Personalized Medical Information Filtering using Evidence Phrases

Mu. Annalakshmi, A. Padmapriya

Abstract*: *Finding the required information in the field of medicine from the World Wide Web has been a challenging task for the users since large number of medical research documents are added to it every day. Personalization of web search would help the professionals or beginners in medicinal field in retrieving the relevant information. The proposed method gathers the users' browsing patterns from the browser and builds evidence phrases based on factors like visit count, bookmarks or downloads. These evidence phrases determine the rank of the websites in the search results. The proposed method is evaluated with the relevance data collected from allied medical professionals. Evaluation shows that the proposed method ranks the user preferred pages in the top of the search results. It helps the users from the field of medicine to find their information needs more quickly without surfing all the search results of the query.

Keywords: User Personalization, User Profiling, Evidence Phrases, Information Filtering, Relevance

I. INTRODUCTION

Information filtering is an essential tool used by web searchers to find the desired information in the web which is rapidly expanding. The need for information filtering is more in the fields like marketing, sociology, economics and medicine. As far as the field of medicine is concerned, a large number of research documents are added to Internet every day. This makes information access for medical professionals even more difficult. Google [19] is the most popular and widely used general search engine and this can be used for medical search also. There are several specialized search engines for medical search but they are more suitable for experts in the field rather than the beginners or novice users. Searches by Google can be used by all kinds of users but they are of greater help to beginners, allied healthcare professionals and novice users.

In general different search engines use several factors to rank the web pages [12]. They have to be more intelligent to identify the users' real search intent by resolving the ambiguity in query terms. This is possible only if the information about the user is available to the search engines.

User profiling or Personalization which has emerged as a significant area of research interest in the recent years is a strategy that aids the search engines in this context. The user profiles can be built either explicitly or implicitly. Explicit profiling requires the users to explicitly specify their preferences or ratings which they are reluctant to do because of the increased effort and time. Also the users view more pages than they rate. But the user preferences can be recorded implicitly by examining the user search history or bookmarks which is far easier due to lesser or no effort from users. The research work [5] lists out some of the interest indicators including both implicit and explicit that helps in preparing user profiles. User profiles can be automatically obtained by many approaches which include using a proxy server to trace the browsing history or desktop bots to record the activities on the personal computer. But both these approaches require that the user has to install the proxy servers or bots.

WordNet [9] is a lexical database for English language which mainly stores the synonyms of a word (when used as noun, verb, adverb or adjective) along with its related words hypernyms, hyponyms, holonyms, meronyms and their corresponding meanings. It can be viewed as both dictionary and thesaurus, and is mainly used in text analysis and artificial intelligence applications. The UMLS, or Unified Medical Language System [8], is a set of files and software that brings together many health and biomedical vocabularies and standards to enable interoperability between computer systems. The UMLS can be used to enhance or develop applications, such as electronic health records, classification tools, dictionaries and language translators. One powerful purpose of the UMLS is linking health information, medical terms, drug names, and billing codes across different computer systems. The UMLS has many other purposes that include search engine retrieval, data mining, public health statistics reporting, and terminology research. Personalization of user profiles and use of UMLS and WordNet serve as the motivating factor for the proposed work.

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The rest of the paper is organized as follows. The related works which act as motivating factor for the proposed work are described in section 2. The proposed method is explained in section 3. The experimental study is summarized in section 4. Section 5 concludes the research work.

II. RELATED WORKS

Many specialized search engines[16]-[18] are available to aid medical researchers in finding the research documents related to their information need. But allied health care professionals like laboratory technicians, radiologists, pharmacists, nurses, students and patients who need some information related to disease or medicine, find these specialized search engines not useful since the information provided by them is of higher standards understandable by experts not ordinary or novice users. Authors of [7] proposed a new fuzzy recommender system comparing the user preferences and Electronic Medical Record (EMR) representation by considering their compatibility and the intrinsic quality of the EMR. The compatibility between EMR context and document is measured using generalized Jaccard coefficient. Clustering algorithms can be used to group related documents in text mining. An optimized k-means clustering algorithm [11] is used in clustering biomedical documents thereby filtering out the non-medical documents. This classification of clusters is done based on UMLS. The research work [14] introduces a Classification based Multistage Filtering for PubMed documents by getting training set of citations from the user and uses it to generate the PubMed documents relevant to the user by using text classification methods and cosine similarity measures.

Webpages that are mostly semi-structured or unstructured in nature can be structured using XML framework [22]. This is implemented using the HTML source code of the web pages. The HTML tags and free form text serve as the tags for the XML framework. The user profiles can be built from the click through data which records the user's query to search engine and the links visited by the user from the list. The author of [1] proposes a concept based method finding both the positive and negative preferences of the user by analyzing the clusters formed using the user's queries. It also uses agglomerative clustering algorithm to find the optimal clustering of queries. It just uses the click through data but not the snippets of the web page. The user profile information can be collected from the search engine by using the queries submitted, the results produced and the clicks made by the user on a particular web page. The proposed work in [2] creates a wrapper for the google search engine to collect information for user profiles from the queries and snippets submitted to google and classifies then using k- nearest neighbour's algorithm. It then re ranks the search results returned by google using conceptual similarity between the user profile information and the web pages. User profiles may be constructed reflecting the user's persistent (long term) or ephemeral (short term) preferences [3]. The collaborative filtering algorithm can also be modified taking into account the static and dynamic users in the neighbourhood. The quality of web search can be enhanced by building user profiles and then re ranking the search results based on the semantic identification of the user current context of query [4]. In [6], a user interest hierarchy to arrange the general to specific interests of the users is introduced. The root of the hierarchy includes the user's long time or general interests and the leaves represent more specific or short term interests. The hierarchy is formed using divisive hierarchical clustering algorithm. The hybrid method generating user profiles based on both content based and collaborative filtering in both static and dynamic forms is proposed in [15]. This profile is then used in information filtering with the help of a profile matcher. Static profiles are explicitly collected from users while the dynamic profiles are obtained by monitoring changes in user's behaviour and preferences. Information filtering can be done by taking into account the search query keywords and their corresponding synonyms [13] in different tags of the HTML source code of the web page. Weight measure is provided to their occurrence which determines the relevance of the web page to the user and also the query. A Collaborative search and sharing framework BESS [21] takes into account the relevance feedback from the users to know about their interests and builds user profiles based on the interests identified. It also uses the profiles created to acquire information in collaboration information seeking context. It also updates the profiles based on the changing interest of the users. The user queries can be reformulated based on the collaborative knowledge from Wikipedia and WordNet as proposed by [10]. Initially the users express their information needs as queries. Series of suggestion for the queries are given based on which the queries are reformulated to get more relevant results. The proposed work enhances the Google search by taking into account user profiles and the related words of the search query obtained from UMLS and WordNet.

III. PROPOSED SYSTEM

The user profiles are collected implicitly from the users by examining their browsing history obtained from the browser they use. The search query is then pre-processed. Pre-processing includes tokenization, stop words removal and stemming. The synonyms for the keywords in the query referred as synsets are retrieved from WordNet and UMLS. The proposed work collects the browsing history from Firefox browser which is stored as SQLite file. This file stores details about the users such as the pages visited by the user, bookmarks made, downloads, etc. The factors that are considered as evidence phrases by the proposed method for profiling are the occurrence of query words or their synonyms in the URL, the frequency of visit to that page, whether the page has been bookmarked, whether the page is successfully downloaded or the download has been paused, the number of times it has been downloaded. The occurrence of the keywords and their synsets in the title of the web pages in browser history are also considered as evidence phrases.

Weights are assigned to these factors showing their significance in building the user profiles.

The sum total of the weights gives the relevance score of the webpage which determines the position of the web page in the search results. The architecture of the proposed system is shown below.

A. Architecture

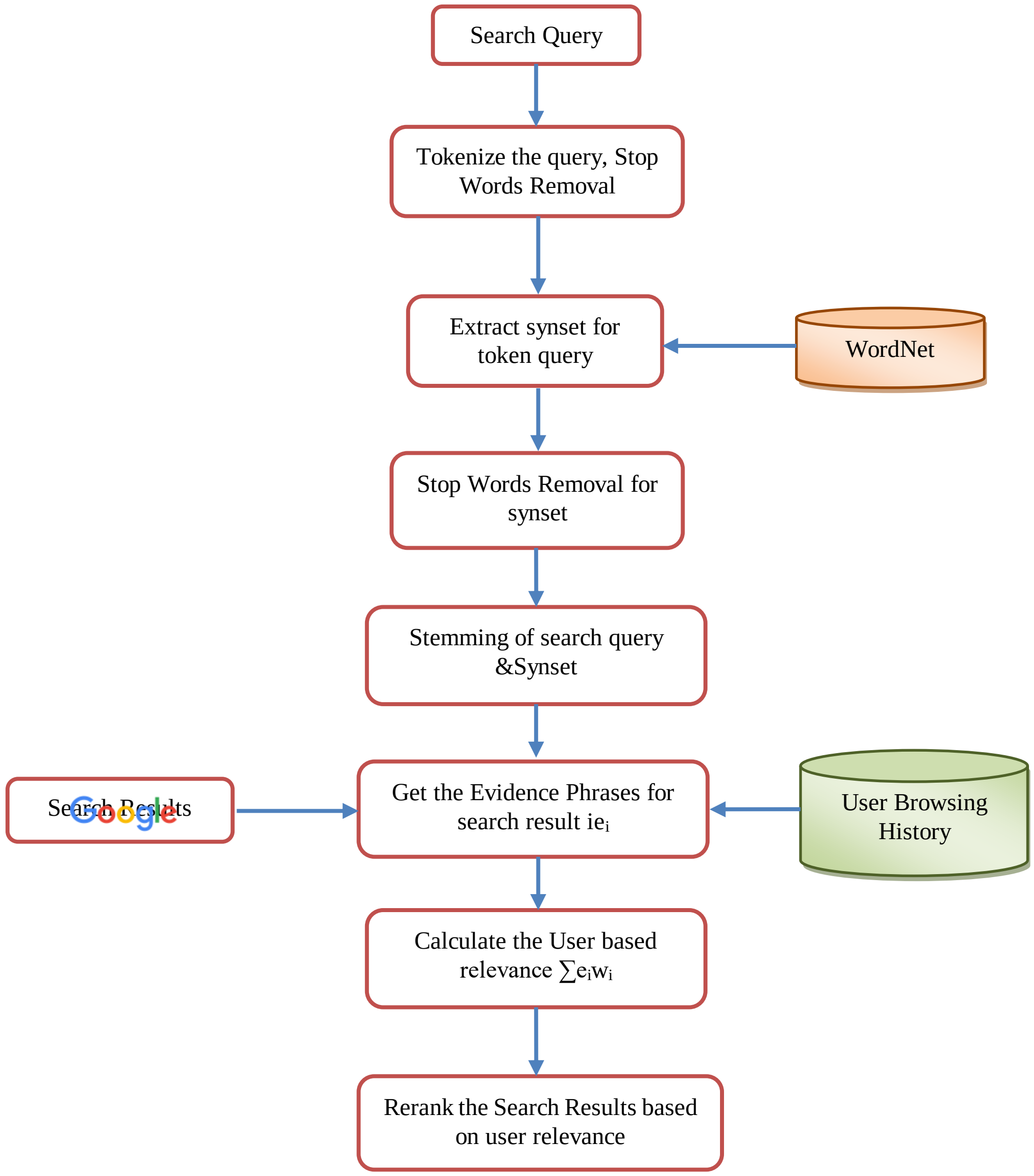

Fig 3.1 Architecture of the proposed system

B. Algorithmic steps

1) The top 30 search results for the search query are obtained from search engine.
2) Pre-processing(Tokenization, Stop Words Removal and Stemming) is done on the query terms.
3) The synsets are generated for the query keywords from WordNet and UMLS and pre-processed.
4) For each search result i, the occurrence evidence phrases such as visit count, bookmarks and downloads are collected from the user's browsing history stored by the respective browser. The occurrence of the keywords and their synsets in the title of the web pages are also considered as evidence phrases.
5) The user based relevance is calculated as $\sum e_i w_i$, where e_i is the evidence phrase found for the search result i and w_i is the weight assigned to the corresponding evidence phrase.
6) The results from the search engine are rearranged based on the user based relevance. This brings the users preferred pages in the top of search results.

IV. PERFORMANCE EVALUATION

The evaluation of the proposed method was done by collecting the browsing history of 50 users along with their relevance ratings for the top 30 search results of 5 queries obtained from search engines. The users belonged to various fields of allied medicine such as pharmacy, clinical laboratory, radiology and nursing students are chosen for conducting the experiments. Since the evaluation requires the browsing history of the users, the number of users is limited to 50. The browsing history was collected for a period of 10 days. Table I shows the sample relevance ratings of 2 users in a 5-point scale (with 5 being more relevant and 1 irrelevant) for the search query "*Consequences of Gestational Diabetes*".

Table-I: Sample relevance ratings of 2 users

Website S. No	Website	Relevance Score by User1	Relevance Score by User2
1	https://www.mayoclinic.org/diseases-conditions/gestational-diabetes/symptoms-causes/syc-20355339	3	3
2	https://www.webmd.com/baby/gestational-diabetes-you	4	3
3	https://www.tommys.org/pregnancy-information/pregnancy-complications/gestational-diabetes/what-are-risks-gestational-diabetes	3	2
4	https://www.diabetes.org.uk/diabetes-the-basics/gestational-diabetes/symptoms-and-complications	3	2
5	https://www.babycenter.com/0_i-have-gestational-diabetes-how-will-it-affect-my-baby_10415148.bc	3	3
6	https://www.ncbi.nlm.nih.gov/pubmed/20121460	3	3
7	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5695409/	5	2
8	https://www.hse.ie/eng/health/az/d/diabetes,-gestational/complications-of-gestational-diabetes-.html	4	2
9	https://www.nhs.uk/conditions/gestational-diabetes/	4	3
10	https://www.news-medical.net/health/How-does-gestational-diabetes-affect-the-baby.aspx	4	4
11	https://parenting.firstcry.com/articles/effects-of-gestational-diabetes-on-your-baby/	4	4
12	https://www.practo.com/health-wiki/gestational-diabetes-symptoms-complications-and-treatment/101/article	4	3
13	https://www.sciencedirect.com/science/article/pii/S0950355205801075	3	4
14	https://www.marchofdimes.org/complications/gestational-diabetes.aspx	4	4
15	https://www.everydayhealth.com/gestational-diabetes/your-babys-health.aspx	5	2
16	https://www.birthinjuryguide.org/birth-injury/causes/failure-diagnose-gestational-diabetes/	4	2
17	https://www.livescience.com/34728-gestational-diabetes-symptoms-complications.html	3	3
18	http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0001-37652018000502279	4	2
19	https://www.diabetesaustralia.com.au/gestational-diabetes	4	2
20	https://www.mydr.com.au/diabetes/gestational-diabetes-q-and-a	4	2
21	http://cmajopen.ca/content/5/3/E604.full	4	3
22	https://www.springer.com/gp/about-springer/media/research-news/all-english-research-news/babies-born-to-mothers-with-gestational-diabetes-are-at-high-risk-of-poor-outcomes/12123174	4	3
23	https://www.cdc.gov/diabetes/basics/gestational.html	5	4
24	https://www.onlymyhealth.com/health-videos/will-gestational-diabetes-hurt-baby-1297676592.html	3	4
25	https://www.researchgate.net/publication/41FFRitFm5rLQihCFPSNPkwLNBTbVZHUAnYc5iRYaWz9emf_gestational_diabetes_mellitus	4	3
26	https://www1.racgp.org.au/ajgp/2018/july/gestational-diabetes-mellitus	5	4
27	http://www.diabetes.org/diabetes-basics/gestational/what-is-gestational-diabetes.html	4	2
28	https://www.medicinenet.com/gestational_diabetes/article.htm	4	5

29	https://www.jwatch.org/na43608/2017/03/07/consequences-gestational-diabetes-could-run-deeper-once	3	2
30	https://www.birthdefects.org/healthy-baby/maternal-illness/diabetes/	4	2

A. Evaluation Metrics

Primary measures used to evaluate information retrieval in general are

Precision(P)[20]is the fraction of retrieved documents that are relevant

$$Precision = \frac{\#Relevant\ items\ retrieved}{\#retrieved\ items} \quad (1)$$

Recall (R)[20] is the fraction of relevant documents that are retrieved

$$Recall = \frac{\#Relevant\ items\ retrieved}{\#relevant\ items} \quad (2)$$

Mean Average Precision (MAP)[20]provides a single-figure measure of quality across recall levels. Among evaluation measures, MAP has been shown to have especially good discrimination and stability. For a single information need, Average Precision is the average of the precision value obtained for the set of top k documents existing after each relevant document is retrieved, and this value is then averaged over information needs. That is, if the set of relevant documents for an information need $q_j \in Q$ is $\{d_1,...d_{mj}\}$ and R_{jk} is the set of ranked retrieval results from the top result until you get to document d_k, then

$$MAP(Q) = \frac{1}{|Q|}\Sigma\sum_{j=1}^{|Q|}\frac{1}{mj}\sum_{k=1}^{mj}Precision(Rjk) \quad (3)$$

The performance of the proposed method is analyzed in terms of the metrics discussed above.

B. Results and Discussion

The following table II shows the ranks of the websites by Google and proposed method.

Table-II: Ranks obtained for 2 Users using the proposed system.

Website	Google Rank	Rank for User 1	Rank for User 2
https://www.mayoclinic.org/diseases-conditions/gestational-diabetes/symptoms-causes/syc-20355339	1	26	24
https://www.webmd.com/baby/gestational-diabetes-you	2	21	13
https://www.tommys.org/pregnancy-information/pregnancy-complications/gestational-diabetes/what-are-risks-gestational-diabetes	3	25	21
https://www.diabetes.org.uk/diabetes-the-basics/gestational-diabetes/symptoms-and-complications	4	28	26
https://www.babycenter.com/0_i-have-gestational-diabetes-how-will-it-affect-my-baby_10415148.bc	5	22	20
https://www.ncbi.nlm.nih.gov/pubmed/20121460	6	29	8
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5695409/	7	3	15
https://www.hse.ie/eng/health/az/d/diabetes,-gestational/complications-of-gestational-diabetes-.html	8	7	19
https://www.nhs.uk/conditions/gestational-diabetes/	9	16	9
https://www.news-medical.net/health/How-does-gestational-diabetes-affect-the-baby.aspx	10	20	6
https://parenting.firstcry.com/articles/effects-of-gestational-diabetes-on-your-baby/	11	18	7
https://www.practo.com/health-wiki/gestational-diabetes-symptoms-complications-and-treatment/101/article	12	13	18
https://www.sciencedirect.com/science/article/pii/S0950355205801075	13	30	12
https://www.marchofdimes.org/complications/gestational-diabetes.aspx	14	17	4
https://www.everydayhealth.com/gestational-diabetes/your-babys-health.aspx	15	1	22
https://www.birthinjuryguide.org/birth-injury/causes/failure-diagnose-gestational-diabetes/	16	14	16
https://www.livescience.com/34728-gestational-diabetes-symptoms-complications.html	17	23	11
http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0001-37652018000502279	18	10	25

https://www.diabetesaustralia.com.au/gestational-diabetes	19	4	27
https://www.mydr.com.au/diabetes/gestational-diabetes-q-and-a	20	5	28
http://cmajopen.ca/content/5/3/E604.full	21	12	10
https://www.springer.com/gp/about-springer/media/research-news/all-english-research-news/babies-born-to-mothers-with-gestational-diabetes-are-at-high-risk-of-poor-outcomes/12123174	22	15	16
https://www.cdc.gov/diabetes/basics/gestational.html	23	10	2
https://www.onlymyhealth.com/health-videos/will-gestational-diabetes-hurt-baby-1297676592.html	24	24	5
https://www.researchgate.net/publication/41FFRitFm5rLQihCFPSNPkwLNBTbVZHUAnYc5iRYaWz9emf_gestational_diabetes_mellitus	25	8	14
https://www1.racgp.org.au/ajgp/2018/july/gestational-diabetes-mellitus	26	2	3
http://www.diabetes.org/diabetes-basics/gestational/what-is-gestational-diabetes.html	27	19	23
https://www.medicinenet.com/gestational_diabetes/article.htm	28	6	1
https://www.jwatch.org/na43608/2017/03/07/consequences-gestational-diabetes-could-run-deeper-once	29	27	30
https://www.birthdefects.org/healthy-baby/maternal-illness/diabetes/	30	8	29

Table III shows the precision and recall calculation using equations (1) & (2) (based on the relevance score given by the users) of google and the results of the proposed system.

Table-III: Precision and recall calculation of Google and the proposed system.

Website S.No	Google		Proposed System	
	Precision	Recall	Precision	Recall
1	0.5	0.0909091	1	0.1818182
2	0.3333333	0.0909091	1	0.2727273
3	0.5	0.1818182	0.75	0.2727273
4	0.4	0.1818182	0.8	0.3636364
5	0.3333333	0.1818182	0.6666667	0.3636364
6	0.4285714	0.2727273	0.5714286	0.3636364
7	0.375	0.2727273	0.5	0.3636364
8	0.4444444	0.3636364	0.5555556	0.4545455
9	0.4	0.3636364	0.5	0.4545455
10	0.4545455	0.4545455	0.4545455	0.4545455
11	0.5	0.5454545	0.4166667	0.4545455
12	0.4615385	0.5454545	0.4615385	0.5454545
13	0.4285714	0.5454545	0.4285714	0.5454545
14	0.4	0.5454545	0.4	0.5454545
15	0.4375	0.6363636	0.375	0.5454545
16	0.4117647	0.6363636	0.3529412	0.5454545
17	0.3888889	0.6363636	0.3333333	0.5454545
18	0.3684211	0.6363636	0.3157895	0.5454545
19	0.35	0.6363636	0.35	0.6363636
20	0.3333333	0.6363636	0.3809524	0.7272727
21	0.3181818	0.6363636	0.3636364	0.7272727
22	0.3478261	0.7272727	0.3478261	0.7272727
23	0.375	0.8181818	0.375	0.8181818
24	0.36	0.8181818	0.36	0.8181818

25	0.3846154	0.9090909	0.3846154	0.9090909
26	0.4074074	1	0.3703704	0.9090909
27	0.3928571	1	0.3571429	0.9090909
28	0.3793103	1	0.3793103	1
29	0.3666667	1	0.3666667	1
30	0.3666667	1	0.3666667	1

The chart for precision of the Google and proposed system are compared in the fig. 4.1. From the figure it is evident that the proposed system offers better precision than Google. This means the proposed system retrieves more relevant results. Similarly the chart for recall of the Google and proposed system is shown in fig. 4.2. It shows that the fraction of relevant documents that are retrieved is improved.

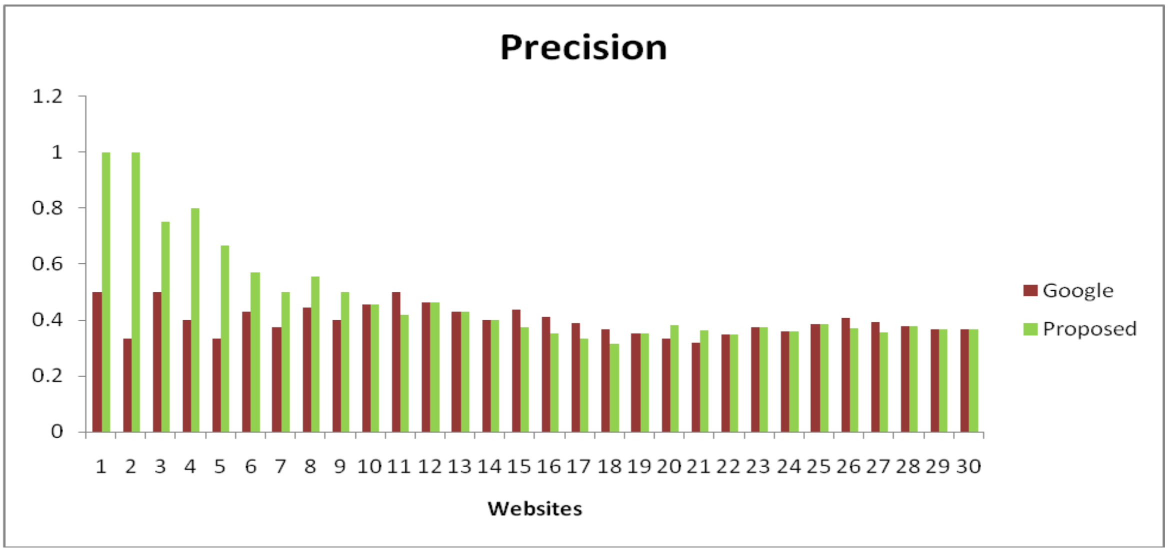

Fig. 4.1 Precision of the websites for Google and Proposed System

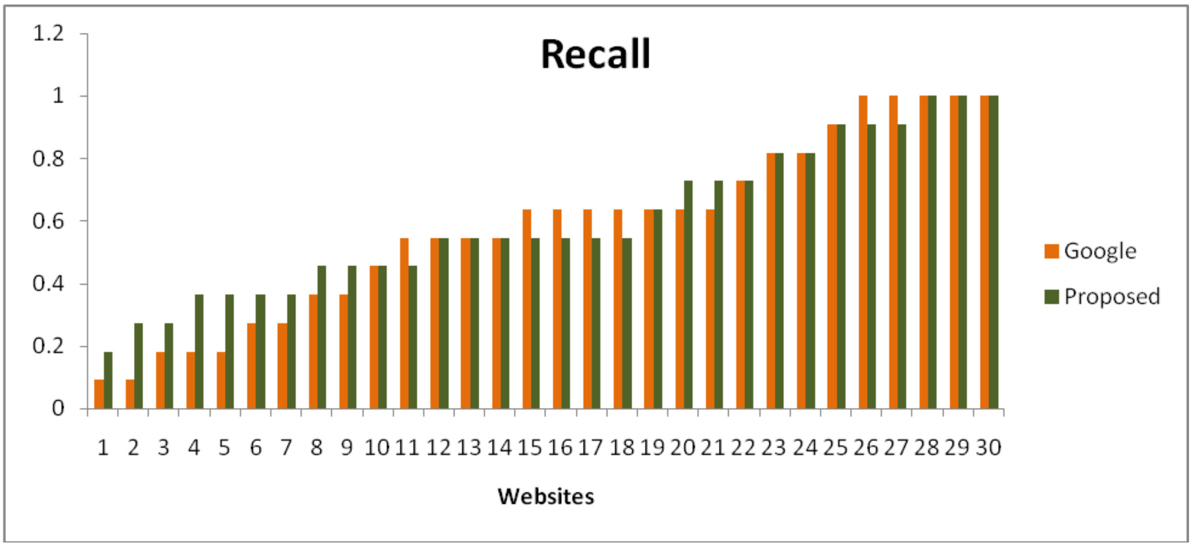

Fig. 4.2 Recall of the websites for Google and Proposed System

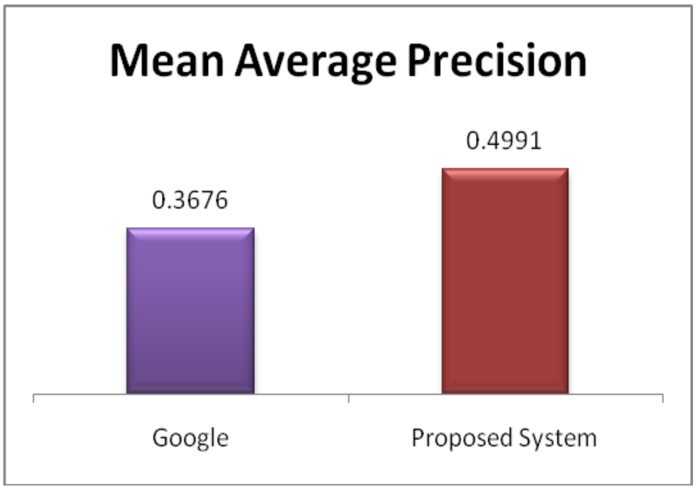

Fig. 4.3 Mean Average Precision of Google and Proposed System

Sample data was collected from 50 users. Each user was asked to evaluate the 30 search results of Google for each of the 5 queries. The 5 sample queries given were

- Types of Autism
- Consequences of gestational diabetes
- Symptoms of Osteoporosis
- What is Alzheimer 's disease?
- Thyroid disorders

The mean average precision calculated (for 50 users and 5 queries) for Google search results is 0.3676 and that of the proposed system is 0.4991. This shows that the proposed system has 13% average increase in precision than Google.

V. CONCLUSION

This paper proposes a method for user personalization in the field of medicine by gathering evidence phrases from the users' browsing history. This is done implicitly without any effort from the users. The proposed method does not take into account the snippets of the web pages considered. Experimental studies show that the proposed method considerably increases the precision of the search results. In future, some more factors can be added to the evidence phrases to improve the precision of the search results. This user personalization can be extended to domains other than medicine.

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