identifying learning pathways. Figure 1 depicts the general procedure of the proposed approach.

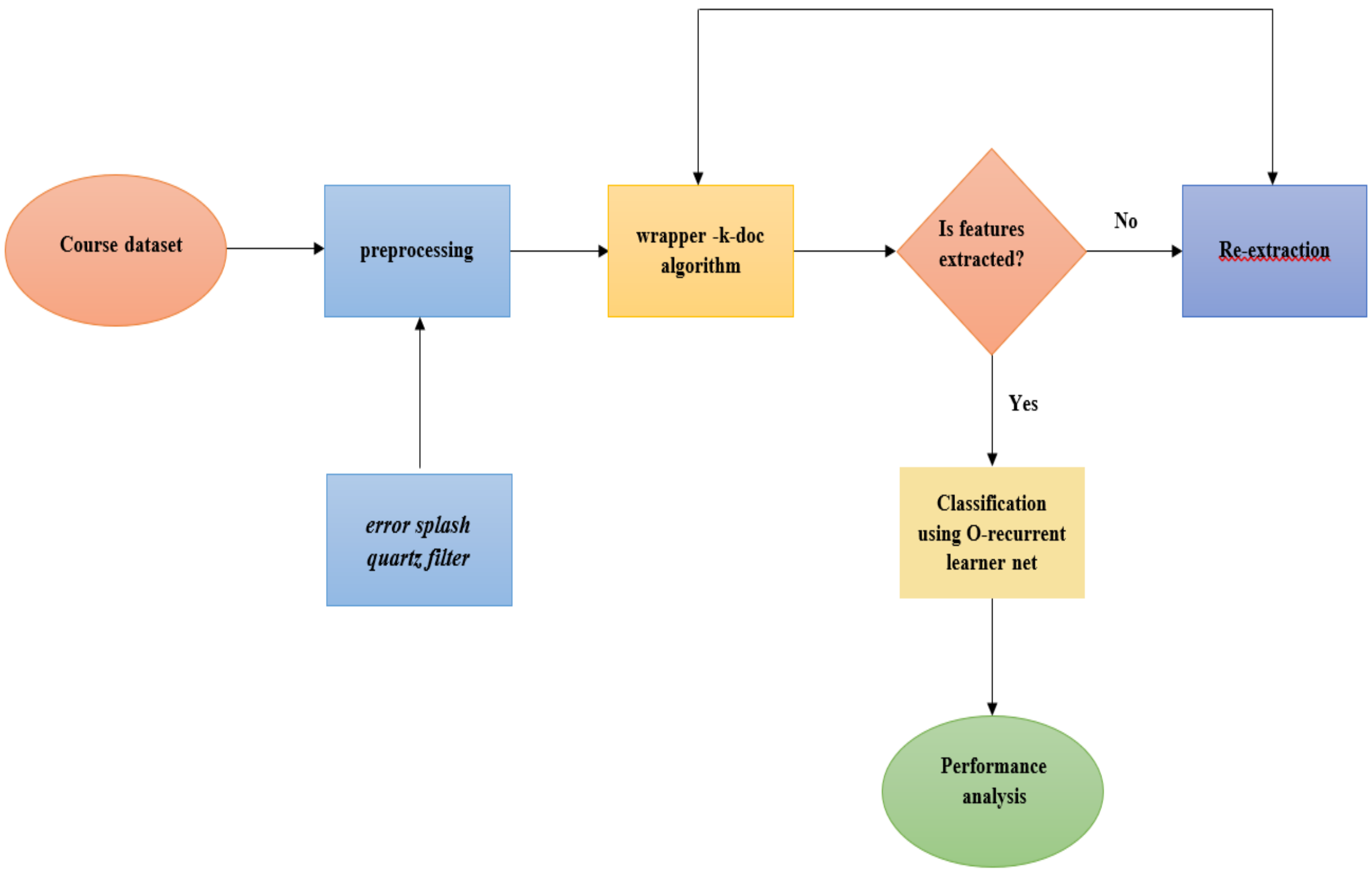

Figure 1 Schematic representation of the suggested methodology

A.Preprocessing

Data processing with an error splash quartz filter often involves normalising the observed values to a conceptually similar scale before averaging, using a separate balance. In order to get values associated with a distinct variable, a rescaling step is necessary for certain kinds of normalization of data.

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$$\widehat{\sigma}^2{}_i = \frac{1}{d-s-1}\sum_{j=1_{j\neq 1}}^{d} \overline{\in}^2{}_j \qquad (1)$$

Where ꜰ stands for the standard deviation and m for the parameter.

After that, the following representation should be used to show that the mistakes are independent:

$$g_i \sim \sqrt{o}\,\frac{T}{\sqrt{t^2+o-1}} (2)$$

Where g is an unpredictable variable

The standard deviation is then used to normalise the variable's movement.

$$K = \frac{\mu^k}{o^k} \quad (3)$$

Where k is the moment scale.

$$\mu^k = m(Q-\mu)^{\wedge}K \qquad (4)$$

Where X is a random variable and m is the expected value

$$o^k = (\sqrt{m(Q-\mu)^{\wedge}K\,})^{\wedge}2 (5)$$

The normal orderly distribution is very useful for normalising the variable's distribution using the mean.

$$C_v = \frac{,m}{\bar{Q}} \qquad (6)$$

Where C_v finds the variance's coefficient.

Next, we may implement the function scaling technique to input values ranging from 0 to 1. The term "standardisation" used to describe this approach changes depending on the context.

$$Q' = \frac{(Q - Q_{min})}{(Q_{max} - Q_{min})} \qquad (7)$$

B.Feature extraction

All components' locations within the feature space are represented as N-dimensional vectors in the database using the proposed wrapper K doc feature extraction techniques. Then, you may choose the traits based on how well they go together. In order to evaluate the subset, the method considers the redundancy and predictive power of each function specifically. This means that the algorithm will choose the choice that maximises the performance of this feature when deciding its future steps, which are supplied by a function. Feature selection, the first and most fundamental phase in data processing, is crucial. For the purpose of making basic decisions on course patterns, independent variable analysis is useful for extracting variables from crime data. We will gather information on the course patterns. Consider the following: class O performance is based on two characteristics f1 and f2, which are evenly distributed across the interval [-1, 1] in a binary classification.

$$O = \begin{cases} 0 \text{ } if \text{ } f1 + f2 \ < 0 \\ 1 \text{ } if \text{ } f1 + f2 \ \geq 0 \end{cases} \quad (8)$$

Equation 9 explains how our suggested wrapper K doc method uses an inter-rater reliability idea to reliably identify the specialised characteristics.

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$$J_t^l = Q_{u,u-1}^l \left[Q_{u,u-1}^l + R\right]^{-1} \qquad (9)$$

The extracted course-related characteristics were given ratings, according to the previous equation. Below, in Eqn. 11, we can see the rate feature category equation.

$$\sum_{i'} \left(\sum_j \ y_{ij} y_{i'j}\right) v_{\ell i'} = K\lambda_\ell u_{\ell i} \qquad (10)$$

Assume k is the total number of characteristics that are considered independent, n is the number of ratings for each cycle, and k is the number of data categories that the assignment is done for. J = 1,... k is the index for the specialised categories, whereas i = 1... K is the index for the characteristics. Assigning the i-th attribute to the j-th feature category was done via kij ratings. Next, determine the level of fitness.

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$$f_1 = \frac{1}{W(W-1)} \sum_{i=1}^{W} O_{ij}(W_{ij}-1) \qquad (11)$$

$$f_2 = \frac{1}{W(W-1)} \sum_{i=1}^{W} O_{ij}(W_{ij}-1) \qquad (12)$$

$$f_3 = \frac{1}{W(W-1)} \sum_{i=1}^{W} O_{ij}({W_{ij}}^2 - W_{ij}) \qquad (13)$$

$$f_4 = \frac{1}{W(W-1)} \sum_{i=1}^{k} O_{ij}({W_{ij}}^2) - (W_{ij}) \qquad (14)$$

$$\bar{f}_n = \frac{1}{W} \sum_{i=1}^{N} f_i \qquad (15)$$

The cost to the goal may be further minimised by constructing heuristic functions. The following equation may be used to determine the feature correlation.

$K\left(\frac{p}{\partial}, \mu\right) = \left[\frac{\varphi(\partial+\mu)}{\varphi(\partial)\varphi(\mu)}\right] p\text{^}(\partial+\mu)\text{^}(\mu-1)$ (16)

After that, some of the important course features that can be extracted can be depicted below.

Category of user ability range= $\frac{1}{l} - 1 \sum_{l-1}^{l-1} a(K+1) - y_i(\mathrm{K})$ (17)

Course repetition =$\sum_{i,j=0}^{n-1} F(i,j)[\frac{(i-\mu i)(j-\mu j)}{\sqrt{(\sigma i^2)}\sqrt{(\sigma j^2}}]$ (18)

Course similarity=$\sum_{i,j=0}^{n-1} \frac{F(i,j)}{F} - (F+2)$ (19)

This method helps to process the data and extract the features of the couses from the data in an effective manner**.**

C.Classification

This optimised O-recurrent learner net classifier receives the features extracted from the wrapper K doc as individual inputs. A grey wolf optimisation using an autoencoder is the central idea of this research. In order to reach the final result, the outputs of the routes are merged and fed into another pathway that uses a different set of network layers. Since NNs have become so popular as a data processing architecture, autoencoders are used in the hyperparameter tuning of GWO. The features extracted from the dataset are usually considered by this neural network model. A dataset with features designated asf_k (k=1,2,3,4……), where k is the index of the network layer, is used by the suggested architecture. Neurones and an activation function make up each layer. To get the final output, the characteristics are first convolved using many network layers, which are called convolutional pathways. Then, the output of each convolutional route is combined.

An encoder function and a multi-layer network represented by the letter "l"

Step 1: To ascertain the output of the Hidden layer, it is necessary to determine its corresponding values $h_l = \sigma_l(W_l \quad {}^T h_{l-1} + \mathrm{b}_l)$ and the network $\dot{z} = \mathrm{h}l$

Step 2: Compute the wolf gradient $\delta = \frac{\partial \varepsilon(z_i \dot{z}_i)}{\partial_y}$

for i ⟵ l to 0 do

Regarding the computation of the current layer gradient:

$$n\frac{\partial \varepsilon(z,\hat{z})}{\partial W_l} = \frac{\partial \varepsilon(z_i \widetilde{z}_l)}{\partial h_1}\frac{\partial h_1}{\partial W_1} = \delta \frac{\partial h_1}{\partial W_1}$$
$$,\frac{\partial \varepsilon(z,\dot{z})}{\partial b_l} = \frac{\partial \varepsilon(z_i(\widetilde{z}_l)}{\partial h_1}\frac{\partial h_1}{\partial b_1} = \delta \frac{\partial h_1}{\partial b_1} \qquad (20)$$

Apply gradient descent using $\frac{\partial \varepsilon(z,\dot{z})}{\partial w_l} = \frac{\partial \varepsilon(z,\dot{z})}{\partial b_l}$

Step 3:Iteratively, the gradient is sent all the way down to the base layer.

$$\delta \leftarrow \frac{\partial \varepsilon(z_i \dot{z_i})}{\partial h_1} \frac{\partial h_1}{\partial h_{l-1}} = \delta \frac{\partial h_1}{\partial h_{l-1}} \qquad (21)$$

Step 4: The aforementioned experimental method involves fine-tuning model A's hyperparameters for each batch of z_i, with the corresponding target variable y_i.

$$a\widehat{z_i} = Z(\theta, x);$$
$$a\theta = \theta - \eta \cdot \frac{1}{M} \sum_{i=1}^{M} \frac{\partial \varepsilon(z_i \widehat{z_i})}{\partial \theta} \qquad (22)$$

Table 2 Hyperparameters of the suggested framework

Hyperparameters	
“Number of layers	17
Activation function	ReLU
Optimizer	GWO
Batch size	32,64,128
Learning rate	0.00010
Loss function	Mean_squared_error”

This method is an established strategy for optimising adaptive learning rates. Improving deep learning methodology was the primary goal of the optimisation strategy being considered. Personalised adaptive learning rates for many aspects may be determined by the algorithm, which is its primary use case. The method's adaptive moment estimation approach is where the name comes from. First- and second-moment gradient estimates are used independently to increase the learning rate of each weight in a proposed network. During each iteration, the Adam optimisation method estimates the moments within each batch using exponentially weighted moving averages. Some mathematical computations may be clarified by applying the selection rule to the divisive parameter value of the GWO. Here is a summary of this rule:

$$E = \{R_1, R_2, R_3, \dots, R_n\} \qquad (23)$$

The tuning rule is defined as follows

$$V_j(E_i) = \begin{cases} z_{j,i} & (1 \le j \le m, 1 \le i \le n) \\ x & (1 \le j \le m, 1 \le i \le n) \end{cases} \qquad (24)$$

Adjusting the learning rate for every parameter using moving averages is the last step of the process. We may utilise Equation (25), which gives us the weighted value update.

$$U_t = U_{t-1} - \alpha \frac{\overline{N_t}}{\sqrt{\overline{U_t}} + \epsilon} \qquad (25)$$

In the context where t represents the number of iterations and w represents the tuned value weight, the default value for α, which is also known as the learning rate or step size, is set to 10^(-8).

The procedure for choosing the hyper-tuned value characteristics is shown in Equation (28).

$$Y_n(e^{j\Omega}) = \sum_{m=-\infty}^{\infty} Y[N]U[n-m]e^{-j\Omega m} \qquad (26)$$

Multiple metrics, including layer depth, output map geographic extent, and total temporal complexity, are used to assess the suggested framework. The mathematical expression of this assessment is given by Equation 27.

$$O\left(\sum_{k=1}^{d} n_{k-1} \cdot s_k^2 \cdot n_k \cdot m_k^2\right) \quad (27)$$

where

"k = index of a layer

d = depth of the layer

n_k = number of parameters in the kth layer

n_{k-1} = number of input channels of the k^{th} layer

s_k = length / spatial size of the tuned value

m_k = spatial size of the output map"

In most cases, the testing period is three times less than the training time, regardless of whether the input is being tested forward or backward. Computing the loss using the cross-entropy approach during the forward propagation phase allows one to assess the performance of the proposed framework. In contrast, updating kernels and weights is a part of the backpropagation step. The loss value is used to update the weights and kernels. To reduce loss as much as possible, the process is used to iteratively adjust the trainable parameters, which include kernels and weights. Specifically, a gradient loss function is used to drive the model towards the area with the highest rate of increase. The training procedure also begins with the selection of hyperparameters. It is also recommended that the proposed network employ Fully Convolutional Networks (FCN) instead of Fully Connected (FC) layers and that the input and output layers be fixed.

To predict the probability of learner path,

$$\begin{aligned} j_t &= \sigma\left(K h_{t,Bi-MDSPN} + b\right) \\ H_t &= \text{ReLU}\left(\grave{J} h_{t,Bi-MDSPN_W} + \grave{b}\right) \\ C_t &= 1 - G_t \\ O_t &= k_t G_t + h_{t,Bi-MDSPN_W} C_t \end{aligned} \quad (28)$$

Displayed are the weight matrices G along with the bias vectors b and b ˜. Many times, the activation function is abbreviated as "ReLU." The encoder and decoder layers of G_t modify the amount of output transformation. The symbol $O_t$represents the resulting vector. Based on the learner's capacity, the learning route may now be precisely defined.

5. Performance Analysis

This study introduces a novel approach to determining an individual's optimal learning path based on their current skill level. Separating the datasets into those for training and testing was the first step. The effectiveness of the suggested approach was tested using this technique. A Python environment was used for all of the testing. A system with an Intel(R) Xeon(R) Gold 5220 CPU and a GeForce RTX 2080 Ti GPU was used to run the experiment using the PyTorch framework. The structured data used in this study comes from an open-source experimental dataset that may be found on a public website.

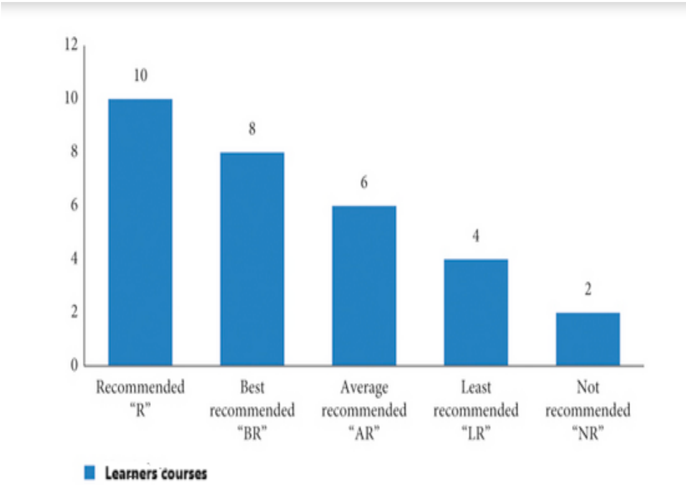


Figure 2 Recommendation score analysis

By calculating the final score to provide the class of the courses based on learners ability (Basic, advanced, etc.) as shown in Figure 3

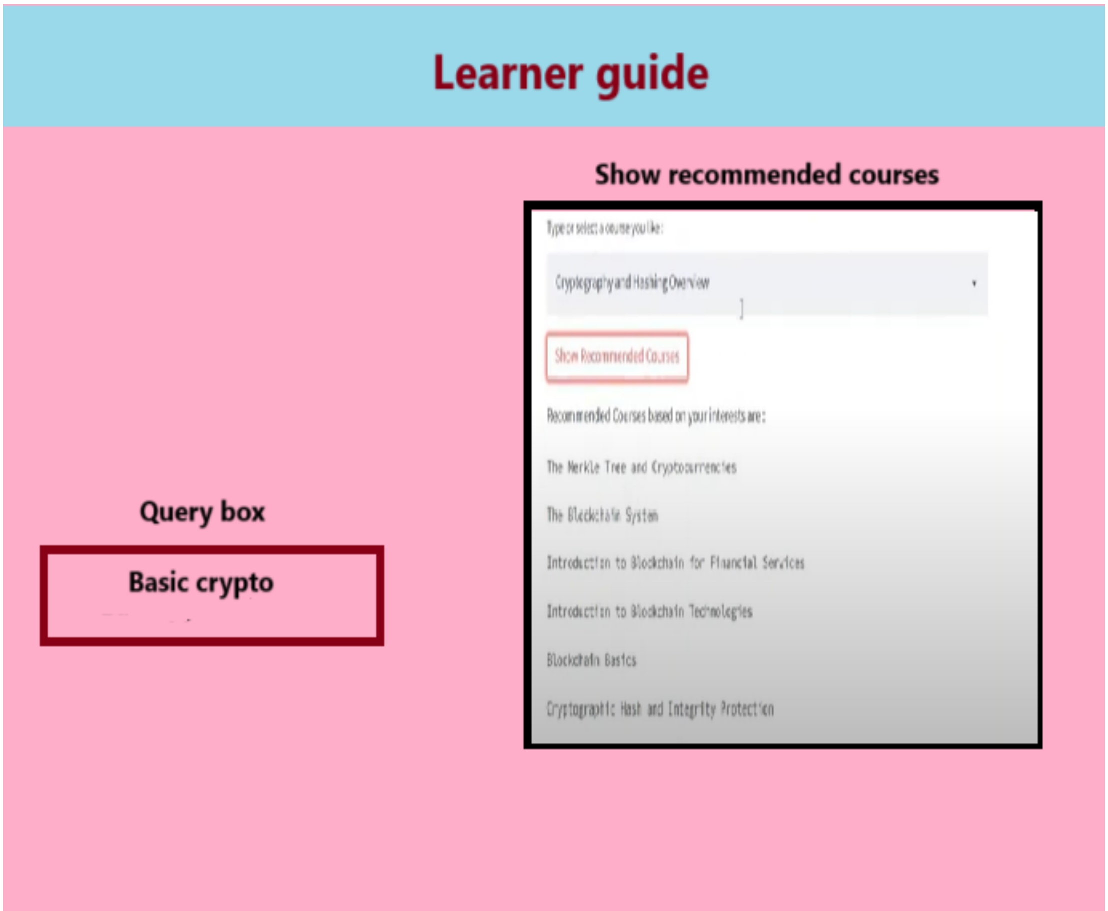


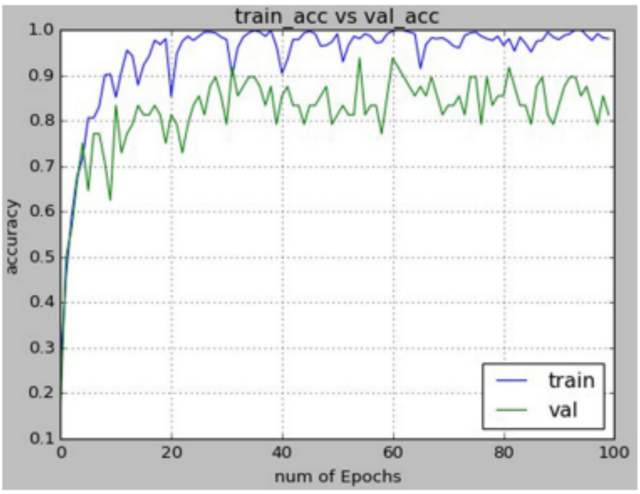
Figure 3 Overall simulation output

The overall recommendation system for the given input is illustrated in Figure 3.

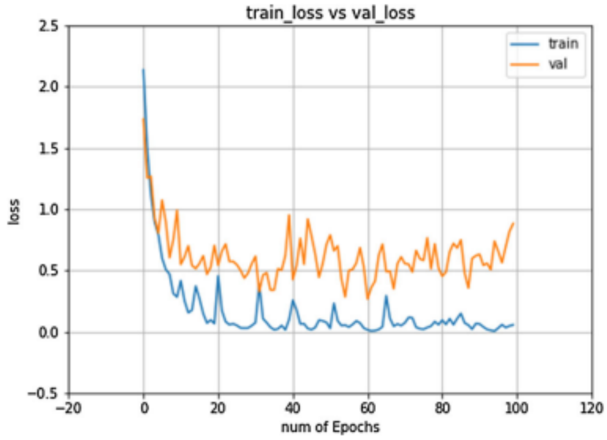
Table 3 Feature input and output analysis Job	Fitness Value	Objective value	f1	f2	f3	f4	f5	Number of Required LOs	*Numbe of Archiv LOs*	Time (s)
Python for Data Science	1.70030	16768650.0	12.766670	21.366670	14.80	611701.0	121.0	16.0	16.0	3.0
PHP Developer (Laravel)	2.02090	16959640.0	12.60	23.90	26.7	420711.0	294.0	24.0	28.0	15
Fresher Frontend ReactJS Developer	1.92730	17281381.0	16.0	19	17	98970.0	196.0	12.0	22.0	14.0
ReactJS Developer	1.83380	17253893.0	10.50	11.50	12.9	126458.0	147.0	9.0	9.0	13.0
Junior Web Dev (Laravel or Nodejs)	2.15140	16850780.0	17	57.4	35.7	529571.0	392.0	37.0	43.0	15.0
Backend Developer (Golang/NodeJS)	2.1330	16910855.0	18	77.3	43.8	469496.0	490.0	37.0	39.0	20.0
Backend Developer (PHP, Go)	2.16160	16718090.0	22	106.56667	62.3	662261	686.0	46.0	57.0	25
Frontend Dev (ReactJS/JavaScript, HTML5)	1.63810	17030443.0	14	34.8	26.3	349908	294.0	19.0	31.0	14
Web Developer (Angular, NodeJS, Python)	2.00180	16746465.0	17	58.5	41.1	633886.0	441.0	34.0	46.0	16.0
Jr/Sr Backend NodeJS (JavaScript/MySQL)	2.120100	16662998.0	21	61.3	44.3	717353.0	490.0	40.0	48.0	20.0
Java Core Developer (MySQL, Linux)	2.2361	16515938.0	66.37	175.12	51.8	864413	588.0	43.0	58.0	23.0

Senior Java Dev (SQL, Oracle)	1.99 510	17303 354.0	66.37	111.74	33. 1	7699 7	39 2.0	30.0	49.0	22 .0
Java Developer (Java, SQL)	2.00 730	16211 307.0	18	84.05	59. 9	1169 044	68 6.0	31.0	67.0	27 .0
Java Web Dev (Spring, JavaScript)	1.61 50	17272 697.0	12.5	31.57	25. 4	1076 54	29 4.0	22.0	31.0	23 .0
Java dev	2.06 910	16220 460.0	24.5	75.32	40. 8	1159 891	49 0.0	46.0	62.0	35 .0
Sr Java Dev (3 years Spring)	2.07 040	16439 912.0	22.81	70.08	44. 4	9404 39	53 9.0	43.0	72.0	28 .0
Fullstack Dev (Java, JavaScript)	1.77 40	16515 581.0	13.15	43.19	31. 8	8647 70	34 3.0	21.0	37.0	21 .0
Java Developers (JavaScript, Spring)	2.23 6100	16467 632.0	22.81	71.08	44. 8	9127 19	53 9.0	41.0	70.0	30 .0
Crypto analysis	2.27	16439 912.0	11.27	37.76	33. 8	1222 67	23 4	22.0	30.0	21

From Table 3, the fitness score was identified and the learning object along with the recommendation of the course based on learner ability was done precisely.



(a)



(b)

Figure 4 Accuracy and loss value analysis

Figure 4 illustrates the Accuracy graph during the training and testing periods and the model's loss was precisely identified.

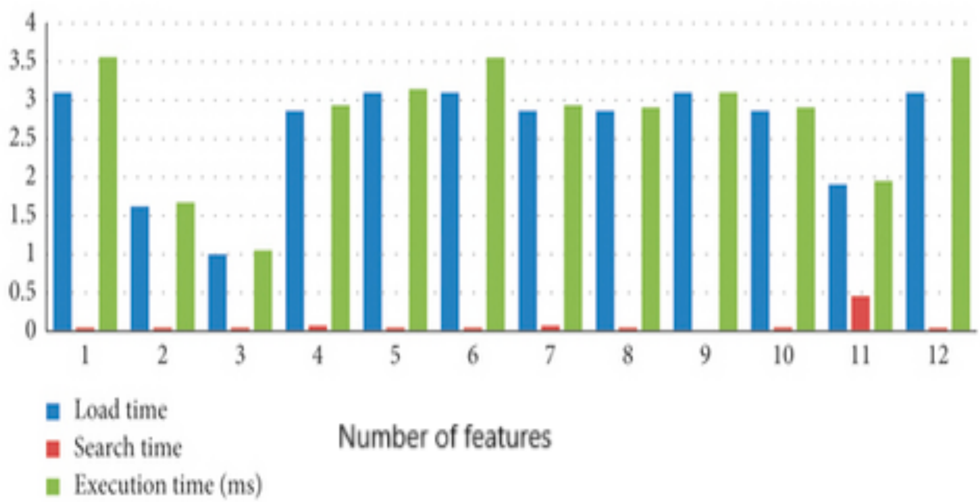


Figure 5 Time consumption analysis

The system uses the recommended machine learning sentiment analysis to get the required recommendations when the user enters a query for ideal hotel selections depending on the guest type they have chosen. When compared to traditional recommenders, the proposed technique has shown promising results in terms of improved response time. Time stamps, measured in milliseconds (ms), are generated by the system for the duration of load, search, and execution. The findings of the response time are shown in Figure 5. Execution time is the sum of the two individual timestamps, load and search. It takes very little time to come up with a list of recommendations using the proposed method, and it shows great performance.

The suggested system's efficacy may be measured using the following metrics: Accuracy, Precision, Recall, F1-Score, True Positive Rate, and False Positive Rate. As can be seen in the equation, accuracy is measured by the ratio of properly categorised records to the total number of records.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (29)$$

According to Equation (29), precision is the percentage of abnormal occurrences that are correctly predicted recommendations out of all the queries

$$\text{Precision}=(TP/FP)+FP \qquad (30)$$

According to Equation (31), recall is the proportion of correctly anticipated queries and recommendations to the total number of recommendations:

$$\text{Precision}=(TP/TP)+FN \qquad (31)$$

To evaluate the precision of the system, the F1 Score takes the harmonic mean of the Precision and Recall, as shown in Equation (32):

$$F\ \text{score}=2(\text{precision}*\text{recall})/\text{Precision}+\text{recall} \qquad (32)$$

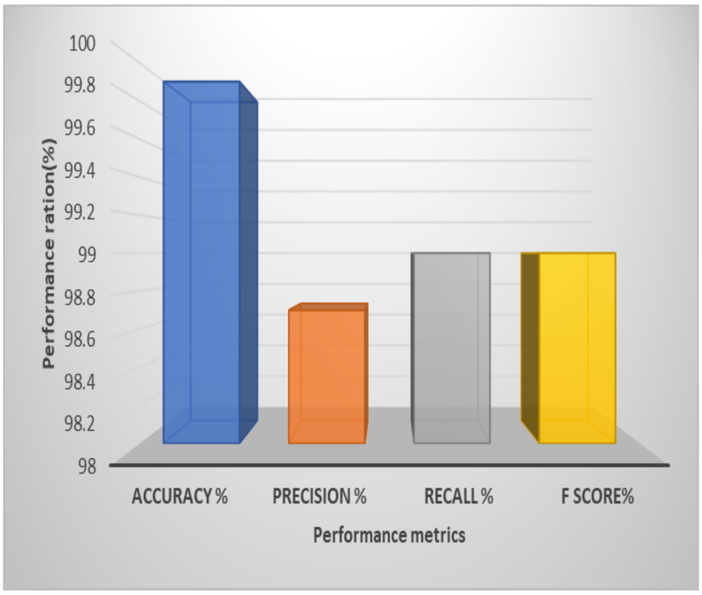


Figure 6 Suggested Methodology Performance Analysis

From the result obtained the suggested methodology exhibits a high range of accuracy (99.9%), precision(98.7%), recall(99%), and F score(99%) showing its efficiency over the learner recommendation system.

Table 4 Comparative performance analysisNo.	**Reference**	**Precision**	**Recall**	**F-measure**
1	**Liu et al. [48]**	**0.56**	**0.60**	**0.59**
2	**Hsieh et al. [49]**	**0.02**	**0.53**	**0.01**
3	**Zhang et al. [50]**	**0.25**	**0.34**	**0.35**
4	**Chang et al. [51]**	**0.43**	**0.29**	**—**
5	**Lin et al. [52]**	**0.62**	**0.51**	**—**
6	**Verma and Virk [53]**	**0.69**	**0.67**	**0.68**
7	*proposed*	*98.7*	*99*	**99**

Table 5 Comparison of execution time with related studies.

No.	**Reference**	**Recommendation time**
1	**Bouras and Tsogkas [54]**	**12 sec**
2	**Jazayeriy et al. [55]**	**28 sec**
3	**Liu et al. [48]**	**27 sec**
4	**proposed**	**2 millisecond**

Tables 4 and 5 indicate that the suggested method outperformed the evaluation measure in terms of recommendation time. When compared to more traditional methods, the suggested method significantly shortens the time it takes to provide a proposal..

6. Conclusion

A major focus of research in the field of online education is the suggested learning trajectory. Achieving it requires finding the best way to do it. This paper details a successful approach that makes use of optimisation and deep learning. The first step is to create a learner-centered concept map by analysing the learner model and the current body of information. Then, a linear conceptual sequence is established using an algorithm, which maintains the didactic precedence links. Then, a multi-objective combinatorial optimisation problem is turned into an adaptive learning trajectory by assigning an optimal learning goal to each successive concept. Finding the almost perfect solution is made easier with the help of the optimised classifier. A learner's unique requirements may be met and cognitive overload mitigated by the suggested learning path. To ensure that the proposed strategy is both efficient and effective, a battery of simulation tests is run. By outperforming state-of-the-art approaches in terms of solution quality, the proposed technique achieves optimum fitness with low time consumption (2Ms). Premature occurrences are prevented and global search capabilities are greatly enhanced. To meet the need for better fitness, our technique may converge in fewer iterations, which is good for search efficiency. To solve the problem of multi-objective combinatorial optimisation, an improved approach may be necessary. By building a customisable learning trajectory on top of learning types. Depending on the practice, other factors, such as the nature of the learning environment and teacher needs, may also be taken into account in practical applications. There is room for improvement in the difficulty of suggesting learning pathways. We want to keep improving our concept in the future so it can meet a wide range of needs.

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