January - February 2020
ISSN: 0193 - 4120 Page No. 5199 - 5212

An Effective Web Page Personalization model using Weighted Clustering and Improved Whale Optimization Algorithm

[1]A. Vaishnavi, [2]N. Balakumar

[1]*Research Scholar, Department of Computer Applications, Pioneer College of Arts and Science, Coimbatore, India. Email: [1]vaishmsc@gmail.com*

[2]*Associate Professor, PG and Research Department of Computer Science, Pioneer College of Arts and Science, Coimbatore, India. Email: [2]balakumar198392@gmail.com*

Article Info
Volume 82
Page Number: 5199 - 5212
Publication Issue:
January-February 2020

Article History
Article Received: *18 May 2019*
Revised: *14 July 2019*
Accepted: *22 December 2019*
Publication: *25 January 2020*

Abstract:
Web page personalization is the procedure of customizing a web page based on the requirements of every particular user or a group of users by utilizing the knowledge attained from the investigation of user's navigational actions. Personalized recommendation predicts the browsing nature of the user by the use of data mining techniques received significant interest in the domain of web personalization research area. This paper presents a clustering with similarity measure based web page personalization model. Here, the web page personalization takes place by formulating queries and profiling by the WordNet ontology. To begin with, the needed data is gathered from various web sources and are grouped by the use of Weighted Clustering (WC) technique. The WC groups the web pages with respect to the fields which are learned by the user learning process. Using the set of four similarity metrics, data resemblance will be computed among the created word net and trained dataset. Among them, the highest resemblance based data is offered by the Improved Whale Optimization algorithm (WOA), where the WOA algorithm is extended by the concept of tumbling effect. A series of simulations were carried out to highlight the betterment of the presented model under various aspects.
Keywords: *Word Net, Web personalization, Clustering, Optimization*

1. Introduction

Generally, keyword based web browsers are not capable of meeting the user requirements while searching process is carried out through internet. The personalized search provides specific problems by focusing on significant results of client investigations that is integrated with examined user profiles. Furthermore, it reduces client's effort during the period of searching any issues or objectives. Recently, some techniques from online searching have been presented. Few models are assumed to be efficient, which is based on creating a single word that denotes the customer attention and applying in online searching operation.

The random group of people concentrates mainly for content providers that often use personal creations. The web page personalizing models are composed with people identifying the reductions as well as applying the inclinations for identifying most suitable medium for all customers [1]. The web page personalization has modifications in

January - February 2020
ISSN: 0193 - 4120 Page No. 5199 - 5212

terms of exploring data of website that is computed effectively [2]. Hence, it is mainly comprised with exploited distance and rules might be with the parameters of [3]. It helps to find the user examining results to obtain the required information, learning introduction, It can alter the region as well as to simplify students' interface with effective and entrance log, also It proposes a training assets with the application of analyzing leaner's concentration and training operation. It assists to obtain intrigued information and provide references to help the user for managing the learning model, training method as well as teaching approach [4, 5]. The significant portion of web personalization system is said to be initial stage, classification and preprocessing the online data [6]. By extracting the association among different kinds of learning such as the assuring the functions must be practiced with the help of web personalization technology [7]. In this case, the main objective should be clear for corresponding user to obtain wider number of outcomes in a frequent manner. Therefore, user must be rapid by implemented results for the purpose of finding the suitable results [8]. Followed by, a personalized learning model is essential to provide required information with the application of data mining techniques such as clustering, optimization and so on [9, 16-26].

[10] introduced alternate model that is depend upon the personalized web search outcomes. By using the presented technique, user creates a profile with the help of basic data, and remains by user feedback up-to-date user profile. While the searching operation is carried out, user query might optimize with 2 stages: with the priority given for user profile and Word Net ontology. [11] defined the influential aspects of Social networking sites (SNSs) at the time of web page personalizing method. Also, the influencing factors are: switching expense as well as user satisfaction. It undergoes a study using the samples of 677 SNS clients from 6 standard educational centers in US with the help of Structural Equation Modeling (SEM) method. Thus, it results in improved personalization, switching cost and satisfaction that denotes the accessibility of SNS.

The meaningful creation of RESTful services based on the HATEOAS pattern that is depicted by [12] where clustering model is relied on same metrics of client and produce an ontology for managing the users as well as corresponding facilities. Here, presented model is installed with the help of a prototype that is applicable to examine the efficiency of system. [13] introduced a web page personalized fuzzy-bat classifying technique. The user questioned on different search engines and combines acquired results on the basis of diverse connections. Various estimations like title, snippet, content, URL, website address, and co-occurrence has been measured using integrated links. Therefore, estimated values has been declared for fuzzy-bat classifier model for ranking the links by comparing with presented technique and previous fuzzy with respect to accuracy and response time. [14] deployed a powerful web page personalizing clustered query sessions. Here, URL has been listed by the compared results with the help of user query to apply Genetic Algorithm (GA).

The computation of GA could be examined using data set of web query sessions that might be used in education, physical activities, entertainment and so on. Moreover, the simulation outcome states that, GA achieved optimal personalization based on requirements of user. Simultaneously, [15] mentioned the method of network for analyzing the users search information. The above network is comprised with historical data of user's predefined searching data. It helps to regain the same web pages which can be discovered with the application of user query. GA is applied while the client searches novel information as well as to relate the techniques of network. Hence, these

January - February 2020
ISSN: 0193 - 4120 Page No. 5199 - 5212

processes tend to achieve best searching outcome in the domain of user query.

This paper presents a clustering with similarity measure based web page personalization model. Here, the web page personalization takes place by formulating queries and profiling by the WordNet ontology. To begin with, the needed data is gathered from various web sources and are grouped by the use of Weighted Clustering (WC) technique. The WC groups the web pages with respect to the fields which are learned by the user learning process. Using the set of four similarity metrics, data resemblance will be computed among the created word net and trained dataset. Among them, the highest resemblance based data is offered by the Improved Whale Optimization algorithm (WOA), where the WOA algorithm is extended by the concept of tumbling effect. A series of simulations were carried out to highlight the betterment of the presented model under various aspects.

2. The proposed model

The plan of web page personalized is to offer the personalization knowledge of various web pages dependent on identified and related data of user query. In the presented work, gather the information from web page sources to personalization information with user inclinations.

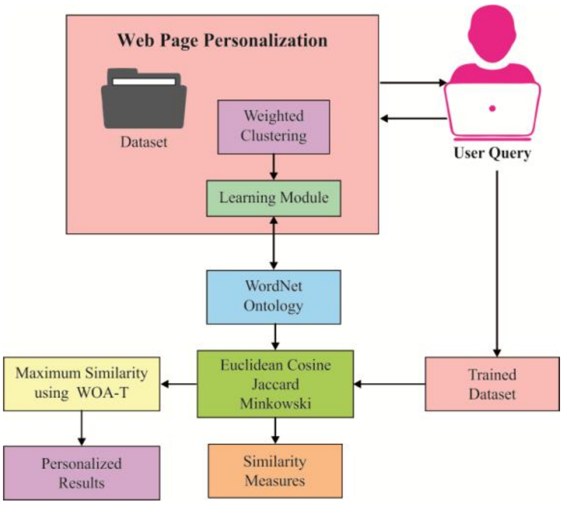

Fig. 1. Working principle of the proposed model

Initially, the gathered information from Syskill and Webert WebPage Ratings are clustered based on their separate fields. Behind clustering, learn the information i.e. user required data that is in the form of text, video or audio and saved use of learned content module. After that, wordnet is created that have the keyword and its description. According to user query, we join the trained dataset as well as word net created database and find the comparison data with utilizing various calculates. The diagrammatic illustration of presented work is showed in Fig. 1.

The initial step is to gather the information from the Syskill and Webert Web Page Ratings that have data relevant to web pages with their ratings of separate user.

2.1. Clustering process

The WC technique aspires to cluster the issues based on their field with the user inclinations. Clustering is complete with Cluster Head (CH) selection and in analysis of the each selection CH; nearby nodes i.e. containing nearer distances from CH are clustered at one. In the same way, three more CHs are choose and at last, clustered into 4 groups.

1. Recover the neighbors of every node (k) with essential its degree d_k as

$$d_k = |N(k)| = \sum_{k'\in K,k;\neq k} \{distance(k,k^f) < node\ transmissionrange\} \quad (1)$$

2. Estimate the degree variation to each node k,$\triangle k = |d_k - \delta|$ after that calculate the sum of the distances through every neighbours as:

$$\mathrm{Distance}_k = \sum_{k'\in N(k)} \{distance(k,k^f)\} \quad (2)$$

3. For each node, calculate the running average of the speed until the current

January - February 2020
ISSN: 0193 - 4120 Page No. 5199 - 5212

timet. This provides mobility$Mob_k = \frac{1}{T}\sum_{t=1}^{T}\sqrt{(A_t - A_{t-1})^2 + (B_t - B_{t-1})^2}$, where $(A_t\ , B_t)$ and $(A_{t-1}\ , B_{t-1})$ are the manages of the node k at the time t and $t-$ correspondingly.

4. Find the cumulative timeC_k, in that a node k acts as a CH
5. For every node, the joined weight is computed as

$$CW_k = w_{1\triangle k} + w_2 Distance_k + w_3 Mob_k + w_4 C_k \quad (3)$$

where, w_1,w_2, $w_3 and\ w_4$ are the weighting factors to equivalent system attributes

6. *CH Selection*: Choose the nodes that have least joined weight as the CH. The neighbors of chosen CH are no longer permitted to take part in the election process.

The above steps 2–6 are frequent still the rest of the nodes not yet chosen as CH or allocated to a cluster. According to this rule we set the information based on their field.
Learning needs a set of positive example of user question and negative examples. In this paper, we learn a model that identifies pages with rating it with user preferences. The learner concept requires to continually search the related information on the field abilities i.e. learn the information from the subjects goats, bio-medical and sheep. It would dependable to generate and update the user profile with rating the web page.

WordNet
The WordNet is a tool to mapping the user recognizing words, expressions as well as connection among them or its synonyms word. This WordNet store is helpful in the applications of data mining and web mining. If user accepts a query associated to the bio-medical, bands, and so on, the system discovers the words connected to a user query with utilizing WordNet and creates a dataset. Search engine explores web to every words or expressions in synonym vector thus collects the entire group of web pages and distributes to web search personalize system. Web search personalize system chooses related pages dependent user exciting words in user profile.

2.2. WOA_T algorithm for Webpage Personalization
To calculate or evaluate the comparison or stability between the data items, the estimate of distance metrics among data items is necessary. It is essential to identify, in what method the data are interconnected, how different information unrelated or related to one other and what evaluates are regarded to similarity. The measures utilized to find the comparison expressions among trained and WordNet dataset.

At the initialization step, U and V denote phrases obtained from trained WordNetdataset. Also i and j indicates ith and jth data from database. According to identical values existed 2 words has been measured with the help of 4 distance value.Euclidian distance is assumed to be distinct distance values for all geometrical issues which is estimated by the variations among 2 data points. Hence, it is considered to be simple, normal distance from two points respectively,

$$Distance_{AB} = \max_{k} |U_{ik} - V_{jk}| \quad (4)$$

Next,the operation of cosine distance value is useful to compute the cosine angle from predefined phrases which is the user query. The Θ provides an angle from 2 vectors then calculated with the help of Eq. (5).

$$\theta = arc\ \cos \frac{U.V}{\|U\|\|V\|} \quad (5)$$

Jaccard is a kind of identical distance measure. As it is applicable to measure the similarity among

January - February 2020
ISSN: 0193 - 4120 Page No. 5199 - 5212

two data sets with the intersection segmented using the combination of data items as depicted in Eq.(6).

$$J(U,V) = \frac{|U \cap V|}{|U \cup V|} \quad (6)$$

Minkowskideals with a distance of generalized Euclidean distance. Minkowski distance for 2 words U and V can be described as

$$Distance_{UV} = \left(\sum_{k=1}^{d} | U_{ik} - V_{jk} |^{\frac{1}{a}}\right)^{a} \quad (7)$$

In Eq. (7), it is clear that, if a = 1 , then it is similar to Manhattan distance; when a = 2, it is same as Euclidean distance. Where d represents the count of attributes present in specified dataset. With the application of 4 distance similarity measures, similarity from 2 intervals for particular dataset is examined as well as related between 4 values.

The whale social actions are the other exciting thing. They live in community or alone. However they are generally seen in communities. In entire generation, few species may live in the family. At nearby surfaces, Humpback whales choose to follow and hunt the community of small fishes or krills. Through producing a unique bubble over '9'-shaped path or circle, foraging is performed. But, using tag sensors it is observed that 9 distinct humpback whales perform feeding events in 300 tag-derived bubble-net. They observed two exercises linked with bubble known as 'doubleloops' and 'upward-spirals'. Around the victim, humpback whales in prior exercises, dives over 12m depth and initiate to produce bubbles in the shape of spiral and it move toward the surface again. Lobtail, capture loop and coral loop are the three various phases in later exercises. It is the major thing to note that this bubble-net feeding type is a distinct behavior which is examined in humpback whales. With a view to carry out optimization, the exercise of spiral bubble-net feeding is geometrically designed. Surrounding victim in geometrical model, victim searching and spiral bubble-net feeding exercise are initially given in this section. Then, the WOA-T is projected.

2.2.1. Encircling victim

Victim position can be identified through Humpback whales and it encircles it. In the search space, the best plan position is not known priori, the WOA considers that the present good candidate result is treated as target victim otherwise it is near to the optimal solution. The search agents would therefore attempts to modify its locations to the top search agent subsequent to top search agent is described. This is demonstrated through the subsequent expressions:

$$\vec{D} = |\vec{C}.\vec{X} * (t) - \vec{X}(t)| \quad (8)$$

$$\vec{X}(t+1) = \vec{X} * (t) - \vec{A}.\vec{D} \quad (9)$$

Here, the present iteration is denoted as t, the coefficient vectors are referred as $\vec{A}$ and $\vec{C}$, position vectors are represented through $\vec{X}$, absolute rate is represented through || and multiplication of element-by-element are represented through (.). In all iteration, if it is better result, X^*should be modified. The $\vec{A}$ and $\vec{C}$ are the vectors that are estimated as follows:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \quad (10)$$

$$\vec{C} = 2.\vec{r} \quad (11)$$

In the iterations, $\vec{a}$is linearly reduced from 0 to 2 and in [0,1], a random vector is represented through $\vec{r}$. With n dimensions, the similar idea can be elaborated to search space over the optimal

TEST Engineering & Management
January - February 2020
ISSN: 0193 - 4120 Page No. 5199 - 5212

solution, the search agents will navigate in hyper-cubes. With bubble-net mechanism, the victims are subjected to be attacked through humpback whales. This technique is geometrically expressed as below:

2.2.2. Exploitation process

Two methods are modeled with a view to geometrically design the humpback whales bubble-net behavior as given below:

Shrinking surrounding method

It is obtained through reducing the $\vec{a}$ rate. It is denoted that the $\vec{A}$fluctuation rate has also reduced through$\vec{a}$. Within the interval [−a, a], $\vec{A}$ refers to the arbitrary rate wherever in the iterations,a is reduced from 0 to 2. In [−1, 1], fixing the arbitrary rate, the novel search agent location can be found among the present best agent position and actual agent position. Within a two dimensional space, the location out of (X,Y) which might be attained through $0 \leq A \leq 1$.

Spiral updating position

This method initially estimates the victim located at X^*, Y^* and the distance among the whale position at (X, Y). To replicate the movement of helix-shaped humpback whales, a spiral expression is produced among the victim and whale location.

$$\vec{X}(t+1) = D'.e^{bl}.\cos(2\pi l) + \vec{X}^*(t) \tag{12}$$

Here, $\vec{D}' = |\vec{X}^*(t) - \vec{X}(t)$ denotes ith distance to the victim from whale, to describe the logarithmic spiral shape b refers to the constant, in [−1, 1], 1 refers to the arbitrary number and it is multiplication via element-by-element.

2.2.3. Exploration process

To find the victim, similar method depending on $\vec{A}$vector can be used. In order to every other location, humpback whales finds arbitrarily. Hence, we employ $\vec{A}$with the arbitrary rates larger when compared to 1 otherwise lower when compared to -1 to push the find agent to move far away from whale. In the exploration phase, we modify the find agent location when compared to exploitation phase. To carry out a global search, $|\vec{A}| > 1$, the WOA is employed. The geometrical model is expressed as

$$\vec{D} = |\vec{C}.\vec{X}_{rand} - \vec{X}| \tag{13}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \tag{14}$$

Let $\vec{X}_{rand}$ is the random position vector selected from the present population.

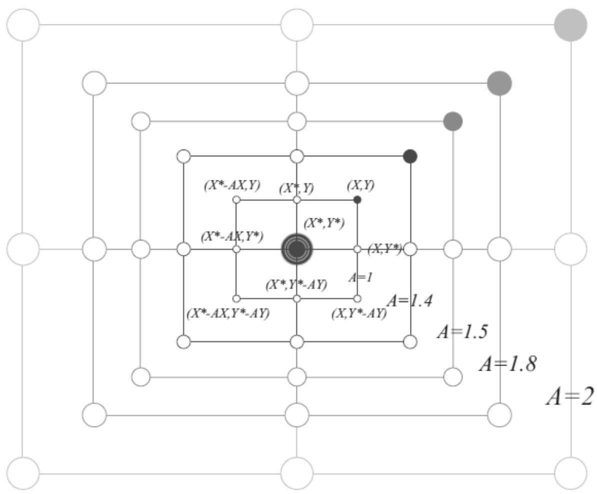

Fig. 2. Exploration process in WOA

In Fig. 2, with $\vec{A} > 1$,few probable locations over a certain solutions are demonstrated. With an arbitrary solution set, WOA initialization takes place. In order to the selected search agent, the agents undergo searching to modify its locations at all iteration or top optimal gained. With a view to offer exploitation and exploration, the parameter is decreased from 0 to 2 related. While$|\vec{A}| > 1$, the random search agent is chosen when the optimal solution is chosen for modifying the search agent's position. WOA is capable to transform among a circular or spiral movement

January - February 2020
ISSN: 0193 - 4120 Page No. 5199 - 5212

based on p rate. At last, when stop condition or a satisfaction level is reached, WOA is stopped.

WOA can be assumed as a global optimizer from theoretical view as it involves exploitation/exploration capability. The projected mechanism of hyper-cube describes a search space adjacent to optimal solution and enables the other search agent to make use of the present best element within the domain. To transform among exploitation and exploration, adaptive search vector modification is used. Two major internal attributes have to be tuned (A and C) in WOA.

2.2.4. Tumbling process

To improve the results of the WOA algorithm, the tumbling effect is included to it. It identifies the parameter values involved in WOA. Here, the motion of whale is selected by the fitness function value. The whales move in a same path as the chemotactic motion of bacteria which is represented as follows. The chemotactic movement of bacterium is defined as follows:

$$a_i^t = a_i^{t-1} + v_i^t \frac{\Delta_i}{\sqrt{\Delta_i^T \times \Delta_i}} \quad (15)$$

Once the whale moves in the direction of fitness function, then the process is referred as swimming. Otherwise, the motion of whales is carried out based on the movement of bacteria.

3. Performance Validation

This section validates the results attained by the presented model under several dimensions.

Table 1 and Fig. 3 provide a detailed comparison of the presented WO-T model interms of precision. Under the existence of 3 clusters, the GA is ineffectual to exhibit good results by attaining a least precision value of 84.81. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate precision value of 86.83 whereas even higher precision value of 86.83 is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum precision value of 90.76. Under the existence of 4 clusters, the GA is ineffectual to exhibit good results by attaining a least precision value of 86.00. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate precision value of 87.96 whereas even higher precision value of 89.25 is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum precision value of 91.30. Under the existence of 5 clusters, the GA is ineffectual to exhibit good results by attaining a least precision value of 86.31. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate precision value of 87.35 whereas even higher precision value of 89.25 is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum precision value of 91.45. Under the existence of 6 clusters, the GA is ineffectual to exhibit good results by attaining a least precision value of 85.21. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate precision value of 86.83 whereas even higher precision value of 88.43 is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum precision value of 90.98.

Table 1 Comparisons of existing with proposed method in terms of Precision

Number of Clusters	WO-T	WC-OFFO	WC-FFO	GA

January - February 2020
ISSN: 0193 - 4120 Page No. 5199 - 5212

3	90.76	88.86	86.83	84.81
4	91.30	89.25	87.96	86.00
5	91.45	89.25	87.35	86.31
6	90.98	88.43	86.83	85.21

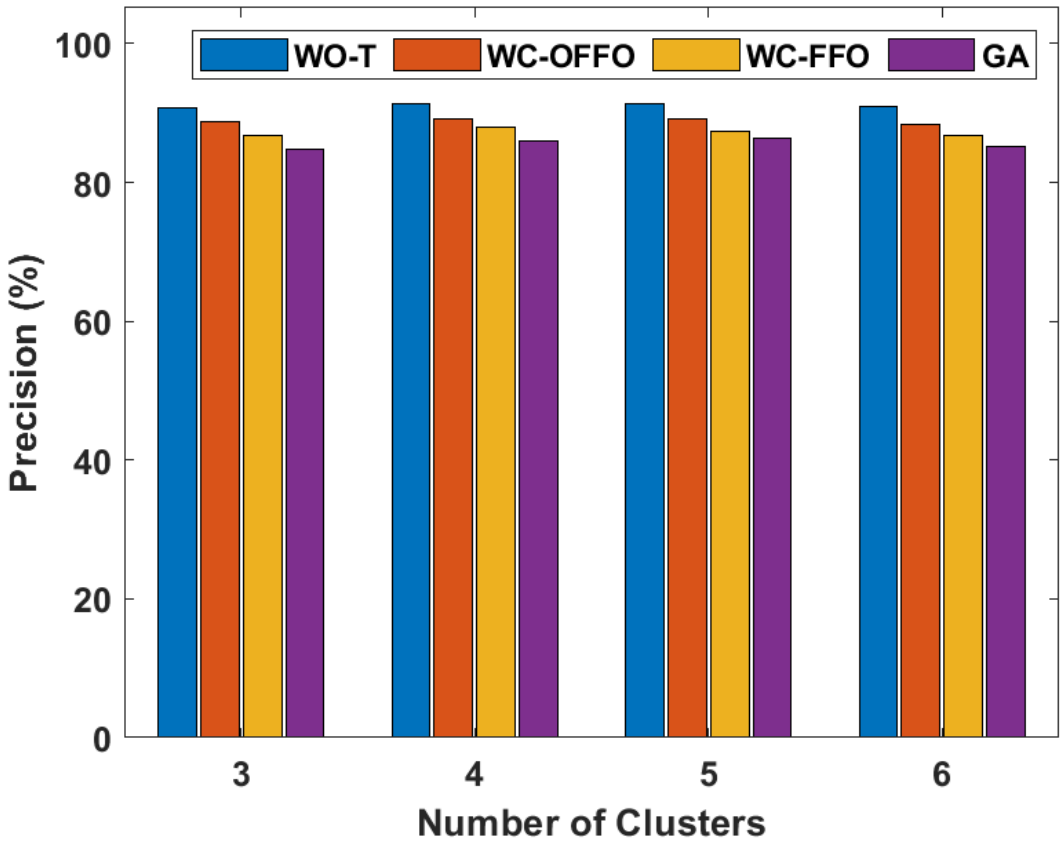

Fig. 3. Comparisons of existing with proposed method in terms of Precision

Table 2 and Fig. 4 provide a detailed comparison of the presented WO-T model interms of recall. Under the existence of 3 clusters, the GA is ineffectual to exhibit good results by attaining a least recall value of 73.95. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate Recall value of 75.24 whereas even higher recall value of 76.30 is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum recall value of 78.36. Under the existence of 4 clusters, the GA is ineffectual to exhibit good results by attaining a least recall value of 74.68. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate recall value of 75.82 whereas even higher recall value of 77.44 is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum recall value of 79.20. Under the existence of 5 clusters, the GA is ineffectual to exhibit good results by attaining a least recall value of 75.66. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate recall value of 76.80 whereas even higher recall value of 78.18 is offered by the WC-

OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum recall value of 80.13. Under the existence of 6 clusters, the GA is ineffectual to exhibit good results by attaining a least recall value of 74.79. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate recall value of 76.51 whereas even higher recall value of 77.73 is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum recall value of 79.32.

Table 2 Comparisons of existing with proposed method in terms of Recall

Number of Clusters	WO-T	WC-OFFO	WC-FFO	GA
3	78.36	76.30	75.24	73.95
4	79.20	77.44	75.82	74.68
5	80.13	78.18	76.80	75.66
6	79.32	77.73	76.51	74.79

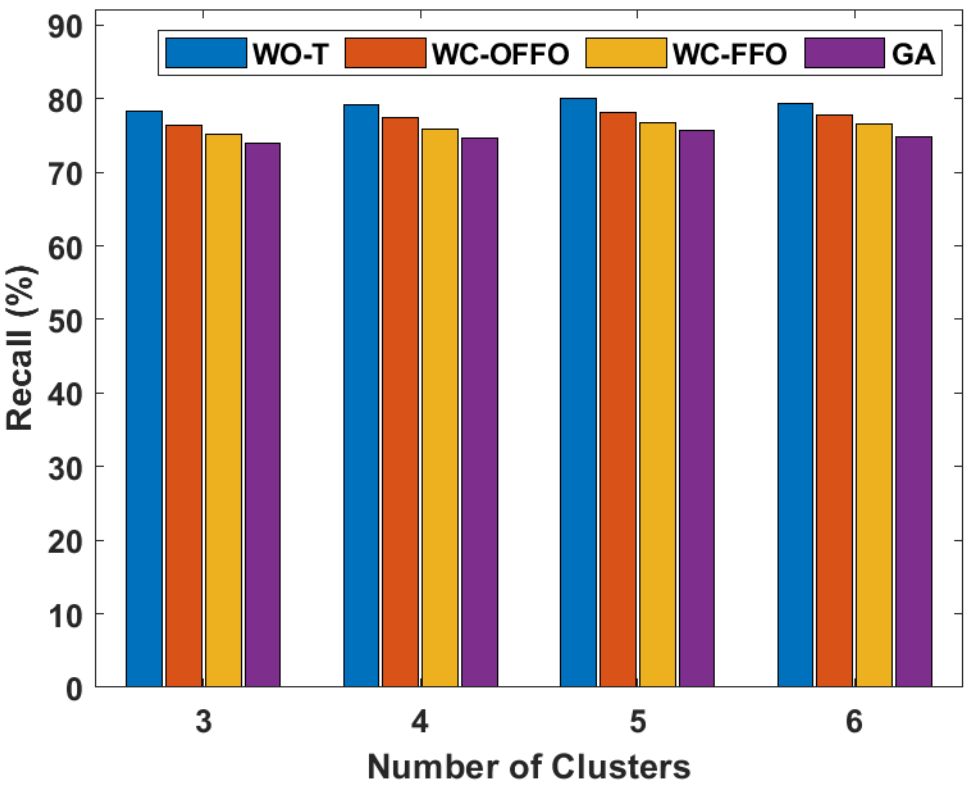

Fig. 4. Comparisons of existing with proposed method in terms of Recall

Table 3 and Fig. 5 provide a detailed comparison of the presented WO-T model interms of F-measure. Under the existence of 3 clusters, the GA is ineffectual to exhibit good results by attaining a least F-measure value of 79.00. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate F-measure value of 80.86 whereas even higher F-measure value of

82.00 is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum F-measure value of 84.34. Under the existence of 4 clusters, the GA is ineffectual to exhibit good results by attaining a least F-measure value of 80.00. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate F-measure value of 81.44 whereas even higher F-measure value of 82.85 is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum F-measure value of 83.50. Under the existence of 5 clusters, the GA is ineffectual to exhibit good results by attaining a least F-measure value of 80.60. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate F-measure value of 81.75 whereas even higher F-measure value of 83.00 is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum F-measure value of 86.60. Under the existence of 6 clusters, the GA is ineffectual to exhibit good results by attaining a least F-measure value of 79.63. On continuing with, the WC-FFO model offers slightly effective results by offering a moderate F-measure value of 81.35 whereas even higher F-measure value of 82.80 is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the maximum F-measure value of 84.93.

Table 3 Comparisons of existing with proposed method in terms of F-measure

Number of Clusters	WO-T	WC-OFFO	WC-FFO	GA
3	84.34	82.00	80.86	79.00
4	83.50	82.85	81.44	80.00
5	86.60	83.00	81.75	80.60
6	84.93	82.80	81.35	79.63

TEST Engineering & Management
January - February 2020
ISSN: 0193 - 4120 Page No. 5199 - 5212

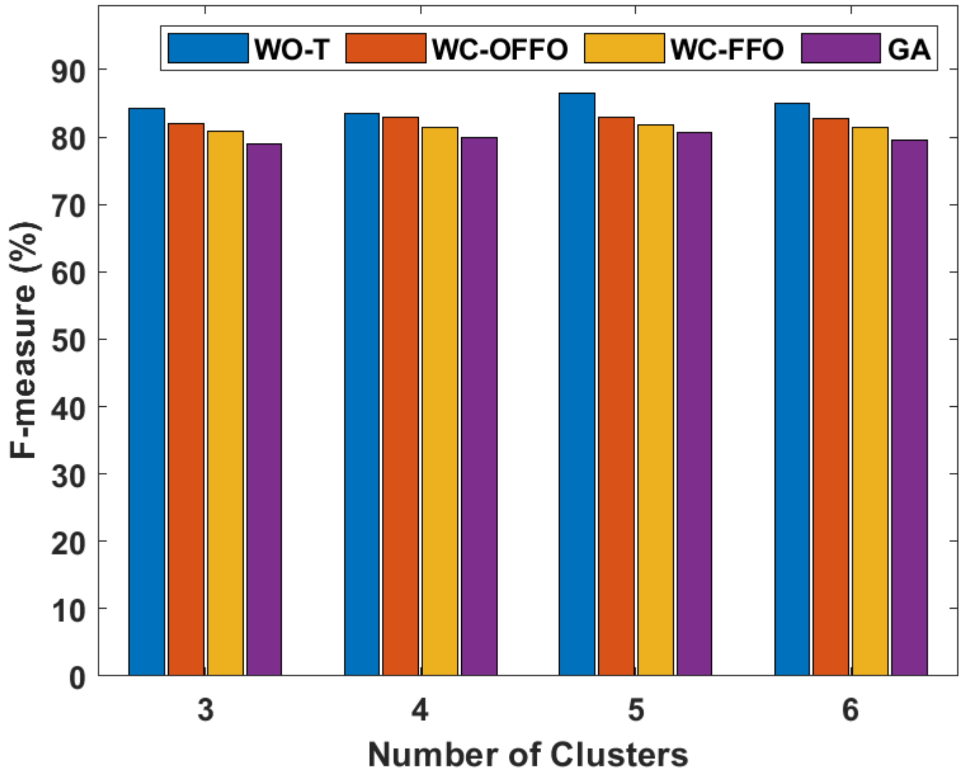

Fig. 5. Comparisons of existing with proposed method in terms of F-measure

Table 4 Comparisons of existing with proposed method in terms of Time complexity (second)

Number of Clusters	WO-T	WC-OFFO	WC-FFO	GA
3	183404	193400	210000	222200
4	203943	216000	235200	242200
5	219304	226500	249600	250000
6	230656	254400	271300	280800

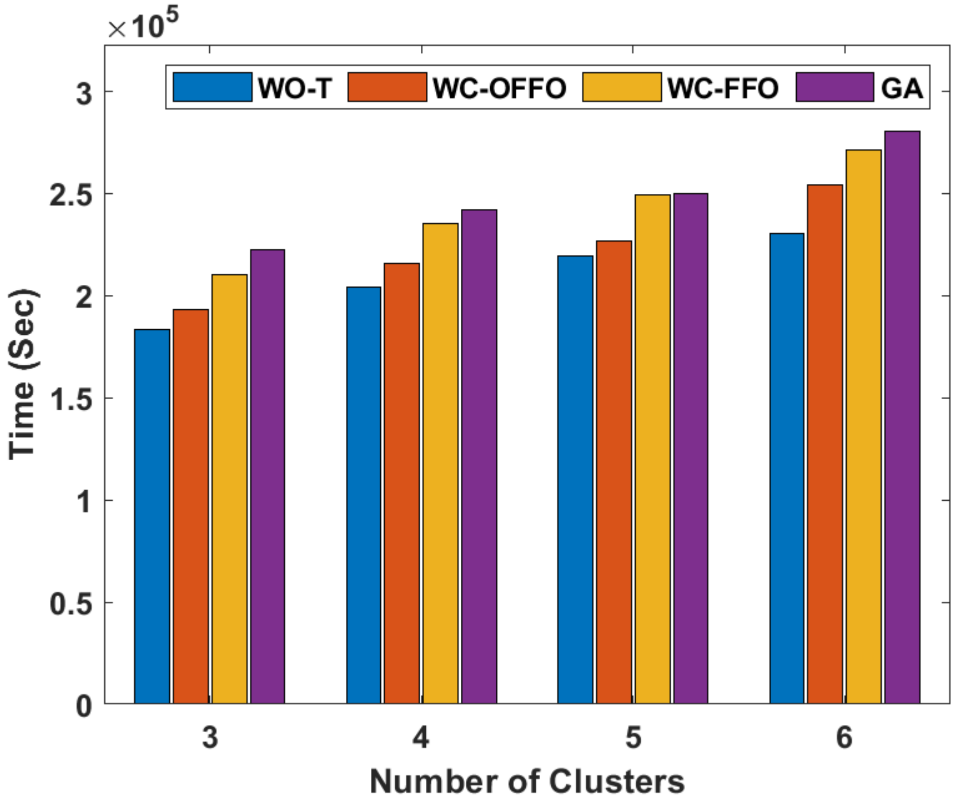

Fig. 6. Comparisons of existing with proposed method in terms of Time complexity (second)

Table 4 and Fig. 6 provide a detailed comparison of the presented WO-T model interms of Time complexity. Under the existence of 3 clusters, the GA is ineffectual to exhibit good results by attaining a highest Time complexity value of 222200s. On continuing with, the WC-FFO model offers slightly lower results by offering a moderate Time complexity value of 210000s whereas even lower Time complexity value of 193400s is offered by the WC-OFFO algorithm. However, the proficient results are offered by the WO-T algorithm with the minimum Time complexity value of 183404s. Under the same way, the three clusters are presented interms of time complexity.

4. Conclusion

This paper has devised a clustering with similarity measure based web page personalization model. In this case, personalization of web pages is done through the formulation of query and profiling by the WordNet ontology. To begin with, the needed data is gathered from various web sources and are grouped by the use of WC technique. The WC groups the web pages with respect to the fields which are learned by the user learning process. Using the set of four similarity metrics, data resemblance will be computed among the created word net and trained dataset. Among them, the highest resemblance based data is offered by the Improved WOA, where the WOA algorithm is extended by the concept of tumbling effect. A series of simulations were carried out to highlight the betterment of the presented model under various aspects.

References

[1] V. Viswanathan, K. Ilango, Ranking semantic relationships between two entities using personalization in context specification. Inf. Sci. 207, 35–49 (2012)

[2] L. Wanner, M. Rospocher, S. Vrochidis, L. Johansson, N. Bouayad-Agha, G. Casamayor, L. Serafini, Ontology-centered environmental information delivery for personalized decision

support. Expert. Syst. Appl. 42(12), 5032–5046 (2015)

[3] A. Hawalah, M. Fasli, Utilizing contextual ontological user profiles for personalized recommendations. Expert Syst. Appl. 41(10), 4777–4797 (2014)

[4] C. Liang, User profile for personalized web search, in 2011 Eighth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD) (2011)

[5] T.T. Dao, T.N. Hoang, X.H. Ta, M.C. Ho Ba Tho, Knowledge-based personalized search engine for the web-based human musculoskeletal system resources (HMSR) in biomechanics. J. Biomed. Inform. 46(1), 160–173 (2013)

[6] D. Yoo, Hybrid query processing for personalized information retrieval on the semantic web. Knowl.-Based Syst. 27, 211–218 (2012)

[7] M. Sah, V. Wade, Personalized concept-based search on the linked open data. SSRN Electron. J. (2016)

[8] Y. Du, Y. Hai, Semantic ranking of web pages based on formal concept analysis. J. Syst. Softw. 86(1), 187–197 (2013)

[9] Y. Guan, D. Zhao, A. Zeng, M.-S. Shang, Preference of online users and personalized recommendations. Phys. A 392(16), 3417–3423 (2013)

[10] I.F.Moawad, H. Talha, E. Hosny,M. Hashim, Agent-based web search personalization approach using dynamic user profile. Egypt. Inform. J. 13(3), 191–198 (2012)

[11] J.-H. Park, The effects of personalization on user continuance in social networking sites. Inf. Process. Manag. 50(3), 462–475 (2014)

[12] S.B.A. Ben Lamine, H. Baazaoui Zghal, M. Mrissa, C. Ghedira Guegan, An ontologybased approach for personalized RESTful Web service discovery. Procedia Comput. Sci. 112, 2127–2136 (2017)

[13] P. Srinivasa Rao, D. Vasumathi, Utilization of co-occurrence pattern mining with optimal fuzzy classifier for web page personalization. J. Intell. Syst. 27(2), 249–262 (2018)

[14] S. Chawla, A novel approach of cluster based optimal ranking of clicked URLs using genetic algorithm for effective personalized web search. Appl. Soft Comput. 46, 90–103 (2016)

[15] K.R.R. Babu, P. Samuel, Concept networks for personalized web search using genetic algorithm. Procedia Comput. Sci. 46, 566–573 (2015)

[16] Elhoseny, M., Bian, G. B., Lakshmanaprabu, S. K., Shankar, K., Singh, A. K., & Wu, W. (2019). Effective features to classify ovarian cancer data in internet of medical things. Computer Networks, 159, 147-156.

[17] Lakshmanaprabu, S. K., Mohanty, S. N., Krishnamoorthy, S., Uthayakumar, J., & Shankar, K. (2019). Online clinical decision support system using optimal deep neural networks. Applied Soft Computing, 81, 105487.

[18] Elhoseny, M., Shankar, K., & Uthayakumar, J. Intelligent Diagnostic Prediction and Classification System for Chronic Kidney Disease, Nature Scientific Reports, July 2019. Press. DOI: https://doi. org/10.1038/s41598-019-46074-2.

[19] Famila, S., Jawahar, A., Sariga, A., & Shankar, K. (2019). Improved artificial bee colony optimization based clustering algorithm for SMART sensor environments. Peer-to-Peer Networking and Applications, 1-9.

[20] Sankhwar, S., Gupta, D., Ramya, K. C., Rani, S. S., Shankar, K., & Lakshmanaprabu, S. K. (2016). Improved grey wolf optimization-based feature subset selection with fuzzy neural classifier for financial crisis prediction. Soft Computing, 1-10.

[21] Lakshmanaprabu, S. K., Shankar, K., Rani, S. S., Abdulhay, E., Arunkumar, N., Ramirez, G., & Uthayakumar, J. (2019). An effect of big data technology with ant colony optimization based routing in vehicular ad hoc networks: Towards smart cities. Journal of cleaner production, 217, 584-593.

[22] Maheswari, P. U., Manickam, P., Kumar, K. S., Maseleno, A., & Shankar, K. Bat optimization algorithm with fuzzy based PIT sharing (BF-PIT) algorithm for Named Data Networking (NDN). Journal of Intelligent & Fuzzy Systems, (Preprint), 1-8.

January - February 2020
ISSN: 0193 - 4120 Page No. 5199 - 5212

[23] Iswanto, I., Lydia, E. L., Shankar, K., Nguyen, P. T., Hashim, W., & Maseleno, A. (2019). Identifying diseases and diagnosis using machine learning. International Journal of Engineering and Advanced Technology, 8(6 Special Issue 2), 978-981.

[24] Shankar, K., Lakshmanaprabu, S. K., Khanna, A., Tanwar, S., Rodrigues, J. J., & Roy, N. R. (2019). Alzheimer detection using Group Grey Wolf Optimization based features with convolutional classifier. Computers & Electrical Engineering, 77, 230-243.

[25] Elhoseny, M., & Shankar, K. (2019). Reliable data transmission model for mobile ad hoc network using signcryption technique. IEEE Transactions on Reliability.

[26] Balakumar, N., & Vaishnavi, A. (2019). WordNet Ontology-Based Web Page Personalization Using Weighted Clustering and OFFO Algorithm. In Smart Network Inspired Paradigm and Approaches in IoT Applications (pp. 151-167). Springer, Singapore.