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# Prediction of User Future Request Utilizing the Combination of Both ANN and FCM in Web Page Recommendation

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**Abstract:** This paper explains about the web page recommendation system. This procedure encompasses consumers' upcoming demand and web page recommendations. In the proposed web page recommendation system, potential and non-potential data can be categorized by use of the Levenberg–Marquardt firefly neural network algorithm, and forecast can be made by using the K-means clustering algorithm. Consequently, the projected representation demonstrates the infrequent contact format with the help of the representation that integrates the comparable consumer access model data that belong to the further consumer. Thereafter, the impending user data are specified to the clustering progression. The third phase of the projected process is collecting potential data with the aid of the improved fuzzy C-means clustering algorithm. The last step of our projected process is envisaging the upcoming demand for the subsequent consumer. The presentation of the projected procedure will be compared to the obtainable procedure.

**Keywords:** Web page recommendation, K-means clustering, Levenberg–Marquardt, firefly, neural network, classification, prediction.

## 1 Introduction

In the data mining procedure, web mining is a process that is used to remove and determine knowledge from data obtainable on the web in the form of web documents, images, audios, videos, etc. The first phase of the data mining process is recognizing possessions, selecting suitable information, simplification, and examining information [19]. Web mining is the function of the data mining procedure that is used to determine models from the World Wide Web. Also, it comprises three kinds of information, such as Internet data, log of Internet access servers, and web structure data [3]. According to the massive expansion of Internet and information technology, electronic commerce (e-commerce) is suitable, inexpensive, and with no restriction in space and time, which is the mainstream of the populace utilization model [14]. Similarly, e-commerce consumers are utilizing an enormous quantity of data and facing complicated options, frequently mislaid in the enormous quantity of information [1]. To ensure service eminence and consumer contentment, it necessitates e-commerce platform in the progression of the consumer to look through information, objective for suggestion, and directing the effectual desire of their possess attention and requirements [10].

Owing to the enormous quantity of hosted documents on the web, online navigation activities develop progressively and, consequently, removing information competently and wisely is a demanding mission [12]. Depending on their entity inclination, interests, and requirements, web personalization systems have materialized to overcome this difficulty, which are intended to supply personalized knowledge to consumers [5]. From the clarification, we establish that an obtainable web page recommendation process contains underlying restrictions. One of the significant restrictions is a normal conventional collaborative filtering process.

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Additional restrictions are cold-start difficulty, data sparseness difficulty, and recommender reliability difficulty. Therefore, the accuracy and exposure of personalized recommended consequences are not suitable to gratify consumers [22]. Additionally, clarification on web page suggestions are regarded as personalization and contextualization, which are measured as essential characteristics to gather the inclination of different consumers [16]. Web recommendation also includes some other methods that are exactly derived from learning web logs and subsequently suggests consumers through a record of pages that are applicable to the consumer contrast their response and to optimize the search outcome by rescheduling or re-ranking and this will diminish to investigate time of preferred web pages [2]. Web page recommendation is a significant process in intelligent web systems. Recommender systems pertain to a variety of procedures and forecast algorithms for envisaging user significance from information, substance, and services from the remarkable quantity of existing data on the Internet. Some of the fundamental algorithms are page rank, Markov models, hyperlink-induced topic search (HITS), etc. [4].

Page rank algorithm is a linkage study algorithm that includes several restrictions. In addition, it supports existing pages because an innovative page that is still a superior one will not contain numerous associations except if it is a component of an obtainable location. An additional restriction is its page position calculation, which is an enormously demanding mission, while the web is not stagnant [21]. Markov representation facilitates envisaging only the subsequent phase of a customer. This is functional in personalizing a web site through supplying active associations to the customer, but it is obvious in envisaging more than one phase in advance [6]. The foremost difficulty of HITS is that the region diagram must be constructed on the fly, i.e. in development, as the influence and hub position are query reliant.

## 2 Related Works

Jalali et al. [8] projected an innovative method to categorize consumer navigation models for online forecast of consumers' upcoming target during mining web server logs. Also, they established an exploited graph for division algorithm to form a consumer navigation model. To facilitate a query consumer navigation model, they created an undirected graph derived from the connectivity among each couple of web pages. Subsequently, they projected an innovative method for conveying weights to the limits of the undirected graph. To categorize existing consumer behavior, they implemented the highest general subsequent algorithm to envisage the consumer's upcoming movement. They utilized various assessment processes to estimate the eminence of group establishment and the eminence of suggestion. The investigational consequences revealed that our method enhanced the eminence of group for the consumer navigation model and the eminence of suggestion for mutual CTI and MSNBC datasets.

Data congestion on the Internet occurs because of the unsteady expansion of information, leading to obscure progression of information exploration. Web suggestion systems support the consumer in obtaining precise information and assist in making information exploration easier. Web suggestion is the procedure of web personalization that suggests web pages to the consumer based on previous browsing records. It is completed via either a comfortable related method or a mutual filtering method. Suguna and Sharmila [17] employed web usage mining (WUM) as the foremost basis for web suggestions in organization among the collaborative filtering method, association rule mining, and Markov representation to suggest web pages to the consumer. Hereafter, the FP-tree algorithm, through additional development in utilizing the least support value, would be useful for discovering the associative model for extra exactness Lian et al. [9].

Patel and Singh [13] offered a complete indication of the procedure for naive Bayesian classification among supervised learning procedures. The foremost intention was categorization of consumer practice in extra precise among session base divide data subsequent to data cleaning perception for the use of additional active web sites and web pages with potential for business development, advertising, and government society situate defense. At this point, they categorized URLs derived from predefined principles. They projected categorization outcomes derived from the time and accuracy of data categorization. In prospect as the reputation of web maintains to augment, there was an upward required to widen utensils and procedure that would aid to develop its general convenience. To develop web sites or build active web pages, they utilized extra large data sets to discover extra-precise categorization.

Recommender systems are supportive tools that supply adaptive web surroundings for web users. In recent times, a number of web page recommender systems have been enhanced to remove consumer activities from the user's navigational course and envisage the subsequent demand as the consumer calls web pages. WUM is a type of data mining process that can be employed to determine this activity of consumer and his/her contact model from web log data. Jafari et al. [7] offered a comprehensive introduction to WUM and concentrated on the process that could be utilized for model removal from web log files. After determining the model, the outcome would be utilized for the model study segment. Investigation of the web consumer navigational model could assist in recognizing consumer activities for creating web recommender systems. Thus, the aims of these web functions would be enhanced Suneetha et al. [18].

Lately, the use of web recommendation procedures is increasing worldwide with the intent of offering modified necessary data to customers. Dissimilar recommendation development and explanation enforce several study challenges to investigators. Web suggestion procedures are categorized into two foremost varieties, such as content-related web suggestion systems and collaborative web suggestion systems. Waykule and Gupta [20] analyzed procedures like association rule mining, weighted association rule mining, and sequential pattern mining and dynamic programming procedures. Subsequent to examining the process, they recognized that one demanding difficulty of such web suggestion systems was that pages that were lately or infrequently included remained with the customer. Such pages were not usually integrated into the group of suggestions. Therefore, they needed encompassing competent processes that could include these pages to the suggestion page set. For the upcoming work, they intend to provide an enhanced process for union regulation mining so as to defeat the difficulty with further restrictions related through an obtainable process.

The quick development and expanding reputation of e-commerce has enforced the obtainable suggestion system to hold a great quantity of clients and to supply them through increased eminence of suggestion. Lopes and Roy [11] concentrated on the problem through a suggestion system and projected a method that uses web convention mining to diminish it. The work carried out in their study supplied an effectual suggestion to record not only consumers but also unregistered consumers. The greatness of the projected system was that it aids in maintaining obtainable clients and attracting innovative clients. The procedures diminished forged optimistic faults that could guide to discontented clients. It could seriously help e-commerce associations in forecasting demands, sales, and commercial objectives, attracting impending clients and also preserving them and receiving a viable boundary in the market. In cooperation of procedure recommended effectual and competent invention offer suggestion for e-commerce location. Results have shown that the procedure offers both enhanced suggestion eminence and exactness.

Recommender systems have been established to be an expensive means for online consumers to handle the information load, and have turned out to be influential and well-regarded tools in e-commerce. Recommender systems are software tools offering proposition for the substance of significance to consumers; therefore, they normally pertain to procedures and methods from data mining. The foremost part of this article is in the region of implementing categorization procedures to augment the presentation of recommender systems. Saleh et al. [15] established an intelligent adaptive vertical recommendation (IAVR) system. IAVR suggests text documents associated with an exact field. Essentially, the document deliberates on the initial segment of IAVR, which includes two components: the first is a distiller and the second is a multi-class classifier. The projected distiller was engaged as a binary classifier that chooses papers associated with the area of significance. It was constructed upon an innovative neuro-fuzzy system in addition to a customized K-nearest neighbor classifier. Conversely, the projected multi-class classifier combines an innovative occurrence of a naïve Bayes classifier that relies on a projected learning procedure known as "accumulative learning," among association regulations. Investigational results have confirmed the efficiency of the projected classifiers, which consequently supported the exactness of the general system's suggestions.

## 3 Problem Definition

This section discusses the problem definition of this research work.

- The existing suggestion system demonstrates definite restrictions such as intellect, adaptability, flexibility, and inadequate exactness.
- Owing to a lack of exactness, absolute and elevated run time obtainable suggestion systems demonstrate the problem of less exposure.
- Pages are lately included or infrequently appointed by a customer who is not illustrated through the obtainable procedure, which is also a significant difficulty.
- Manipulating a suggestion system that regards chronological information is still a significant difficulty.
- The foremost difficulty of many online web sites is the arrangement of several options to the consumer at a time; this frequently results in a demanding and time-consuming mission of discovering the accurate invention or information on the site.
- Estimating the presentation and the efficiency of the great dataset is complicated in the majority of obtainable processes, and requires extra time.
- The arithmetical group only offers hard clustering, which is not equivalent to the actual world function.
- In obtainable web page suggestion systems, the consumer measures only the chronological feature of a web client conference by means of chronological mining algorithms that offer only the model that subsists in the progression. In our investigation, we have projected a system that engenders the suggestion to the consumer, allowing for the chronological information that subsists in their convention model of web pages.

These are the foremost disadvantages of diverse obtainable works, which prompted us to perform the study on web page suggestion. The projected representation utilizes a mixture of clustering and categorization procedures to engender suggestions allowing for chronological information. The clustering procedure assists the system in setting a comparable consumer summary, and the classifier discovers the representation from a comparable customer to engender suggestion.

## 4 Proposed Methodology

In the intellect web system, web page recommendation is a significant process. The fundamental and demanding processes are functional knowledge discovery from web usage data and reasonable knowledge depiction for effectual web page suggestion. The foremost intention of the projected system is to envisage consumer upcoming request in a shorter time by means of clustering and categorization procedures. The classification procedure is used to classify the consumer into potential and non-potential consumer, and the clustering procedure is used to cluster the consumer through comparable significance mutually. This projected document is used to envisage consumer upcoming request by means of clustering and classification procedures. The projected process encompasses four steps: initially choose the input web log data and afterward preprocess the input web log file. The second step of the projected process is classification. Firefly-based artificial neural network (FANN) is used for the classification of the consumer into potential or non-potential consumer. In this article, a feed-forward neural system will be practically equipped by the hybrid algorithm, described as LM + firefly, which is the organization of Levenberg–Marquardt calculation in the firefly algorithm. The feed-forward neural system is the preliminary and actually straightforward kind of forged equipped neural system. Subsequently, the potential consumer data are specified to the clustering progression. The third step of the projected process is clustering the potential data with the aid of improved fuzzy C-means (IFCM) clustering algorithm. The ultimate procedure of our projected process is envisaging the upcoming demand for the equivalent consumer. The presentation of the projected procedure will be compared to the obtainable procedure. Our projected process will be executed in JAVA with web DB database and further web log databases.

## 4.1 Preprocessing

In this preprocessing segment, the input web log file is estimated and the essential characteristic form of the web access log is removed. The enduring characteristic of the web access log file is being detached from the innovative input file. Initially, to choose the input web log data and afterward preprocess the input web log file, subsequently the preprocessed data are specified into the categorization segment. These will be carried out through the help of Levenberg–Marquardt categorization.

## 4.2 Classification by LMFF-ANN

The second segment of the projected process is classification. FANN is utilized for the classification of the consumer into potential or non-potential consumer. In this article, a feed-forward neural system will be practically equipped by the hybrid algorithm, described as LM + firefly, which is the organization of Levenberg–Marquardt calculation in the firefly algorithm. The feed-forward neural system is the preliminary and actually straightforward kind of forged equipped neural system. Subsequently, the potential consumer data are specified to the clustering progression.

### 4.2.1 Levenberg–Marquardt-Firefly-ANN Classification

In this article, a feed-forward neural system will be practically equipped by the hybrid algorithm, described as LM + firefly, which is the organization of Levenberg–Marquardt calculation in the firefly algorithm. Accordingly, the estimated Hessian matrix $J^TJ$ is invertible, and the Levenberg–Marquardt algorithm establishes an additional estimation to the Hessian matrix:

$$H = J^T J + \mu I, \tag{1}$$

where $\mu$ is a constantly optimistic combination coefficient. $I$ is the identity matrix. From Eq. (1), it can be observed that the fundamentals of the most important diagonal of the estimated Hessian matrix will be greater than zero. Thus, through this estimation [Eq. (2)], it can be certain that matrix $H$ is constantly invertible. Through the mixture of Eqs. (1) and (2), the updated regulation of the Levenberg–Marquardt algorithm can be offered as

$$W_{K+1} = W_k - ({J_k}^T J_k + \mu I)^{-1} J_k e_k. \tag{2}$$

Due to the mixture of the steepest descent algorithm and the Gauss–Newton algorithm, the Levenberg–Marquardt algorithm controls the two algorithms for the period of the preparation progression. Suppose the combination coefficient $\mu$ is very tiny (nearly zero), then

$$\alpha = \frac{1}{\mu}. \tag{3}$$

Suppose the combination coefficient $\mu$ is very large in Eq. (3), then it can be deduced as the knowledge coefficient in the steepest descent process. These acquired values will provide the input of the firefly algorithm.

– **FANN**

FANN is used for the classification of the consumer into potential or non-potential consumer. In this article, a feed-forward neural system will be practically equipped by the hybrid algorithm, described as LM + firefly, which is the organization of the Levenberg–Marquardt calculation in the firefly algorithm. The firefly algorithm is a meta-heuristic algorithm that is inspired by the irregular behavior of fireflies. The primary intention for a firefly's flash is to serve as a signal system to attract other fireflies. Yang has established this firefly procedure through supposition. The neural network contains several categories. One of the fundamental categories is the feed-forward backpropagation neural network (FFBNN) classifier, which is successfully subjugated for the principle of categorization. The neural network is usually a three-layer typical classifier capable through *n* proposition nodes, *n* input nodes, *l* hidden nodes, and *k* output nodes. It is essentially hypothesized that if mutually undetectable stages are engaged, then the further undetectable level is associated with every pair in a solitary significant component and the subsequent level is certainly the valid undetectable layer instantly, subsequent to categorizing the input data from the preliminary undetectable level. For the principle of our inventive mission, the interrelated input stage appears as the involvement strategy and the hidden substance as the further construction component. The eventual phase entail a categorization phase in which the hybrid classifier firefly algorithm-related neural network is gracefully engaged to establish the categorization.

– **Neural Network Function Steps**

The restructured values of the firefly algorithm are provided as input, fix loads for the entire neurons excluding those in the input layer.

The neural network is premeditated by the removed attribute $\{A_1, A_2, A_3, A_4, A_5\}$ as the input component, $HU_a$ as the hidden component, and age $f$ as the output component.

The assessment of the projected bias task for the input layer is distinguished through Eq. (4), which is specified below:

$$X=\beta+\sum_{n'=0}^{H_{NH}-1} w_{(n')}A_1(n')+w_{(n')}A_2(n')+w_{(n')}A_3(n')+\ldots+w_{(n')}A_5(n'). \tag{4}$$

The activation function for the output layer is evaluated by Eq. (12), as shown below:

$$\text{Active }(X)=\frac{1}{1+e^{-X}}. \tag{5}$$

The learning error is represented as follows:

$$LE=\frac{1}{H_{NH}}\sum_{n'=0}^{N_{NH}-1} Y_{n'}-Z_{n'}, \tag{6}$$

where $LE$ is the learning rate of FFBNN, $Y_{n'}$ are desired outputs, and $Z_{n'}$ are actual outputs.

– **Learning Algorithm – Backpropagation Algorithm**

The backpropagation algorithm is efficiently exploited as the learning algorithm in the feed-forward neural system. The backpropagation algorithm essentially signifies a managed learning policy and supplementarily distinguishes the collapse of $\delta$ regulation. For the principle of execution compilation, a dataset of the fundamental efficiency for diverse inputs is necessary. Typically, the backpropagation algorithm is the ultimate choice for the feed-forward networks and the learning algorithm necessitates that the service principle engaged by means of the neurons must vary.

– **Backpropagation Algorithm Steps for FFBNN**

The weights of the neurons of the hidden layer and the output layer are premeditated and erratically decide the heaviness. However, the input layer acquires the steady weight.

The predictable bias task and the establishment task are estimated through Eqs. (7) and (8) for the FFBNN.

The backpropagation fault is estimated for each one node and subsequently the weights are restructured as per the subsequent Eq. (14):

$$w_{(n')}=w_{(n')}+\Delta w_{(n')}. \tag{7}$$

The weight $\Delta w_{(n')}$ is adapted as per Eq. (8) shown below:

$$\Delta w_{(n')} = \delta \cdot X_{(n')} \cdot E^{(BP)}, \tag{8}$$

where $\delta$ is the learning rate, which is usually in the range of 0.2–0.5 and $E^{(BP)}$ is backpropagation error.

The process is constant by the aid of steps represented in Eqs. (5) and (6), until the backpropagation fault is condensed to the least value, i.e. $E^{(BP)} < 0.1$.

On accomplishing the least value, the FFBNN becomes known to be suitably appropriate for the transmission segment.

Accordingly, the FFBNN classifier is successfully practiced and the organization standards are experienced through utilizing the characteristic. The categorization of fault is implemented, which categorizes the complete fault engendered from the classifier. The eventual segment is the classification phase in which the hybrid classifier Levenberg–Marquardt-firefly algorithm-related neural network is successfully engaged to establish the potential and non-potential data. Afterward, the potential data are specified into the clustering segment and it will be gathered through the aid of fuzzy C-means (FCM) clustering. At this point, the hybrid neural network-modernized values are provided as input to the firefly algorithm.

– **Solution Representation**

In the finest-quality selection of the decision tree invention, the fundamental confront is disturbed through the method in which the explanation include to be signified. The explanation binds through the firefly algorithm completion. We describe one firefly (explanation) as a probable clarification in the populace. The preliminary populace of fireflies is engendering illogically for the firefly algorithm. The preliminary populace of size $Y$ is distinct, as follows:

$$Y = A_d \quad (d = 1,\ 2,\ \ldots,\ n), \tag{9}$$

where $n$ is the quantity of fireflies. The initialized constant location values are produced through the subsequent Eq. (11):

$$u_k^* = u_{\min} + (u_{\max} - u_{\min}) \times r, \tag{10}$$

where $x_{\min} = 0$, $x_{\max} = 1$, and $r$ represents a uniform arbitrary number between 0 and 1.

– **Fitness Evaluation**

Basically, the fitness task is distinct by the intention of the existing analysis. At this point, the optimization formula is acquired using Eq. (9), which is derived from the reduction of the intention task, as follows:

$$W(y) = \min \sum_{i=1}^{m} w(y_i) H_x(y_i), \tag{11}$$

where $H_x(y_i)$ is the entropy and $w(y_i)$ is the weight of the entropy of each attribute.

– **Firefly Updation**

The association of the firefly $p$, when concerned to an additional striking (brighter) firefly $q$, is estimated through Eq. (12) specified below:

$$u_p' = u_p + \gamma(r) \times (u_p - u_q) + \phi\left(\text{rand} - \frac{1}{2}\right). \tag{12}$$

In Eq. (11), the second expression is an explanation of magnetism, the third expression establishes randomization through '$\varphi$' (the randomization limitation), and "rand" is a random quantity formed and consistently distributed between 0 and 1.

$$\text{Attractiveness: } \gamma(r) = \gamma_0 e^{-\theta r^m}, \quad m \geq 1, \tag{13}$$

where $r$ represents the detachment among two fireflies, $\gamma_0$ signifies the preliminary magnetism of the firefly, and $\theta$ represents the incorporation coefficient.

$$\text{Distance: } r_{pq} = \left\| u_p - u_q \right\| = \sqrt{\sum\nolimits_{k=1}^{d} (u_{p,s} - u_{q,s})^2}, \tag{14}$$

where $u_{p,s}$ signifies the $s^{\text{th}}$ element of the spatial direct of the $p^{\text{th}}$ firefly and $d$ signifies the entire quantity of dimensions. As well, $q \in \{1, 2, \ldots, F_n\}$ distinguishes the randomly preferred catalog. Even though $q$ is estimated randomly, it must be dissimilar from $p$. At this point, $F_n$ communicates to the quantity of fireflies. The feed-forward neural system will be practically equipped by the hybrid algorithm, described as LM + firefly, which is the organization of the Levenberg–Marquardt calculation through the firefly algorithm. The feed-forward neural system is the preliminary and actually simple kind of forged equipped neural system. After that, the potential consumer data are specified to the clustering progression. The third step of the projected process is clustering the potential data through the aid of the IFCM clustering algorithm, which is clarified below.

## 4.3 IFCM Clustering

The third step of the projected process is clustering of potential data by the aid of the IFCM clustering algorithm. The ultimate procedure of our projected process is envisaging the upcoming demand for the equivalent consumer. FCM is a data clustering procedure wherein each data position belongs to a cluster level that is recognized through an association mark. It offers a process of how to cluster data positions that occupy a few multidimensional spaces into a precise quantity of dissimilar clusters. The foremost benefit of FCM clustering is that it permits regular memberships of data position to clusters considered as level in [0, 1]. This provides the flexibility to convey that data position can belong to more than one group. The projected process utilizes FCM for grouping the input data. The intention task of the projected FCM algorithm is successfully clarified as follows:

Now the cluster center calculation is done by using Eq. (15):

$$a_j = \frac{\sum_{i=1}^{n} M_{ij}^{m} d_i}{\sum_{i=1}^{N} M_{ij}}. \tag{15}$$

where $M_{ij}$ is the membership of $j^{\text{th}}$ data in the $i^{\text{th}}$ cluster $a_j$, $a$ is the cluster center, $d_i$ is the input data, $m$ is the any real number >1, and || * || is the similarity between any measured data and the center.

Membership updation is done by using Eq. (16):

$$M_{ij} = \frac{1}{\sum\nolimits_{k=1}^{a} \left( \dfrac{\| d_i - a_j \|}{\| d_i - a_k \|} \right)^{\frac{2}{m-1}}}. \tag{16}$$

If $\| M^{(K+1)} - M^{(K)} \| < \in$, then stop, where $\in$ is a termination criterion between 0 and 1.

According to the process of FCM, the input data are collected. Following the FCM progression, we acquire the quantity of cluster sets such as $C_1, C_2, C_3, \ldots, C_n$. This collected dataset is utilized for additional dispensation. Clustering is an ultimate progression of our projected process, which envisages the upcoming demand for the equivalent consumer. The presentation of the projected procedure will be compared to the obtainable procedure.

## 5 Results and Discussion

The original conviction-oriented future request-based web recommendation of FCM clustering and superior LMFF-ANN algorithm is executed in the operational platform of JAVA in CloudSim (Figure 1). The time, memory, clustering time, clustering accuracy, and recommendation accuracy values are also predictable, and their standard values are distinguished by those of the existing technique. Table 1 demonstrates the file dimension value of our projected analysis.

In Table 1, for various iterations, the corresponding clustering accuracy is estimated. Figure 2 shows the graphical representation of the accuracy of various iterations using our proposed method. In our proposed future request prediction in web recommendation research, we have measured a prediction based on these clustering accuracy measures. The results will be taken based on iteration. In iteration 10, a 71.12 clustering accuracy is obtained. In iterations 15, 20, and 25, evaluation measures such as 72.36, 73.45, and 76.64 are obtained. When we compared these results to the existing research, our proposed approach yielded better performance.

In Table 2, for various iterations, the corresponding clustering time is estimated. Figure 3 shows the graphical representation for the clustering time for various iterations using our proposed method. In our proposed future request prediction in web recommendation research, we have measured a prediction based on these clustering time measures. The results will be taken based on iteration. In iteration 10, a 9658 clustering accuracy is obtained. Iterations 15, 20, and 25 obtain evaluation measures such as 11,256, 12,369, and 14,569.

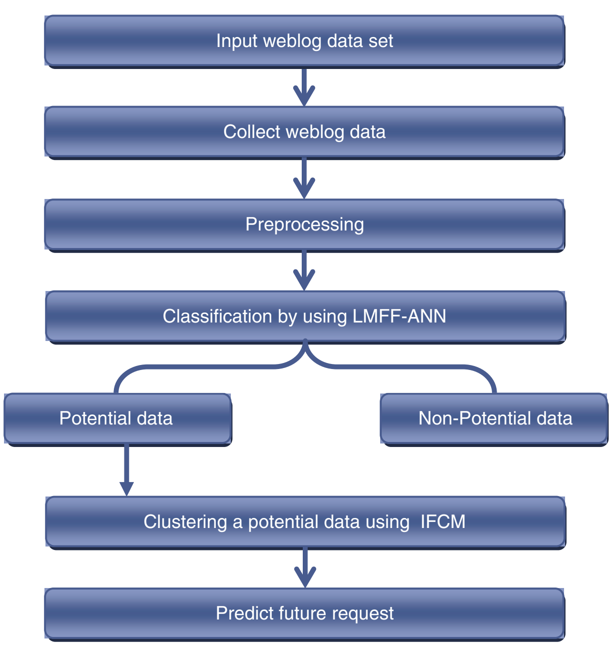


**Figure 1:** Proposed Future Request-Based Web Recommendation.

**Table 1:** Clustering Accuracy for Our Proposed Research.

| Iteration | Cluster accuracy |
|---|---|
| 10 | 71.12 |
| 15 | 72.36 |
| 20 | 73.45 |
| 25 | 76.64 |

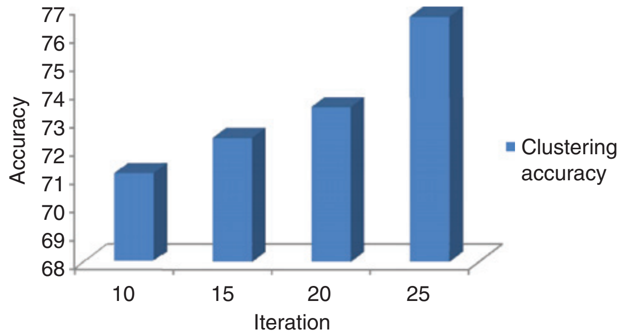


**Figure 2:** Graphical Representation of Clustering Accuracy for Our Proposed Research.

**Table 2:** Clustering Time Measures for Our Proposed Research.

| Iteration | Clustering time (ms) |
|---|---:|
| 10 | 9658 |
| 15 | 11,256 |
| 20 | 12,369 |
| 25 | 14,569 |

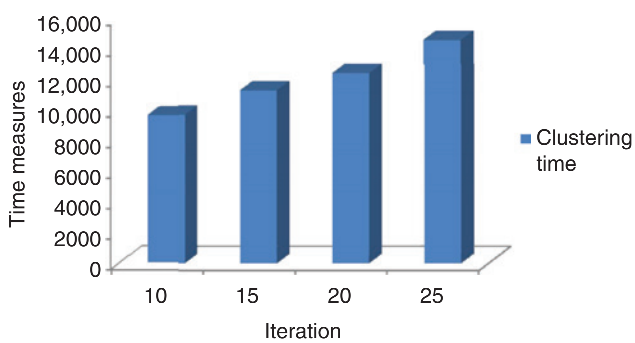


**Figure 3:** Graphical Representation of Clustering Time Measures for Our Proposed Research.

Here, we have explained the time measures for a given iteration when we compared these proposed time measures to the existing method. Our method would take a minimum amount of time to complete a process.

In Table 3, for various iterations, the corresponding recommendation accuracy is estimated. Figure 4 shows the graphical representation for the recommendation accuracy for various iterations using our proposed method. In our proposed future request prediction in web recommendation research, we have measured a prediction based on these clustering time measures. These results will be taken based on iteration. In iteration 10, a 78.12 clustering accuracy is obtained. In iterations 15, 20, and 25, evaluation measures such as 79.36, 80.11, and 82.36 are obtained.

**Table 3:** Recommendation Accuracy Measures for Our Proposed Research.

| Iteration | Recommendation accuracy |
|---|---:|
| 10 | 78.12 |
| 15 | 79.36 |
| 20 | 80.11 |
| 25 | 82.36 |

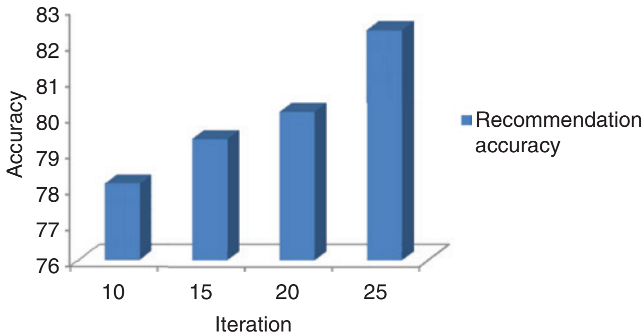


**Figure 4:** Graphical Representation of Recommendation Accuracy for Our Proposed Research.

**Table 4:** Overall Time Measures for Our Proposed Research.

| Iteration | Overall time (ms) |
|---|---:|
| 10 | 18,456 |
| 15 | 22,369 |
| 20 | 24,968 |
| 25 | 29,874 |

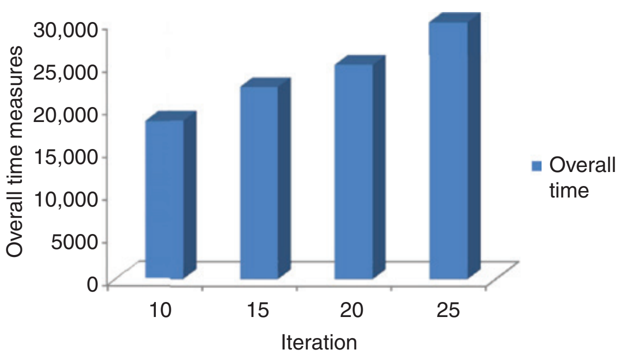


**Figure 5:** Graphical Representation for Overall Time Measures for Our Proposed Research.

In Table 4, for various iterations, the corresponding overall time measures are estimated. Figure 5 shows the graphical representation for the overall time measures for various iterations using our proposed method. In our proposed future request prediction in web recommendation research, we have measured a prediction based on these overall time measures. These results will be taken based on iteration. In iteration 10, an 18,456 clustering accuracy is obtained. In iterations 15, 20, and 25, evaluation measures such as 22,369, 24,968, and 29,874 are obtained.

## 5.1 Comparative Analysis

At this point, the obtainable tasks are compared to our projected function, to verify that the projected function is the improved one. This proposed IFCM is obtained to compare the outcome of our clustering process. Table 5 shows the proportional outcome. The graphical depiction of the proportional study is given in Figure 6.

As the outcome of our evaluation, we can declare that our projected function shortens the assessment obtain time. The existing K-means analysis obtain time for 10 comprehensive assessments is 18,987 ms, which is high when compared to the least assessment obtain time of our projected IFCM of 18,456 ms. In the

**Table 5:** Comparison for Proposed and Existing Time Measures.

| Iteration | Existing K-means work time measures (ms) | Proposed IFCM Work time measures (ms) |
|---|---|---|
| 10 | 18,987 | 18,456 |
| 15 | 23,568 | 22,369 |
| 20 | 25,124 | 24,968 |
| 25 | 29,986 | 29,874 |

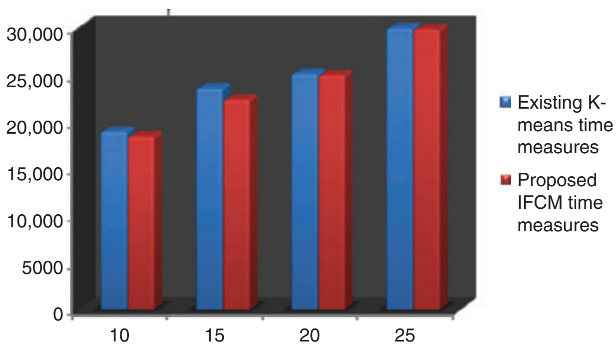


**Figure 6:** Graphical Representation for Proposed and Existing Time Measures.

subsequent 15 assessments, the obtain time in obtainable K-means is 23,568, which is high when compared to our projected technique that provides 22,369 ms. Moreover, in the subsequent 20 assessments, the obtain time in obtainable analysis is 25,124 ms, which is high when compared to our projected technique that takes 24,968 ms, the smallest amount in the series. Finally, by 25 assessments, the obtain time length is 29,986 ms, which is high when compared to our projected IFCM that takes 29,874. We can declare that our projected diminished the assessment obtain time when compared to the obtainable technique.

## 6 Conclusion

In this article, we have shown that the conviction-oriented cloud server contributor can be predictable by the IFCM. In our proposed future request prediction in web page recommendation system, we have initially selected an input file from the web log data and data to be preprocessed. Then, these preprocessed data are classified with the aid of the LMFF-ANN technique to classify potential and non-potential data. To take potential data for clustering, this phase is performed with the aid of the IFCM technique. The achievement is allocated for the service contributors depending on the clustering time, memory, recommendation time, and overall time measures to be explained. The service contributors are categorized by the conviction. Our IFCM logic will attain very high exactness.

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