Introduction

The English content on web has shrunk from 39 to 27% in last decade (Narasimha Raju and Bhadri Raju, 2015). On other side web content for languages like Chinese, Japanese, Hindi, Arabic etc. is showing gradual growth. The increasing number of users on internet who desire to access information expressed in languages other than their own has established cross lingual information retrieval as a major issue in information retrieval. The retrieval is bilingual if one source language (e.g., English) and one document language (e.g., Hindi) is used. The multilingual retrieval system accepts user query in one language while outputs documents in multiple languages. Sometimes an intermediate language is used as a means of translation, thereby making process transitive (Gollins and Sanderson, 2001).

The basic solution to CLIR is to translate the query into target language and consequently compute document scores using retrieval model like vector space or probabilistic model. This is one of the solutions. Other strategies can be: Direct matching of terms in different languages without translation, translating each document into query language or translating query and document into some common representation (Oard, 1998). Over the years query translation has evolved as the most well-liked strategy by researchers. But simple cross language query translation is less effective as compared to monolingual retrieval when typical measures like mean average precision and recall are used. Researchers suggest that by adopting simple linguistic techniques as translating phrases over individual words or limiting translation alternatives for query terms as provided by bilingual dictionary can raise the performance of CLIR to 75% of monolingual effectiveness (Oard and Diekema, 1998; Davis and Ogden, 1997; Hull and Grefenstette, 1996). In this study, we propose an effective method for limiting the size of translation candidates set for query words for optimization of our proposed query translation and disambiguation model.

The constitution recognizes Hindi and English as the only official languages of India (Chakrawarti and Bansal, 2017). In this study, we have tried to bring together a body of work that completely describes English to Hindi cross lingual information retrieval system. This
has many key folds. Our goal is not merely to describe the state of the art but to demonstrate the effect of the techniques involved in our framework on retrieval effectiveness for the two languages (English and Hindi) differing in their characteristics. While developing the process, the major concern has been on the following issues: (i) Restructuring of source query (ii) analyzing translation candidates and (iii) ambiguity removal.

Indian language internet user base has reached 234 million users at the end of 2016 surpassing the English internet users. This growth is likely to reach 536 million by 2021 compared to English internet user base. In particular Hindi internet user base is likely to outgrow English user base by 2021 (KGMP, 2017). This impressive growth in Indian language internet users motivates us to design and develop an English-Hindi Cross Language Information Retrieval (CLIR) System.

The paper commences by the related work in section 2 and contrastive analysis for the language pair English and Hindi in section 3. The contribution of the components of the processes is discussed in section 4. Section 4 also talks about the algorithm framed for short listing the translation candidates obtained for query terms from bilingual dictionary along with the demonstration through an example. Section 5 evaluates cross lingual retrieval system. Our results indicate that retrieval effectiveness is positively correlated with translation candidates set size and hence validate the utility of ‘Analyzer’ component in our CLIR framework and in increasing the effectiveness of our disambiguation algorithm. Finally we conclude in section 6.

Related Work

Query translation can be done by using any of the three resources namely Machine translation, Machine readable dictionaries or Parallel corpus. The dictionary translation is more preferred by researchers as this approach is simple and practical. But the method suffers from the problem of translation ambiguity as there is often one-to-many translation in bilingual dictionary for source query words. To eradicate this problem researchers have tried measuring co-occurrence frequency of query terms. The method relies on the hypothesis that words appearing in the same document tend to share related senses and thereby represent a coherent content.

Croft and Ballesteros select the translation with the highest coherence score for Spanish-English language pair and reveal that the method is very successful for language pairs with scarce resources (Ballesteros and Croft, 1998).

Adrani approached the similar problem and used maximum similarity score between translation candidates for different query terms (Adrani, 2000). Later Gao et al. claimed that increase in distance between two terms weakens the association between them. They refined the disambiguation algorithm by incorporating decaying factor with the mutual information statistics. Liu et al. (2005) published an algorithm on maximum coherence model. They maximized the overall coherence of the query to estimate the translation probabilities of query terms using an iterative machine learning approach based on expectation maximization. Zhou et al. (2007) viewed the co-occurrence of possible translation terms within a given corpus as a graph and determines the importance of a translation using global information recursively drawn from the entire graph.

Giang et al. (2013) used mutual summary score based on word distribution in document collection to outperform basic model. Duque et al. (2015) Technique combines both the dictionary and co-occurrence graph to select the most suitable translation from the dictionary.

Contrastive Analysis of English and Hindi Language

Before we start discussing the proposed CLIR system for English-Hindi language pair, we need to see English from Hindi viewpoint, to make our system capable of performing contrastive analysis of the two languages. Both languages differ in morphological richness. Hindi is morphologically rich language whereas English has relatively simple morphology (Bhattacharyya, 2012).

Language topologists categorize English as an Subject-Verb-Object (SVO) and Hindi as Subject-Object-Verb (SOV) language. This classification is merely encoding of grammatical relations between Subject, Verb and Object between the two languages. In English a verb is preceded by the subject and followed by an object, while in Hindi the subject is followed by an object which is then followed by a verb. But in Hindi, the constituents of a sentence can be relatively moved freely around in the sentence without affecting the core meaning. E.g., the following sentence pair conveys the same meaning with different word order:

- राम ने सीता को देखा Ram ne Sita ko dekha
- सीता को राम ने देखा Sita ko Ram ne dekhaa

The identity of Ram as the subject and Sita as the object in both sentences comes from the case markers में (ne – nominative) and को (ko – accusative) whereas, the two English sentences have exactly opposite meanings with similar change in the order of words.

Rats kill cats Cats kill rats

This is because English does not have a morpheme for an accusative marker. The missing accusative marker is compensated by the subject position in English.
increases the structural differences between the two languages in the following way:

- In English, prepositions precede the words to which they relate. In Hindi, such words are called postpositions because they follow the words they govern.

  On the table (English) मेज पर (mej par) (Hindi)

- Verb gets different meanings by using articles in English.

  look at, look for, look after etc.

  whereas there are no articles in Hindi. Definiteness of a noun is indicated through pronoun, context or word order.

- The order between main verb and auxiliary verb is reversed.

  खा रहा है (kha raha hai) (Hindi) is eating (English)

- English does not mark gender on the verb whereas Hindi does.

  I go(English) while in Hindi वो जाता है वो जाती है

- Hindi gets advantage over English as it does not have a subject sharing rule.

  रवि ने फल खराब और शाम तक खा भी गया (Ravi ne phal khareede aura sham taka kha bhii gaya).
  Here karma(phal) in first sentence is same as kartaa in the second sentence.
  While the English sentence

  Shyam dropped the melon and burst

  Is interpreted by native Hindi speaker as

  श्याम ने तरबूजा गिराया और तरबूजा फूटा (Shyam ne tarabuuja giraayaa aura tarabuuja phutaa)
  To give the above sentence correct interpretation, English constructs the sentence as

  Shyam dropped the melon and it burst

  श्याम ने तरबूजा गिराया और वो रो पड़ा (Shyam ne tarabuuja giraayaa aura wo ro padaa)

  In English, subject position can’t be empty. This forces English to bear an extra overload of dummy ‘it’ and existential ‘there’.

  It is Monday today (English) आज सोमवार है (Hindi) aaj somvar hai
  There are kites in the sky (English) आसमान में पतंग है (aasmaan me patang hai) (Hindi)
  Again look at the following two sentences in English:

  E: Sita is eating mango
  E: Is Sita eating mango?

  The above two sentences differ only in the word order. This change in word order makes first sentence as declarative while second as interrogative sentence. There is no explicit morpheme to mark the interrogativeness in English.

  From the Hindi translations of these sentences:

  H: सीता आम खा रही है (Sita aam khaa rahi hai)
  H: क्या सीता आम खा रही है? (kyaa Sita aam khaa rahi hai?)

  It is clear that Hindi has an explicit word ‘kyaa’ to mark the ‘yesno’ question while English codes this information in word order. The missing marker corresponding to yes-no question is compensated by the ‘subject auxiliary verb inversion’ in English. This weakens the proximity between main verb and auxiliary verb.

  Consequences of Missing yes-no interrogative marker:

  - Subject Position can’t be empty as it indicates declarativeness or interrogativeness of the sentence.
  - Insertion of auxiliary do in interrogatives:

    If a verb form does not involve an auxiliary verb, then a dummy ‘do’ is inserted, as shown below.

    She eats mango.
    Does she eats mango?

    Thus, we conclude that English structurally differs from Hindi because of the absence of accusative marker and yes-no marker in English. To recompense for this shortcoming, English depends on its word order which in turn increases the differences between the language pair (Bhattacharyya, 2012; Bharati and Kulkarni, 2005; Bharati and Vineet, 2000).

**English to Hindi Cross Lingual Information Retrieval System**

Ideally, any CLIR system should retrieve all the relevant documents, ranked in decreasing order of relevancy for any user query. However, search results omit many relevant documents and often include many documents which are irrelevant. The primary reasons to
this inconsistency can be attributed to few facts like morphological analysis of search keys, translation of search keys, selection of search keys translations and search key ambiguity.

Keeping in mind the grammatical complexities between the two languages and the primary reasons stated above, we have proposed the following CLIR system whose data flow has been shown in Fig. 1.

Figure 1 illustrates the data flow between the key components in our reference architecture. Before we initiate the preprocessing of query terms, the query needs to be tokenized. Here we are lucky enough as both English and Hindi languages are written with space-delimited words and thereby extracting terms from an English query or indexing terms from Hindi documents becomes too simple.

![Data flow in proposed CLIR System](image_url)
The process is as follows:

**Stop Word Removal**

We use an English stop word list of 507 English words to remove stop words from the queries formulated for evaluation.

**Word Form Normalization**

Normalization is quiet simple for morphologically simple languages, such as English. Porter stemming algorithm is used to reduce inflected query words to base form in our system (Porter stemmer).

**Translation**

The most crucial step in performing Cross-Lingual Word Sense Disambiguation is the choice of a good bilingual dictionary (Andres et al., 2015). We use publicly available online bilingual English to Hindi dictionary Shabdanjali developed in IIIT, Hyderabad and containing 28K Hindi words to translate English queries to Hindi language queries (Shabdanjali English-Hindi Dictionary). The dictionary required conversion from ISCH to UTF-8 encoding and some basic normalization.

**Analyzer**

Dictionary translation leads to spurious equivalent translations in target language. All the translations are not desirable as many being synonyms of each other. The proposed model thereby concentrates only on the translation candidates of a query term having different meanings dropping the synonyms. Previous researches whereas treats all translation candidates equally and give undue advantage to query terms with more number of translations. We use Hindi WordNet, a lexical database for Hindi which is provided by the Linguistic Data Consortium and developed by IIT Bombay for filtering undesired translations (Pande et al., 2001). It contains 103438 unique Hindi words and 39271 number of synset.

To remove the synonyms, we suggest an easy algorithm as outlined below. This step in our CLIR system aims to optimize our proposed disambiguation model termed ‘Two Level Disambiguation model’. It will also improve the relevancy of documents retrieved against the user queries.

**Algorithm**

**Input**: Source query \( Q \) = \{ \( q_1, q_2, \ldots, q_n \) \}.

1. For each \( q_i \) (\( i = 1 \) to \( n \)), retrieve a set of translation candidates \( S_i \) from bilingual dictionary.
2. For each translation candidate \( h_j \) (\( j = 1 \) to \(| S_i | \)), do steps 2.1 and 2.2
   2.1 Retrieve all synonyms from Hindi Wordnet. Call it set \( P_r \).
   2.2 Remove sense \( h_k (k = 1 \) to \(| S_i | \) and \( k \neq j \)) from \( S_i \) if it occurs in set \( P_r \).

**Output**: For each \( q_i \), the set of senses \( S_i \) contains only those translation candidates which have different sense.

To demonstrate the above algorithm, let us consider a query ‘Renewable power’. From the bilingual dictionary ‘Shabdanjali’ we retrieve a list of translation candidates of ‘power’ as:

\[
S_i = \{ \text{सामर्थ्य, हुकूमत, इंक्लायर, इंक्लायर, इंश्वरत्व, कुदरत, बुता, अधिकार, अधिपति, विक्रम, ऊज़ा, विद्युत, उड़ा, धोया, क्षमता, जोर, जोर, विद्युत शक्ति, ताकत, अपरिमित परिमाण, ताकत, आसुरी ताकत, अतिशिक्षितवाली राष्ट्र, पराक्रम, प्रतिभा, प्रभाव, अगणित संख्या, प्राथिक, राजकीय सता, बल, बिजली, बिसार, राज, राजय, वश, विभव, विश्राम, शक्ति, शासन, सकता, सता}. \]

Next we retrieve the synsets of first term ‘सामर्थ्य’ from Hindi Wordnet:

\[
P_k = \{ \text{औजार, औजार, बिसार, हैसियत, सामर्थ्य, सामर्थ्य शक्ति, निष्क्रय, इंक्लायर, इंक्लायर, योग्यता, काबिलियत, काबिलियत, काबिलियत, काबिलियत, उपयुक्तता, लियाकत, लियाकत, हुनर, सलौक, सलौक, माध्य, शक्ता, अहिंसा, इल्मीयत, इस्तेदाद, ताकत, ताकत, समर्थता, क्षमतापूणता, शक्तिपूणता}. \]

The common terms in the above two sets are [इंक्लायर, इंक्लायर, क्षमता].

Removing common terms, set \( S_i = \{ \text{सामर्थ्य, हुकूमत, इंश्वरत्व, कुदरत, बुता, अधिकार, अधिपति, विक्रम, ऊजार, विद्युत, उड़ा, धोया, क्षमता, जोर, जोर, विद्युत शक्ति, ताकत, अपरिमित परिमाण, ताकत, आसुरी ताकत, अतिशिक्षितवाली राष्ट्र, पराक्रम, प्रतिभा, प्रभाव, अगणित संख्या, प्राथिक, राजकीय} \].
The common terms in the above two sets are {शासन, राज्य, राज, अधिकार, सता}.

Removing common terms, set $S_i = \{\text{सामाध्य}, \text{हकूमत}, \text{ईश्वरत्व}, \text{कुदरत}, \text{बूता}, \text{अधिपति}, \text{विक्रम}, \text{उज्ज, विद्युत, ओझर, विद्युत, शक्ति, अपरिमेय परिपार्श्व, आसुर, बल, जोर, शितार, अधिकारित्व, अधिकारित्व, अधिकारित्व, प्रभुता, संपन्नता, संपन्नता, मिलनियत, मिलनियत, अमल, अमल, इक्तियार, इक्तियार}\}.$

There is no change in set $S_i$ for the next two terms ईश्वरत्व and कुदरत. Next we retrieve the synsets of term ‘कुदरत’ from Hindi Wordnet.

$P_k = \{\text{शक्ति, बल, क्षमता, ताकत, ताकत, दम, दमख, कुदवत, कूदत, बूता, हीर, दम-खम, दमख, दम-खम, दम, जोर, जोर, जोर, जोर, वृजन, वृजन, बाज, अव्दान, पवार, सतत, सतत, बीयर, क्षत्र} \}

The common terms in the above two sets are {शक्ति, बल, ताकत, ताकत, जोर, जोर}.

Removing common terms, set $S_i = \{\text{सामाध्य}, \text{हकूमत}, \text{ईश्वरत्व}, \text{कुदरत}, \text{बूता}, \text{अधिपति}, \text{विक्रम}, \text{उज्ज, विद्युत, ओझर, विद्युत, शक्ति, अपरिमेय परिपार्श्व, आसुर, बल, जोर, शितार, अधिकारित्व, अधिकारित्व, अधिकारित्व, प्रभुता, संपन्नता, संपन्नता, मिलनियत, मिलनियत, अमल, अमल, इक्तियार, इक्तियार}\}.$

Similarly continuing for other terms in set $S_i$, the final set contains only the translation candidates which have different meanings:

$S_i = \{\text{सामाध्य}, \text{हकूमत}, \text{ईश्वरत्व}, \text{कुदरत}, \text{बूता}, \text{अधिपति}, \text{विक्रम}, \text{उज्ज, विद्युत, ओझर, विद्युत, शक्ति, अपरिमेय परिपार्श्व, आसुर, बल, जोर, शितार, अधिकारित्व, अधिकारित्व, अधिकारित्व, प्रभुता, संपन्नता, संपन्नता, मिलनियत, मिलनियत, अमल, अमल, इक्तियार, इक्तियार}\}.$

In this way the cardinality of the set $Si$ is reduced from 40 to 21 and thereby leaving behind only the translation candidates having different meanings.

**Disambiguation**

Cross Lingual word sense disambiguation performs disambiguation of source language words while translating them to target language (Rekabsaz et al., 2017). We have proposed a disambiguation algorithm termed as ‘Two level disambiguation model’ which performs disambiguation at two levels. At first level we deal with the translation candidates in pairs only. This is done with the aim to obtain partial data for the likelihood of a translation in the perspective of other query terms. For a given query word, instead of taking binary decision for its translation alternatives, we measure the importance of each of the candidates in the context of given query. A translation candidate is assigned a high importance factor if it is rational with the semantic meaning of the user query. At second level we aim to find the most suitable translation for the given query. We compute the coherence between all possible combinations of translation candidates of query terms. This resolves the problem of translations being selected independently from selected and unselected translations of remaining query terms. Select the combination with highest score as the target language query.

**Algorithm**

**Input:** Source query $Q = \{q_1, q_2, \ldots, q_n\}$.
1. For each $q(i = 1 \text{ to } n)$, retrieve a set of translation candidates $S_i$ from bilingual dictionary.
2. For each translation candidate $h_j(j = 1 \text{ to } |S_i|)$, do steps 2.1 and 2.2
   2.1 Retrieve all synonyms from Hindi Wordnet. Call it set $P_k$.
   2.2 Remove sense $h_k(k = 1 \text{ to } |S_i|)$ if it occurs in set $P_k$.
3. For each $q(i = 1 \text{ to } n)$, do step 3.1
   3.1 For each $h_j(j = 1 \text{ to } |S_i|)$, do steps 3.1.1 to 3.1.5
      3.1.1 Retrieve all example sentences for its synset, hypernyms and homonyms from Hindi WordNet.
      3.1.2 Count the usage of a translation candidate $h_i$ in example sentences of translation candidates $I_{p_i}$ of other query terms $q_i$, where $1 \leq k \leq n, k \neq i$ and $p = 1 \text{ to } |S_i|$. 
      3.1.3 Find the sum of usage of $h_i$ to obtain $UC_i$, the Usage Count of a particular translation candidate with respect to translation candidates of other query terms.
      3.1.4 Normalize $UC_i$ to obtain $IF_i$, Importance Factor of translation candidate $h_i$.
4. For $i = 1 \text{ to } n$, do step 4.1
   4.1 For every combinations $C = \{h_1, h_2, \ldots, h_n\}$ where $h_i$ is a translation candidate of $q_i$, do step 4.1.1
      4.1.1 Compute WSDC as:
      \[
      WSDC(C) = \sum_{k, j=1}^{n} \left( DC(h_i, h_j) \ast IF(h_i) \ast IF(h_j) \right), \text{where} \]
      \[
      DC(h_i, h_j) = \frac{2 \ast freq(h_i, h_j)}{freq(h_i) + freq(h_j)}
      \]
      \[
      freq(h_i) = \text{The number of occurrences of term } h_i \text{ in training corpus}
      \]
      \[
      freq(h_j) = \text{The number of occurrences of term } h_j \text{ in training corpus}
      \]
      \[
      freq(h_i, h_j) = \text{Co-occurrence frequency of terms } h_i \text{ and } h_j \text{ in a sentence in documents.}
      \]
5. Select the combination with the highest WSDC score as the target language query $Q'$ of the source query $Q$:
   \[
   Q' = \arg \max_C WSDC(C)
   \]

**Output:** Disambiguated Hindi query $Q'$ for English query $Q$.

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**Experiment**

In this section we will discuss how the addition of the component ‘Analyzer’ to our CLIR architecture increases the efficiency of our proposed disambiguation algorithm.

**Evaluation Environment**

An evaluation environment consists of a set of 50 topics which are designed as web user queries; and web documents which are searched to find documents relevant to the topics. The web documents are fetched from Google (http://www.google.com/) and Bing (http://www.bing.com/) indexed database. The relevance judgments for the Hindi documents obtained with respect to English queries is established with the help of three Hindi speaking volunteers from Indian Institute of Technology (BHU). Document which is judged as relevant by all the three volunteers is marked as relevant else treated as irrelevant. Evaluation is done by computing Mean Average Precision (MAP) for first 50 documents retrieved on two different search engines Google and Bing. For our Cross-Language Information Retrieval evaluation, we also measure how well the cross-language IR performs with respect to monolingual information retrieval on the same set of web documents.

**Result Analysis**

The following methods are compared to investigate the effectiveness of our model for query translation and disambiguation:

- **Monolingual:** Retrieval using the Hindi queries translated manually by Hindi language expert. Monolingual run provides unreachable performance ceiling for any cross lingual information system as translation process is inherently noisy
- **Proposed model:** Retrieval using the proposed two level disambiguation model
- **Proposed model with analyzer:** Retrieval using two level disambiguation model using polysemous translation candidates only

Table 1 describes our experimental results. For each method, we give average values of P@k with k= 10, 20 and 50 using Google search engine.

Table 2 compares the MAP value of two level disambiguation method with analyzer with baseline method i.e., monolingual run and proposed disambiguation method for English queries. The performance of disambiguation method is 79.53% while using analyzer it increases to 87.45% of monolingual run.

Table 3 gives average values of P@k with k = 10, 20 and 50 with Bing search engine.
Table 1: Run statistics for English queries with Google search engine

| Experimental run                        | P@10 | P@20 | P@50 |
|----------------------------------------|------|------|------|
| Monolingual                            | 0.483| 0.420| 0.309|
| Two level disambiguation               | 0.383| 0.336| 0.240|
| Two level disambiguation with analyzer | 0.421| 0.387| 0.272|

Table 2: Mean average precision of experimental runs for queries with Google

| Experimental run                        | Mean Average Precision (MAP) | Percentage monolingual |
|----------------------------------------|-------------------------------|------------------------|
| Monolingual                            | 0.518                         | --                     |
| Two level disambiguation               | 0.412                         | 79.53%                 |
| Two level disambiguation with analyzer | 0.453                         | 87.45%                 |

Table 3: Run statistics for English queries with Bing search engine

| Experimental run                        | P@10 | P@20 | P@50 |
|----------------------------------------|------|------|------|
| Monolingual                            | 0.412| 0.358| 0.263|
| Two level disambiguation               | 0.310| 0.271| 0.199|
| Two level disambiguation with analyzer | 0.334| 0.291| 0.162|

Table 4: Average retrieval precision of experimental runs for queries with Bing

| Experimental run                        | Mean Average Precision (MAP) | Percentage monolingual |
|----------------------------------------|-------------------------------|------------------------|
| Monolingual                            | 0.441                         | --                     |
| Two level disambiguation               | 0.333                         | 75.5%                  |
| Two level disambiguation with analyzer | 0.358                         | 81.1%                  |

Table 4 compares the MAP value of two level disambiguation method with analyzer with baseline method i.e., monolingual run and proposed disambiguation method for English queries using Bing search engine. The performance of disambiguation method is 75.5% while using analyzer it increases to 81.1% of monolingual run.

We have used same set of English test queries (designed on the lines of TREC and CLEF guidelines) and Hindi document collection, which is used to evaluate our disambiguation algorithm. Here we have evaluated our algorithm on Bing search engine along with Google to check whether the proposed algorithm is favored by a particular search engine. The MAP of two level disambiguation algorithm which is more than 75% of monolingual search with both search engines proves the effectiveness of our algorithm and no favourism of search engine.

Adding the component analyzer to our disambiguation algorithm increases the effectiveness of the disambiguation algorithm. All the synonyms obtained from bilingual dictionary during translation phase for a query word are removed keeping behind a single word before the query is disambiguated (same has been explained by an example above). After this process only polysemous translations of query words are left. These synonyms are replaced by the same word in Hindi documents too. This will increase the co-occurrence of correct translations in Hindi documents, thereby increasing the probability of correct translation to be selected as final translation of English query word. This in turn increases the number of relevant Hindi documents retrieved on both search engines for given English query. This is in accordance with the test result shown in Table 2 and 4.

Conclusion

In earlier works using machine readable dictionaries, user queries were formed including all translations for all query terms. Due to this some retrieval methods which treat term contribution as independent can give undue advantage to query terms having more number of translations. This is in general an objectionable trait for any retrieval system.

In this study we have tried to optimize our proposed query translation and disambiguation model by addition of a new valuable component Analyzer in the basic Cross Language Information Retrieval (CLIR) system. Our effort has been able to resolve the objectionable trait of any retrieval system and provides precise and quality target language translations. Hence we have been able to propose an inexpensive and easy to be implemented CLIR system.

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Author’s Contributions

Pratibha Bajpai: Development, experimentation, validation of algorithms and writing the manuscript for the journal.
Parul Verma: Concept development and proof reading.
Syed Q. Abbas: Concept development and proof reading.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that there are no ethical issues involved.

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