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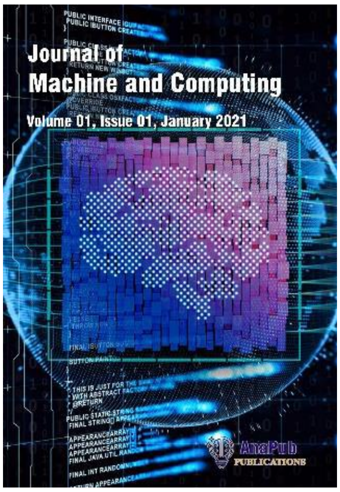

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Adaptive Reinforcement Learning with Improved Artificial Bee Colony Optimization for Personalized and Enriched News Recommendation

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Abstract: Online news contents is increasing exponentially and news are collected from various sources. Personalized news recommendation system has been developed for supporting individual users and this approach will increase the user engagement and satisfaction. Traditional news recommendation system suffers with volatility of user preferences and feedback comment given news feeds. This paper proposes an adaptive reinforcement learning framework by designing with improved artificial bee colony optimization technique. This recommendation framework will enhance personalized news recommendations. The proposed news recommendation system uses reinforcement learning technique for creating an interactive user mode and adaptive recommendations based on continuous learning model. The traditional news recommendation system rely on static user item relationships, ARL optimization to participate in a long time through exploration and exploitation strategies. The efficiency and accuracy in a learning environment has been improved by applying IABC technique. The improved artificial bee colony optimization technique enhance learning rate, guided searching strategies, and efficient exploration. These improvements will enhance the results through fast convergence speed and solution quality. The news recommendations are performed concerning the personalized wish list and most common attributes in the research of news content. The Agent node will create a suggestion list with news feeds based on personally collected information from individuals. Based on the user news reading strategy, the environment will perform the rewarding mechanism. The proposed Agent node is designed using the IABCO algorithm, which makes a suggestion list with enriched news content by using adaptive threshold value selection based probability of success. The performance evaluation has been conducted with following parameters, like precision, recall, F1 Score, Click Through Rate (CTR), Average Click Position, Diversity, and Coverage. A comparative analysis is carried out with existing news recommendation systems and this result shows that the proposed news recommendation system achieves 93.6 % precision, 92% recall, and 92.9% F1 score values. This result shows that the superiority of proposed news recommendation approach and this would be able to provide highest accuracy value, which is nearly 97.5%.

Keywords: Personalized News Recommendation, Adaptive Reinforcement Learning, Artificial Bee Colony Optimization, User Engagement, Bio-Inspired Algorithms, Agent model, Individual Learning.

I. INTRODUCTION

Digital content delivery is a solution for sharing information with a larger audience, which can be achieved more effectively through the Internet. Online news distribution platforms are the most wanted and attractive application for 65% of online viewers, and these applications are replacing the traditional news feeding systems, like newspapers, TV news channels, and printed media. Traditional news readers are slowly migrating to digital news reading applications due to the convenience and timeliness of services offered by digital news applications [1] [2].

Every day, many news articles are published by news content writers, and it is incredible for users to browse through all the available websites [3]. The personalised recommendation techniques for news article suggestions are conducted according to the user's interest. News feeding or suggestion applications are critical platforms to help users improve their reading experience [4]. Personalised news recommendation systems have attracted users from academic and industry in recent years [3][5].

The workflow for the news recommendation system is shown in Figure 1. The news reading applications collect information from the search and interest of the user. The news pool maintains a large set of news articles from different sources. The news candidate selection phase collects the user interest and gives input to the personalised news recommendation system. This system first suggests the top-ranked news from the suggested news list from the recommendation system; then, it updates the user profile based on the news recommendations. Traditional news recommendation systems have been replaced with a personalised environment. Extensive research works are carried out to study these problems from different perspectives. The number of news articles is increasing daily, and older articles will be removed from the current news list quickly. Due to this nature, news recommendation systems are facing cold-start problems. The news articles are designed with rich textual and multimedia content such as titles, relevant images, and the body of the content. Advanced natural language processing (NLP) techniques are used to understand news content by analysing the textual content of the news articles. However, the news websites are not explicitly designed with user feedback, like rating or review commands on news platforms. The personal interest of a user could be inferred based on the news clicks.

Moreover, the great challenge of designing a user-personalised model depends on the user's needs and interests, which are usually diversified and dynamic. This is the more complex part of designing a personalised news recommendation system and requires attractive solutions to solve the problem [6][7][8][9]. The existing personalized news recommendation systems are surveyed comprehensively by the researchers [10][11][12] [13]

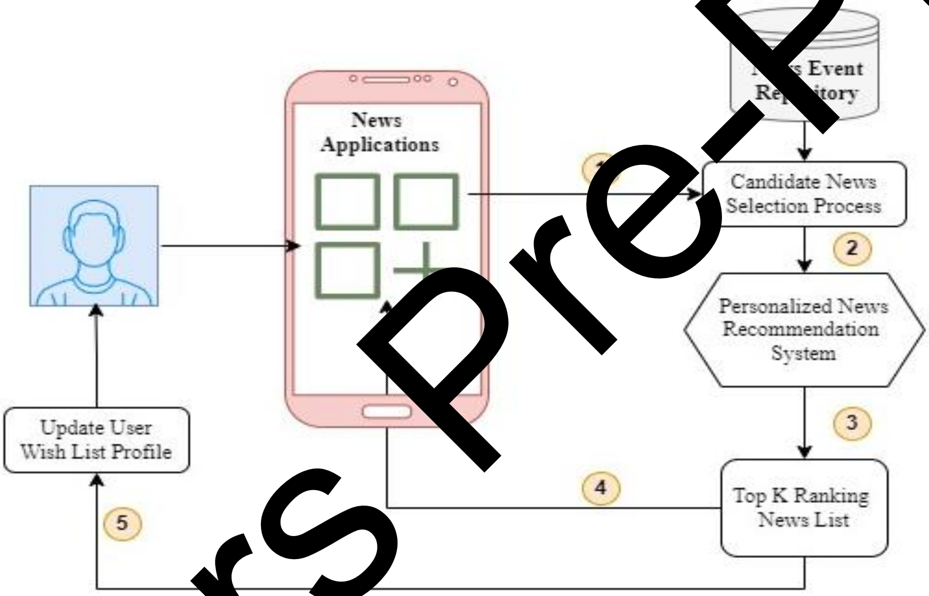

FIGURE 1. Generalized working principle of news recommendation systems.

A. Personalized News Recommendation Systems

Many online news websites are customised with personalised news recommendation techniques [19]. The non-personalised systems are designed with news recommendations exclusively based on non-personalisation factors [20], news popularity [21-24], editor view [25], and geographical location [26, 27]. The existing personalised news recommendation systems are usually classified into three categories: collaborative filtering methods, content-based methods, and hybrid classification models. Recently, content-based classification methods have included traditional semantic-based, contextual bandit, and deep learning-based methods.

The personalised news recommendation systems are trained with user preferences based on news categories and user interests. The news feed needs to be updated more quickly, and this will keep changing with different content sets. Therefore, news features and news candidates are changing dynamically. The user interest in selecting and reading the news content might be changed based on the mood of individuals. The generalised framework for personalised news recommendation systems with reinforcement learning has been designed as shown in Figure 2.

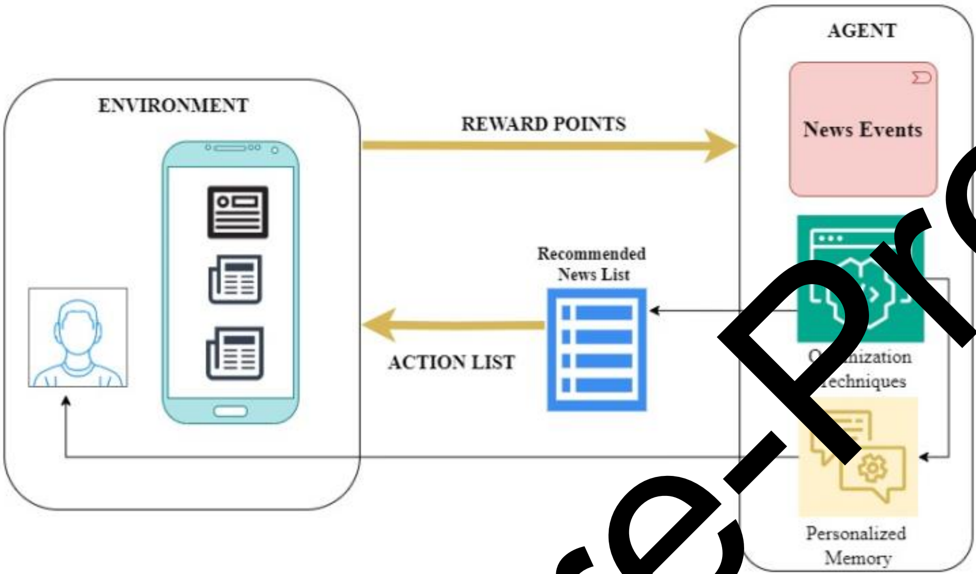

FIGURE 2. General framework for reinforcement learning based personalized news recommendation system.

Based on the personalised memory elements, the recommendation system will display a different set of news categories for every new instance. The optimisation mechanisms are working towards identifying and preparing a recommended news list, which will be input for the user selection environment. The reward points will be calculated based on the user preference from the recommendations. The agent will improve the news selection process based on the news criteria and reward points awarded by the environment. The online recommendation methods are working towards capturing the dynamic changes in the news features and user interest through online updates, and these methods try to optimise the reward points.

B. Contributions

The following contributions are incorporated into the proposed methods

1. This paper proposes a novel personalised news recommendation system using reinforcement learning techniques, based on the Improved Artificial Bee Colony Optimization technique, for providing suitable and enriched news recommendations for active news readers through adaptive threshold selection method.

2. In the proposed method, the agent will prepare news interest from the readers and select suitable news recommendations for the individual reader using probability of success in news selection.
3. The Improved Artificial Bee Colony Optimization Algorithm will update the user interest list based on the environment reward points based on positive or negative points return by environment.
4. The proposed method introduces a weight factor for each news article, and the weight factor value ranges from 0 to 1.This weight factor will introduce freshness in the news recommendations for next level of recommendations.

The remainder of this paper is organised as follows; Section 2 discusses reinforcement learning-related news recommendation systems with research gaps in the existing news recommendation models. Section 3 provides a detailed discussion of the proposed personalised news recommendation system using reinforcement learning. The experimental evaluation and comparative analysis are presented in Section 4, while Section 5 provides conclusions and future directions for the personalised news recommendation method.

II. Related Works

Wouter et al. [28] presented an extension for the existing Hermes framework based on the user profile to store terms or concepts found in the news items. Kompan et al. [29] proposed a content-based news recommendation system using a cosine-similarity search mechanism that adequately represents the news recommendations. They have experimented with the proposed method in the environment of the largest electronic Slovakia newspaper.

Li et al. [30] modelled a personalised news recommendation system based on a contextual bandit problem. This method sequentially selects news articles based on the contextual information about the user and articles. In addition to this, the selection system uses user click feedback to maximise total user clicks.Li et al. [31] proposed a two-stage personalised recommendation system based on the exclusive characteristics of news articles and user-inherited interest in the reading behaviour of individuals. Liu et al. [32] developed a framework for predicting a user's current interest based on the activities of that particular user. They have combined the concept of a content-based recommendation mechanism with collaborative filtering to create personalised recommendations for news articles. The Markov Decision models are supporting for designing an excellent decision support system with the combination of random process and user controls.

The Markov Decision Process (MDP) is a mathematical model for supporting decision making system under the situation, where outcomes are partly random process and partly under the control of decision maker. The MDP framework is defined with following components.

a. State Space: the state space is defined all the set of possible states and each state is typically represents a specific set of configuration of the relevant attributes that defines environment at a given time
b. Action Space: the action space is defined all set of possible actions can be taken by agents and each action is defined a decision or move to next level that the agent can make to influence the current or next state
c. State Transitions: state transitions are describes about "how the environment changes are taking place from one state to another state as a result of agents actions. This transition is represented by using probability distribution over possible next states given the current state and actions
d. Reward Shaping: reward shaping involves for designing the reward calculation function that assigns a numerical value (reward) to each state or state-action pair. This reward guides the agents learning process based on the desirability of states or actions

Lu et al. [33] proposed a framework based on a neural optimisation technique for Partially Observable Markov Decisions, and the author claims that the proposed method effectively uses collected historical data from the real-world environment and automatically achieves a suitable list of news articles. Xiangyu Zhao et al. [34] proposed a principle approach to create a set of complementary items and the corresponding strategy to display pages in 2-D, and they have proposed novel page-wise recommendations based on deep reinforcement learning techniques. This method optimises the page items with the proper display order based on the real-time feedback collected from the users. Lixin Zou et al. [35] introduced an RL framework to optimise by using Q-Network, which is designed in a hierarchical LSTM to model the complex user behaviours, and S-Network simulates the environment to assist with the Q-Network. Manoharan et al. [36] proposed a fuzzy logic-based approach for predicting the interest of the user and their categories by analysing the implicit user profile. The viral news articles and their categories are analysed through data mining social media feeds from Facebook and Twitter.

Bangari et al. [37] presented a review of the different reinforcement algorithms, Deep Q Learning Network (DQN), Twin Delayed DDPG (TD3), and Deterministic Policy Gradient (DDPG) to design for the news recommendation system and also discussed challenges identified from the reinforcement recommendation systems

Kabra et al. [38] proposed a novel news recommendation system for providing a top k number of suggested lists of news based on context-aware recommendations. The item features and user feedback will used as input for the reinforcement learning-backed dynamic algorithm.

Song et al. [39] proposed a framework for a news recommendation system using deep Q-learning with double exploration networks. They have used an offline dataset and a new reward point calculation method in the proposed method.Guanjie et al. [40] proposed a news recommendation system using a Deep Reinforcement Learning framework, and this method uses a Deep Q-learning based recommendation system with explicit future reward points.

Fangzhao et al. [41] presented a large-scale dataset for news recommendations, known as MIND. This method has been constructed from the user click logs from Microsoft News; the MIND dataset has 1 million users and contains more than 160K English news articles. Each entry is designed with rich textual content, a News title, click and non-click counts, a category of news, and content.

Wireless uplink transmission scenario uses unmanned aerial vehicle (UAV) serves as aerial base station for establishing data communication from ground users. Li et al. [50] proposed an optimized solution for the trajectory planning problem by using quantum-inspired reinforcement learning approach. This method adopts probabilistic selection strategies and new reinforcement method.

A novel quantum-inspired experience replay framework is proposed by Li et al. [51] to support for the DRL agents to achieve better trade-off in sampling priority and diversity. This framework is closely related to experienced transitions connected with quantum bits and using Grover iteration based amplitude amplification technique.

A. Research Gap

The existing recommendation models must address the following issues, creating a more significant gap between the user needs and the recommended news list.

1. The existing personalised recommendation systems are designed based on the current reward mechanism, like click through rate.
2. Few recommendation systems use user feedback as input other than click or non-click labels, which will improve the recommendations. Still, these studies are clear about the parameter selection for designing an efficient recommendation system.
3. The existing recommendation systems are tedious due to recommending similar types of news to users.
4. Existing news recommendation models suffer with local and global optima in searching the news content based on the available list of personalised interest.

III. Materials and Methods

This section discusses the basic assumptions and fundamental ideas behind the artificial bee colony optimization algorithm. A detailed discussion has been given in the following about the dataset used for conducting performance evaluation

A. Basic Mathematical Assumptions

Assumption 1*:* The available news instances are mentioned as $AV_{news} = \{X_i, 1 \leq i \leq N\}$; here, N represents the total number of news instances in the particular time interval. Each news instance is represented as follows:

$$X_i = \{T \leftarrow (News_{Attributes}), Y \leftarrow (\text{Set of keywords from } X_i), C_{X_i}, Sentiment^{X_i}_{Score}\}$$

Here, $T_{X_i} \leftarrow \{x_i, 1 \leq i \leq n\}$ and $Y_{X_i} \leftarrow \{y_j, 1 \leq j \leq m_1\}$. The C_{X_i} mentioned the list of categories covered by the news instant X_i.

Assumption 2: The sentiment score $Sentiment^{X_i}_{Score}$ for the news instant X_i is measured as follows:

$$SScore^{X_i}_{Y} \leftarrow \sum_{j=1}^{m_1} Avg^{y_j}_{Score} \rightarrow (1)$$

$$Avg^{y_j}_{Score} \leftarrow \frac{\#(y_j)}{\sum(\text{Words in } X_i)} \rightarrow (2)$$

Assumption 3: The news readers are commonly known as users U_k in the proposed method, and the interest list for the particular user has been represented as follows:

$IL_{U_k} = \{Reading_{Categories}, Class_{U_k}, Keywords^{U_k}_{likes}\}$, the reading categories and liking keywords are created as follows:

$$Reading_{Categries} \subseteq News^{s}_{Categories} \rightarrow (3)$$

$$Keywords^{U_k}_{likes} \subseteq News^{S}_{Keyword} \rightarrow (4)$$

The super set for news categories and keyword list is constructed as follows:

$$News^{s}_{Categories} \leftarrow \bigcup_{i=1}^{N} C_{X_i} \rightarrow (5)$$

$$News^{s}_{Keywords} \leftarrow \bigcup_{i=1}^{N} Y_i \rightarrow (6)$$

B. Improved Artificial Bee Colony Optimisation Algorithms

The artificial bee colony (ABC) optimisation algorithm is a nature-inspired, swim-based, meta-heuristic algorithm. This algorithm has been developed based on the inspired behaviour of honey bees [42]. This algorithm, based on the foraging behaviour of honey bee colonies, has been proposed by Tereshko and Loengarov [43]. The ABC algorithm contains three essential components. The first two components are working as the role of employee and onlooker in the process of foraging bees. These foraging bees are taking the role of searching for rich food sources to collect honey. The third component maintains a set of bees as scouts, and they carry out a random process to find the food positions. The solutions from the search space consist of a set of optimisation parameters that represent the source position. The number of employed bees is equal to the number of food sources. The rich food source is known by its fitness value, and this value will be associated with its position. The employed bees are responsible for investigating the food sources based on the fitness values and sharing the collected information with onlooker bees to identify the best solution. The number of employed bees, onlooker bees, and the number of solutions in the populations are the same. In the proposed IABC algorithm, the probability of success in the selecting optimal food source for collecting enriched information from the news content is calculated based on adaptive probability based threshold value selection. The following section discusses the phases involved in the Improved Artificial Bee Colony Optimization (IABCO) Algorithm.

Initial Phase

Let $X = \{x_i\}, 1 \leq i \leq SN$ be the initialised population generated randomly in the entire space. The food source x_{ij} in the initial phase is calculated as follows (equation 7):

$$x_{ij} = x_j^{MIN} + \alpha \times (x_j^{MAX} - x_j^{MIN}), 1 \leq i \leq SN \text{ } and \text{ } 1 \leq j \leq D \rightarrow (7)$$

Employed Bees Phase

This phase is used to generate new solutions V_i by using a random neighbourhood searching process over the available population x_i using the following equation (8):

$$V_{ij} = x_{ij} + \alpha \times (x_{ij} - x_{kj}) \rightarrow (8)$$

Here, *k* and *j* are the randomly selected values from *SN* (number of solution population), *D* (dimensional vector) and the condition of $(k \neq i)$. If V_i produces an excellent result than x_i, x_i is replaced with V_i. The counter value will be reset or increased by 1 based on the result acceptance.

Onlooker Phase

This phase applies a selection probability to select food sources based on fitness ratio. The Probability can be calculated as follows:

$$Probability_i = \frac{Fitness_i}{\sum_{i=1}^{SN} Fitness_i} \rightarrow (9)$$

Then, the fitness value for the food source x_i is calculated as follows:

$$Fitness_i = \begin{cases} \frac{1}{1 + f(x_i)}, & if\ \ f\ (x_i) \geq 0 \\ 1 + |f\ (x_i)|, & Otherview \end{cases} \rightarrow (10)$$

From (9) and (10), it is easy to infer that the food source with the more considerable fitness value has the highest Probability of being selected by the onlooker bees.

Scout Bee Phase

The onlooker bees, known as scouts, select their food sources randomly. The ABC algorithm could not improve the employed bee's solutions through a maximum number of trials (Maximum Limit or Abandonment Criteria).

Algorithm 1: Improved Artificial Bee Colony Optimization Algorithm

1: Generate Random Initial Populations by using the equation (7)

2: Compute Fitness value for each population $Fitness_i, 1 \leq i \leq SN$

3: Initialize $Counter = 1$

4: **Do**

a. **For** each employee bee from $E_{bee_i}, 1 \leq i \leq SN$

i. Compute V_{ij} using equation (8)

ii. Compute Fitness value $Fitness_{V_i}$

iii. Apply Greedy Selection Process over x_i and V_i

b. End For

5: Calculate Probability values $Probability_{x_i}$ for the solution x_i using equation (9)

a. **For** each onlooker bee from $OL_{bee_i}, 1 \leq i \leq SN$

i. Choose a solution x_i with support of probability value of $Probability_{x_i}$

ii. Create a new solution, V_j

iii. Computes its fitness value $Fitness_{V_j}$

iv. Apply Greedy Selection Process over x_i and V_i

b. End For

6: If an abandoned solution is attained, then

Replace it with a new solution (equation (10))

The available list of best solutions keeps track of and increments the counter.

While $(Counter \leq Max_{iterations})$

A. *Description of Dataset*

This section discussed types of news and number of news instances participated in the dataset [41]. The news articles are in the MIND dataset are categorized into 8 main distinct types and each topic represents different domain specific. These categories are helps to improve the performance of personalized news recommendation based on individual user needs. The primary news categories are included with sports, entertainment, politics, business, technology, health, lifestyle, and science. The following chart (figure 3) explains the distribution of news articles across different categories and this chart helps to understand the dataset's composition of news types.

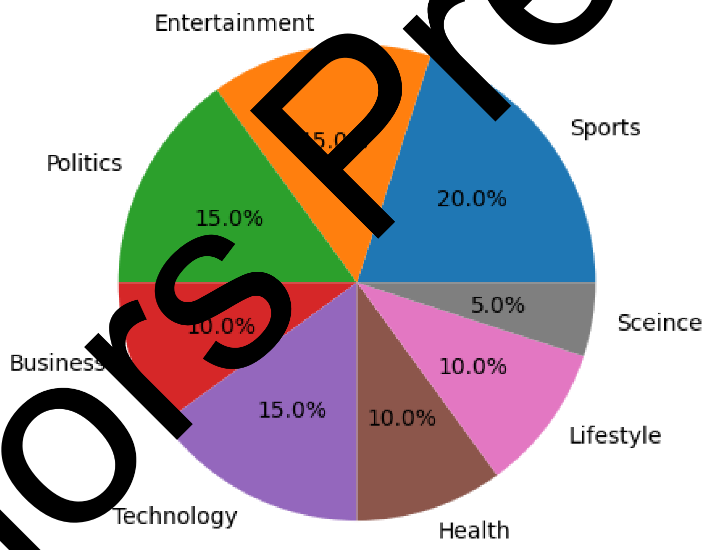

FIGURE 3. Distribution of News Articles in MIND['41] Dataset

Each news instance in the dataset represents a news article with following attributes for providing more information, news ID, title, abstract, category, subcategory, content, data of publishing, user ID, impression log, and click log. These attributes are providing enough information for news reading and types clearly

IV. Proposed Personalised News Recommendations System

This section discusses the proposed news recommendation system using a reinforcement learning model based on the ABC optimization algorithm. Nature-inspired algorithms are a suitable solution for the semi-supervised learning environment, and these algorithms exploit the concepts of the natural behaviour of living things. The proposed architecture for the news recommendation system is shown in Figure 4.

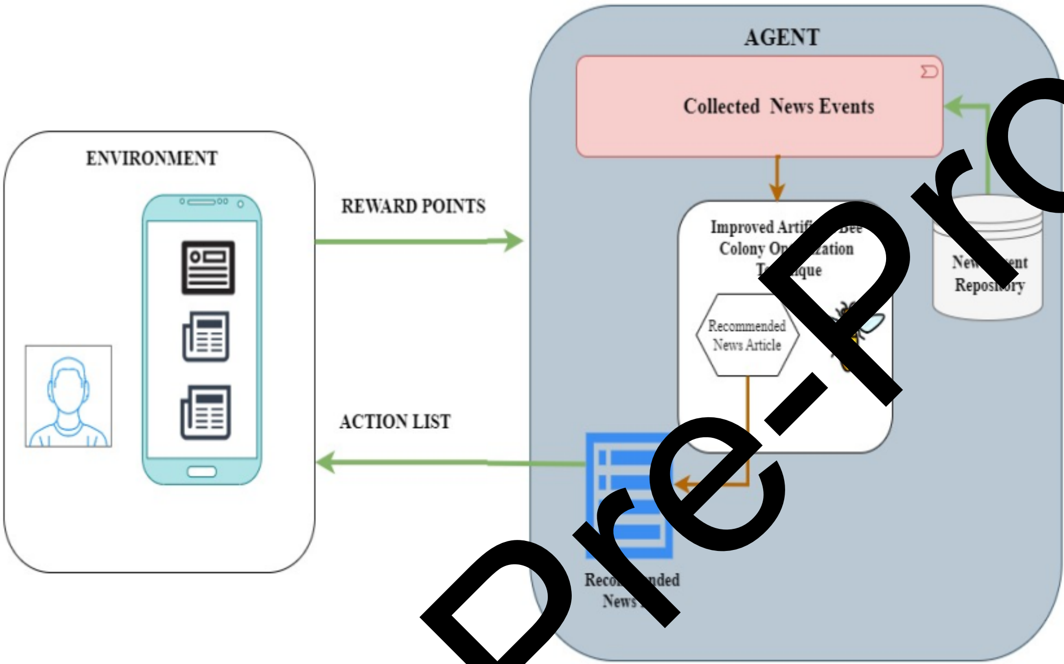

FIGURE 4. Proposed Architecture for the News Recommendation Method using Reinforcement Learning

In the proposed method, the agent has been designed based on an artificial bee colony optimisation mechanism. The agent will create a recommended list of the news based on the personalised interest derived from the user behaviour by using several clicks, the category of news liked and the news searching category. This recommended news list will be given as input to the environment, and the user selects news from this recommended list; based on the news selection, reward points will be calculated.

Proposed Enhanced Reinforcement Learning Algorithm

This section discussed the proposed enhanced reinforcement algorithm for the personalised News recommendation method. The initial stage is constructed with recommended news feeds from the available news list, and the news recommendations will be prepared based on ABC optimisation technique. The following algorithm 2 explains the working principle of the proposed enhanced reinforcement learning algorithm.

Algorithm 2: Proposed Enhanced Reinforcement Learning Algorithm

1. The initial stage has been constructed based on the available list of new instances. The available list of news instances is indicated as $AV_{news} = \{X_i, 1 \leq i \leq N\}$, and each $X_i \in AV_{news}$ will be measured with the sentiment score $Sentiment_{Score}^{X_i}$ by using the equation (1).
2. The available news instances AV_{news} with sentiment score $Sentiment_{Score}^{X_i}$ for news instance will be given as Input for the Agent Node and apply ABC algorithm (***Algorithm 1***) for the initial stage of segmentation according to the sentiment score based on user interest by using equation (3) and (4).
3. The news readers interest list for a Learner U_k will be created as $IL_{U_k} = \{Reading_{Categries}, Class_{U_k}, Keywords_{likes}^{U_k}\}$, and this list will be updated based on equation (3) and equation (4)
4. Select a suitable and recommended list of news instances for the news reader U_k will be given as follows.

   $$SRNList_{U_k}\{(X_j, [Click\ or\ Non - Clicked], Sentiment_{Score}^{X_i})\}_{j=1}^{M}$$

5. Apply Artificial Bee Colony Algorithm based generative AI model (**Algorithm 2**) over $SRNList_{U_k}$ for selecting the enriched news article from this list
6. The enriched news instances are taking the top position in this list $ESList_{Course}^{l}$.
7. This recommended enriched news list $ESNList_{X_i}^{U_k}$ will be given as input for the Environment Node, and the news reader will click and read the more suitable news instance from the$ESNList_{X_i}^{U_k}$list.
8. The news reader interest list IL_{U_k} will be updated based on the news instance selection.
9. This process will return an Expected Reward point, and this will be calculated as follows,

   $$ER_T = \sum_{i=0}^{T} \gamma^i Sentiment_{Score}^{X_{i+1}} \rightarrow (11)$$

Here, γ^iweight factors the particular course. The weight factors are assigned within the interval of $[0,\ 1]$

V. Experimentation, Result and Analysis

This section discussed about the experimental setup and result analysis for the proposed news recommendation system in a detailed way

5.1 Experimental Setup

This section discussed the dataset, experimental setup, and performance evaluation. The experiment was conducted with the Microsoft News Dataset (MIND) [41]. MIND is a large-scale dataset of news recommendation systems, and this has been collected from the anonymisedbehaviour of logs on Microsoft's news website. This dataset contains 160k English news articles with more than 15 million impressions logs, which 1 million users have generated. Each impression log contains click and non-click events and historical news click behaviours of the user. The dataset contains four different file behaviors.tsv, news.tsv, entity_embedding.vec and relation_embedding,vec. The behaviors.tsv (Click History and impression logs of users) and news.tsv (information of news articles) files are taken for conducting the experiments.

B. Performance Evaluation

The performance evaluation for the proposed news recommendation system is measured based on how well the proposed recommendation system suggests relevant news articles to the users according to history of access.

The performance evaluation is conducted with following key metrics,

1. ***Precision , Recall and F1 Score***

The precision is measured based on the proportion of recommended news articles closely relevant to user likes and this will be calculated as follows,

$$Precision = \frac{\#(Eelavent\ News\ Articles)}{Total\ avilabled\ news\ articles} \rightarrow (11)$$

The proportion of relevant news articles that are recommended by the proposed system from the total available relevant news articles and recall will be calculated as follows,

$$Recall = \frac{\#(Relavent\ News\ Articles\ Recommended)}{Total\ \#(Relavent\ News\ Articles)} \rightarrow (12)$$

The F1-score is computed from the precision and recall values by using equation

$$f1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \rightarrow (13)$$

The following news recommendation methods are considered for the performance evaluation: Zheng et al. [40] (P1), François Chollet et al. [45] (P2), Steffen Rendle [46] (P3), Cheng [47] (P4), Li [30] (P5) and Wang et al. [48] (P6). Zheng et al. [40] method uses the deep Q learning method, François Chollet et al. [45] employ the logistic regression method, Steffen Rendle [46] uses the factorisation method, Cheng [47] uses comprehensive and deep learning method, Li [30] uses linear upper confidence bound method, and Wang et al. [48] exploit the hidden linear upper bound method. The experiment evaluation uses the same news recommended list generated based on sensitive scores and reward points [30][40][48] and probability values based on click [45][46][47]

The following tables are providing a detail about precision, recall, and F1-score for the news articles recommend for the variety of 10, 20, and 30 news article readers. The testing dataset is prepared with1697 news articles instances for conducting the performance evaluation. The categories of news instances are evenly distributed and user category of wish list is prepared based on like and dislikes. The evaluation is conducted as offline evaluation mode. The following table I shows the results of precision, recall, and F1-score, according to precision results the proposed method provides more relevant articles for the users compare to other related recommended systems. The recall and F1-score value also shows that the proposed method provides an excellent news recommendation for the different news reading category of users. The table II and figure 5 shows the average performance result for the proposed news recommendation system,

TABLE I: Performance Analysis for Article Selection

News Recommendation Method	**Precision**	**Recall**	**F1-Score**
Zheng et al. [40]	84.63	81.34	82.95
François Chollet et al. [45]	81.92	79.24	80.55
Steffen Rendle [46]	86.75	84.33	85.52
Cheng [47]	82.73	80.73	81.71
Li [30]	89.61	86.55	88.05
Wang et al. [48]	90.71	89.36	90.02
Proposed Method	93.63	92.33	92.97

Click Through Rate, Diversity, and Average Click Position

Click Through Rate (CTR) measures the proportion of user click on from the recommended news articles and this will indicates the direct user engagement over the recommended news articles. The CTR has been calculated as follows by using equation (14),

$$CTR = \frac{No.\,of\,Articles\ Clicks}{Total\ No.\,of\ Recommended\ News\ List} \rightarrow (14)$$

The diversity measure the recommended list of news articles are not from similar categories and this will ensure the user diversity of reading. The diversity is measured for the recommended article with other article in the list as shown in the equation

$$Diversity = 1 - \frac{\sum_{i \neq j} Similarity\left(NA_i, NA_j\right)}{n.\,(n-1)} \rightarrow (15)$$

The Average Click Position is used to evaluate the average position of clicked news articles from the recommended list. The value for ACP is lower than relevant articles are ranted higher.

$$ACP = \frac{\sum_{i=1}^{N} Pos\,\left(\#(Relavent\ News\ Articles)\right)}{Total\ Number\ news\ articles} \rightarrow (16)$$

3. Coverage

The coverage will be measured based on proportion of unique news articles or particular categories that are recommended to users. This will ensure the diversity of news article recommendations.

$$Coverage = \frac{Unique\ No.\,of\ Articles\ Recommended}{Total\ No.\,of\ Available\ Articles} \rightarrow (17)$$

The following table II and figure 6 provides the click through rate, diversity, average click position, and coverage value for the proposed method along with other news recommendation systems.

TABLE II. Performance Analysis for Recommended Articles

News Recommendation Methods	CTR	Diversity	ACP	Coverage
Zhang et al. [40]	24.91	17.64	21.34	39.13
François Chollet et al. [45]	23.31	19.34	23.45	40.21
Steffen Rendle [46]	24.53	19.11	20.13	41.32
Cheng [47]	25.46	18.79	25.43	39.33
Li [30]	24.54	20.55	21.33	41.25
Wang et al. [48]	26.43	21.78	25.21	42.34
Proposed Method	30.13	34.41	29.76	54.75

4. Normalized Discounted Cumulative Gain (NDCG)

Normalized Discounted Cumulative Gain (NDCG) is measured based on the position of relevant news articles in the recommended news list, assigning higher scores to relevant news articles appearing earlier.

$$NDCG = \frac{DCG}{IDCG} \rightarrow (17)$$

Here, Discounted Cumulative Gain (DCG) is measured as follows,

$$DCG = \sum_{i=1}^{N} \frac{(2^i - 1)}{\log_2(i+1)} \rightarrow (18)$$

The Ideal Discounted Cumulative Gain (IDCG) is the maximum possible DCG for recommended set of news articles.

5. Mean Reciprocal Rank

The Mean Reciprocal Rank (MRR) is measured the rank position of the top most relevant news articles form the recommended news list by using the equation. Higher rank values indicate better performance.

$$MRR = \frac{1}{N} . \sum_{i=1}^{N} \frac{1}{Rank_i} \rightarrow (19)$$

The following table III and figure 7 provides results for the normalized distribution cumulative gain, mean reciprocal rank, and coverage of like and dislike category of news articles.

TABLE III: PERFORMANCE ANALYSIS FOR DISCOUNTED CUMULATIVE GAIN

News Recommendation Methods	**NDCG**	**MRR**
Zheng et al. [40]	88.31	87.23
François Chollet et al. [45]	86.54	88.76
Steffen Rendle [46]	84.21	85.45
Cheng [47]	91.34	90.21
Li [30]	90.23	87.56
Wang et al. [48]	85.34	90.12
Proposed Method	94.35	95.34

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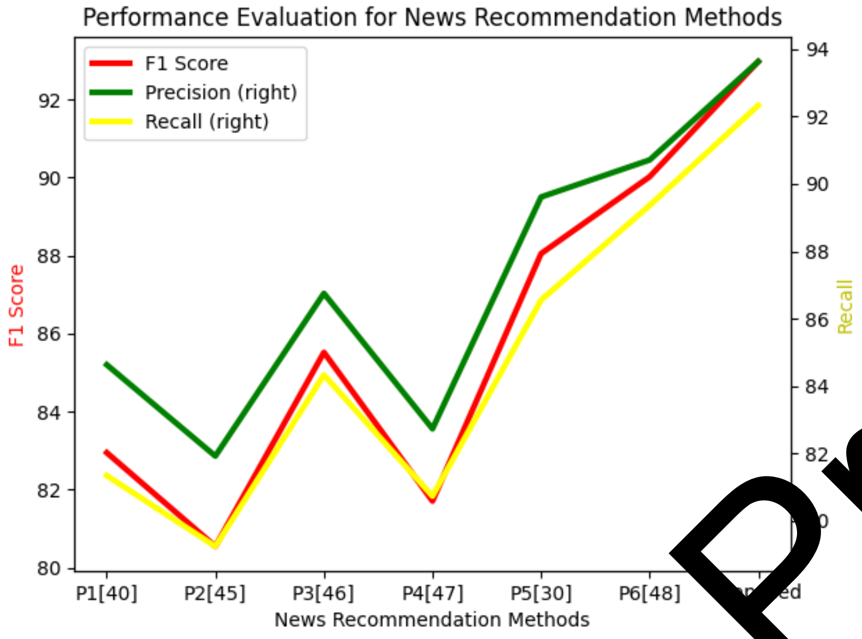

FIGURE 5. Performance Evaluation with Precision, Recall, and F1-Score.

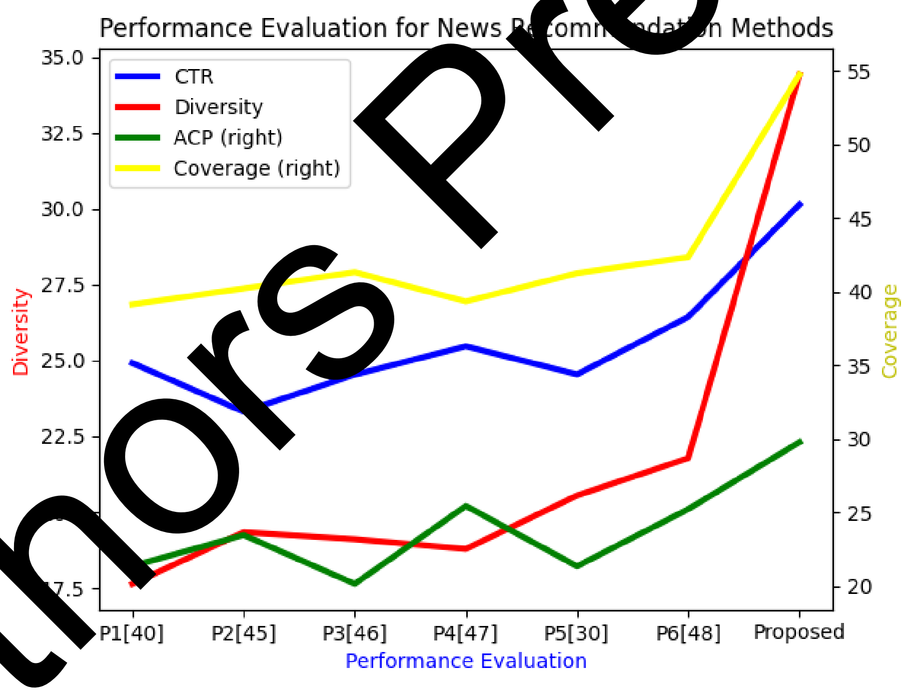

FIGURE 6. Performance Evaluation with CTR, Diversity, ACP, and Coverage.

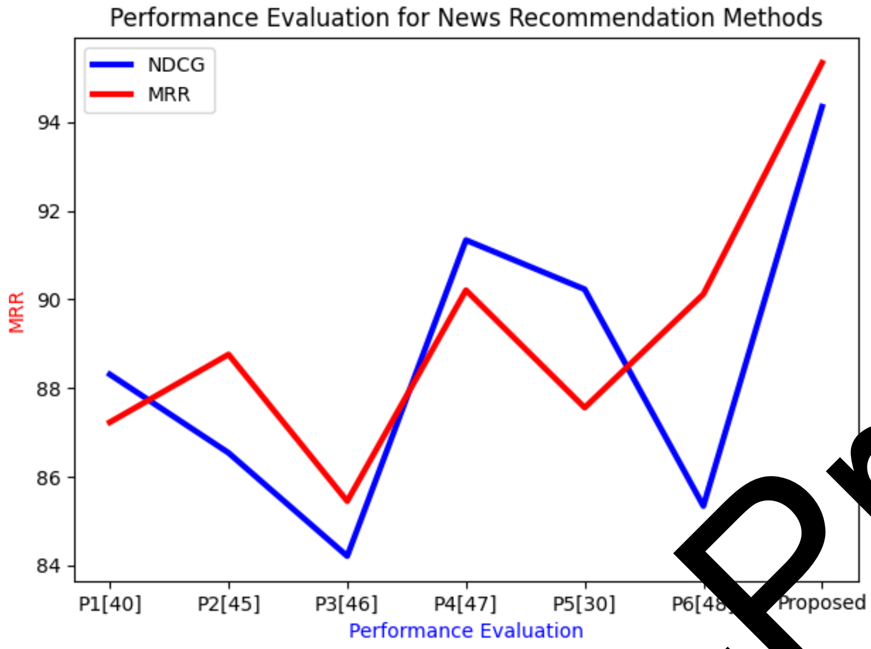

FIGURE 7. Performance Analysis with NDCG and MRR.

C. *Reward Curve*

The reward curve for the proposed IAROA based reinforcement learning technique is given in the figure 10 (400 episodes) and it shows that the maximum reward points could be achieved for the proposed method based on increasing the number of episodes for training the proposed method. The figure 8 and 9 shows the results for reward curve with 100 and 200 episodes.

According to the reward curve from the figure 8, 9, and 10 the learning progress of the proposed technique achieves high reward from maximum number of times. The convergence rate for the proposed method is increasing based on the number of episodes.

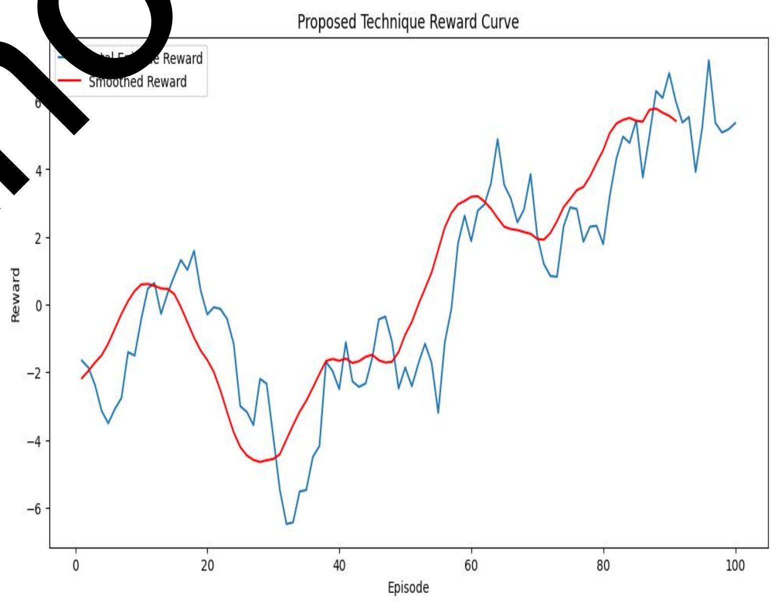

FIGURE 8. Reward Curve for the proposed technique with 100 Episodes.

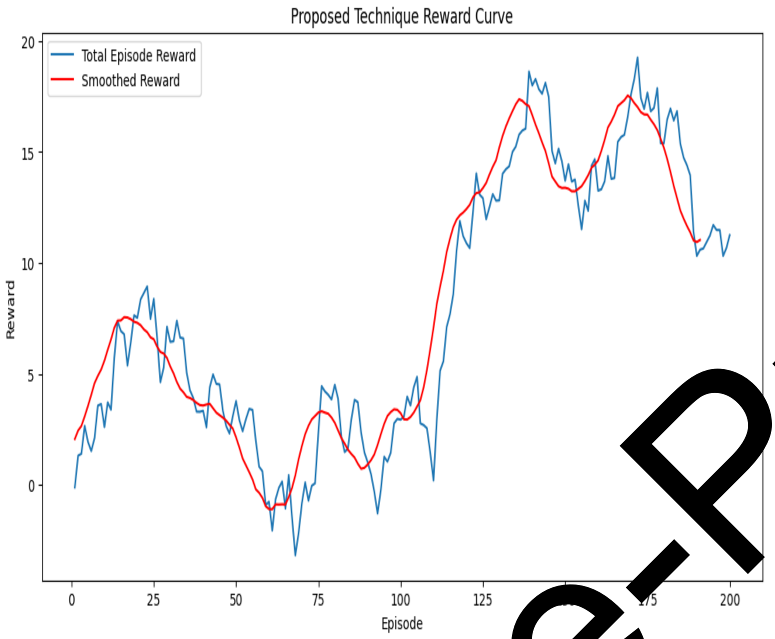

FIGURE 9. Reward Curve for the proposed technique with 200 Episodes.

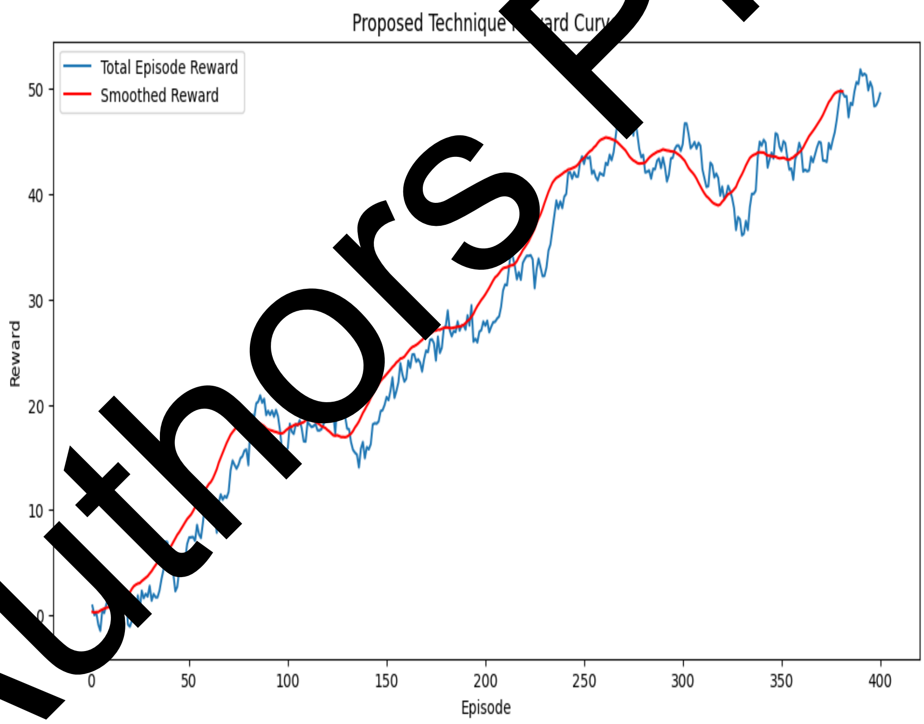

FIGURE 10. Reward Curve for the proposed technique with 400 Episodes.

Result Analysis

According to the result analysis for the proposed news recommendation approach, the proposed news recommended system using reinforcement learning approach and this technique is using expected reward calculation (ER_T) by using equation (11). The proposed recommendation system is achieving highest efficient result for news recommendation individually. The reward curve shows the efficient of recommendation based on the number of iterations involved. The performance analysis based on Normalized Discounted Cumulative Gain (NDCG) and Mean Reciprocal Rank (MRR) is high with nearly 94% and 95% and this will lead to high efficiency in news recommendations. The Click Through Rate (CTR), Diversity, Average Click Position, and Coverage has been achieved with 30%, 34%, 30%, and 54% for the proposed recommendation system. Precision, Recall, and F1 Score is nearly 94%, 92%, and 93% and the accuracy for the proposed news recommendation system is nearly 95%.

VI. Conclusion and Future Scope

This paper has proposed a novel news recommendation system using a reinforcement learning technique with agent design based on the ABC optimisation algorithm. The proposed recommendation system exploits the ABC optimisation algorithm to prepare enriched news articles as recommended news lists. The user interest list will be updated based on the news click done by the particular user, and this will introduce freshness in the news recommendation system. The environment will return a high reward point based on the sentiment score and weight factor. The newsreader interest list will be created based on the number of clicks and the number of keyword matches. The performance evaluation for the proposed method was measured based on Click-Through Rate (CTR). The proposed method achieves the highest CTR rate (0.6063) compared to other news recommendation systems. The accuracy of the proposed method was measured through the diversity of news clicks, and the proposed method once again achieves the maximum diversity (0.3345) value compared to other news recommendation systems. According to the performance evaluation, the proposed technique achieves nearly 94% of precision, 92% of recall, and 93% of f1-score and this evaluation shows that the proposed technique produces high accuracy for news recommendation.

In the future reach, may be focused on developing fully automated recommended system by considering various factors like, time, mood, and emotions of users based on detailed analysis with different factors.

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