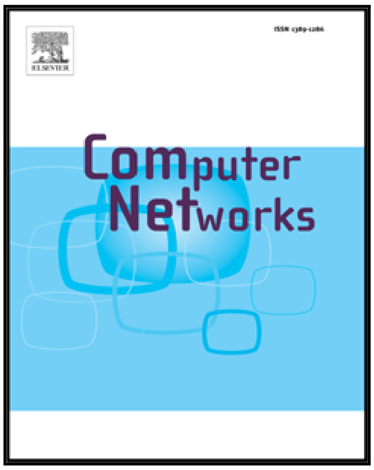

Multi Swarm Optimization based Automatic Ontology for E-Assessment

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Abstract: The utilization of ontology in the e-assessment area has grown tremendously. The context of e-learning is significant to the students for educational purposes. This makes the testing process easy for the students and also for the teachers. The majority of the approaches that deals with the ontology issue have suggested that the individual ontology models have merely a fraction of the assessment domain. To trounce such drawbacks, here, an automated ontology creation is proposed for the e-assessment systems. Initially, the text is extracted from the web utilizing the Unsupervised Quick Reduct (UQR) algorithm. This is trailed by the summarization of the texts using the multi-swarm optimization (MSO) based on preference learning. Finally, the sentence of the summary is then transmuted to multiple choice questions (MCQ). The keys are created using statistical pattern (SP). The efficiency of the system is examined using the experimental outcomes like error rate, precision, recall and accuracy. In accuracy, the proposed UQR algorithm achieves 97.7%, MSO achieve 96.2% accuracy and key generation achieves 94.7% accuracy. The proposed automatic ontology system indicates better when weighed against the top-notch methods.

Keywords: automated ontology, e-assessment, unsupervised quick reduct algorithm, multi-swarm optimization, statistical pattern.

1. INTRODUCTION

In the recent age, learning took a new trend owing to the evolving technology. E-Learning is basically a web-based communication platform that allows a student to learn irrespective of the geographic distance and time. There is access also to diverse learning tools say discussion boards, assessments and content repositories [1-5]. Context e-learning provides students with a platform for improving their knowledge. Improving the learning capacity and managing the evaluation process by themselves are the goals of ideal students [6]. The traditional barriers in education are totally broken by the commencement of the e-learning system. The testing and valuation phase is not a manual process anymore but it is completely automated.

Automated ontology has appeared as an interesting research area in the field of e-learning and assessment [7-9]. Assessment is basically a procedure for discussing the information and evaluating the knowledge of students. Along with these, interesting questions are automatically generated for a different domain. These questions are taken from web documents, journals, research papers and articles that are mentioned by the users. The automatic ontology aimed at e-assessment can well be implemented using fuzzy systems [10], neural network [11] and other optimization techniques [12-14].

In general ontology, there are three components such as sentence with blank, key and the distracters. Ontologies are being widely used in information retrieval, question answering and decision support systems. Some applications of ontology on different industries are egovernment, oil and also gas industry, e-health, military, along with e-culture et cetera. The blank part of the sentence has point out the intention knowledge of the users. The key is nothing but the right answer that has to be placed in the blank. The other options are called the distracters. The automated ontologies provide some benefits in discovery, flexible access along with information integration [15].

Remaining paper is prearranged as: Section 2 gives the details of the related words. Section 3 provides the complete framework of the proposed system. Section 4 proffers the investigational outcomes and also section 5 wraps up the paper.

2. LITERATURE SURVEY

There are a few works that were put forward over the years for ontology in e-assessment. This section offers an outline of the existent works with regard to ontology in e-assessment.

Bo Sun *et al.* [16] suggested a position centered attention model along with keywords centered model to automatically label questions with the knowledge units. The model employed mechanisms to capture useful information as of the keywords to improve the tagging performance. This model utilized the deep neural network to signify questions utilizing the contextual information. This method was used for questions from different subjects and different language backgrounds. This approach doesn't achieve better performance in PBAM (Locally) and PBAM (Fully).

Sergio *et al.* [17] described the design of pattern classification along with its application to align cases as of disparate ontologies. The model was validated via experiments that were performed on the data that was obtained as of the Ontology Alignment Initiative 2014 campaign. The outcomes showed a higher precision measurement. But this methodology still required to be extended in view of other metadata attributes, possibly utilizing other similarity computing strategies.

Marouane *et al.* [18] developed an e-learning model in a big data environment to improve the quality of the learning process. An efficient e-assessment method was designed to determine the prerequisites of the educational resource objectives. A MapReduce centered Genetic Algorithm (GA) model was used. Ant Colony Optimization was used as the optimization technique. This approach has cost-effective structural design.

Farhan *et al.*[19] put forward a technique for assessment of student's answer utilizing Latent Semantic Analysis. The semantic similarity was calculated between the question of the teacher and the answer of the student. The students' answer was marked centered on semantics. This method was developed by the combination of a software-defined network and the internet of things in a large, complex and interconnected network. This technique attained better result but it doesn't improve an algorithm for soft cosine similarity.

V. Nandini and P. Uma Maheswari [20] formulated a method for the automatic appraisal of descriptive answers on online examinations utilizing semantic relational features. This method had several stages like the classification of the question, classification of the answer and the evaluation of the answers along with grading them with appropriate scores. A syntactical relation centered features extraction technique was suggested for automatic assessment[23] of descriptive sort answers. This had good performance but it needs more accuracy compared with the other systems.

Galit and Michal [21] explored the effect of restraints on the difference of the student's response. The students were requested to settle on whether the existential statement was correct. If answered yes, then an example was constructed in a multiple linked representation environment. Using the design-centered research methodology, a 2 cycle study was described. This focused on one e-task in the subject of tangency to a function.

Asma *et al.* [22] recommended a semi-automatic technique centered on the process of creating natural language (NL) questions for assisting the ontologies validation and also their evolution. This method consists of factorization, automatic generation, in addition to NL questions ordering as of medical ontologies. Also, it introduced a second technique for mappings validation impacted by the changes in the ontology. The method utilized the perspective of the changes to suggest correction alternatives presented as MCQ. This technique gave a better result but the reliability improvement was required.

3. PROPOSED AUTOMATED ONTOLOGY METHOD

The proposed work is developed for the automatic ontology creation for e-learning and assessment purpose. The relevant information is extracted as of the web page on a user domain. This extorted information is summarized for the formation of questions which is done using MSO based on preference learning. Then, the formation of key and distracters are done using the SP. Figure 1 gives the architecture of the proposed work.

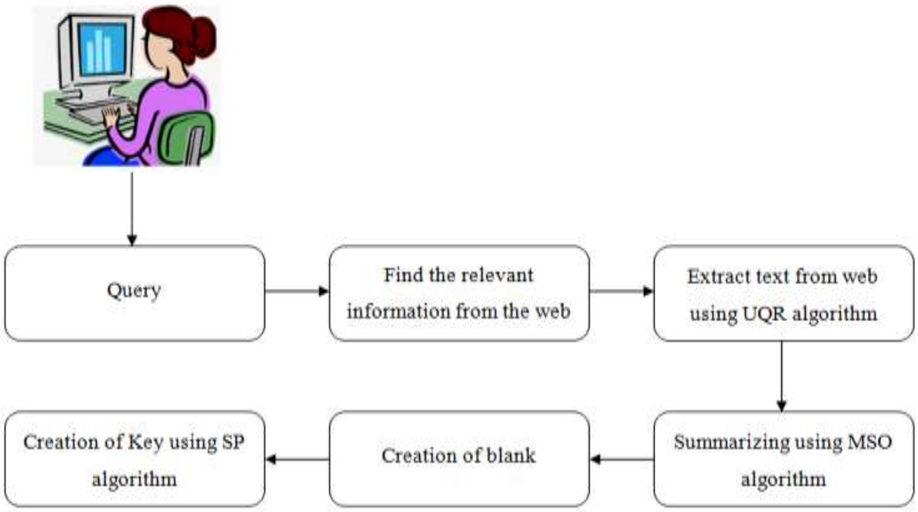

Figure 1: Block diagram of the proposed system

3.1 Query and Finding the relevant information

The proposed work commences with the creation of query via the user. The users can attach to the large scale e-assessment system as of any place and at a time through the network. The query that originates from the user is a topic that is passed the search engine Application Programming Interface (API) and returns the response with the Uniform Resource Locator (URL) of the relevant information. Relevant information is obtained from the web pages. The web pages hold information with which questions and key related to any domain can be created.

3.2 Extract text from Web

After finding the pertinent information as of the web, it is significant to extort the helpful information from it. Normally, a web page contains several components like links, audio, Video, tables, images et cetera. This information may be irrelevant to the user's domain. So it is necessary to eliminate these unwanted components. However, the useful information associated with the web page is enclosed with the POS <P> tags. The irrelevant information within this tag is removed and only the text is extracted. It is also noted that the irrelevant information as of the web is removed without losing the important information. The text enclosed within the tag is extracted using the unsupervised quick reduct (UQR) algorithm. These Hyper Text Markup Language (HTML) entities are converted into American Standard Code for Information Interchange (ASCII) codes before the text is processed. Finally, the ASCII codes are transmuted into texts. This procedure is exhibited in fig 2.

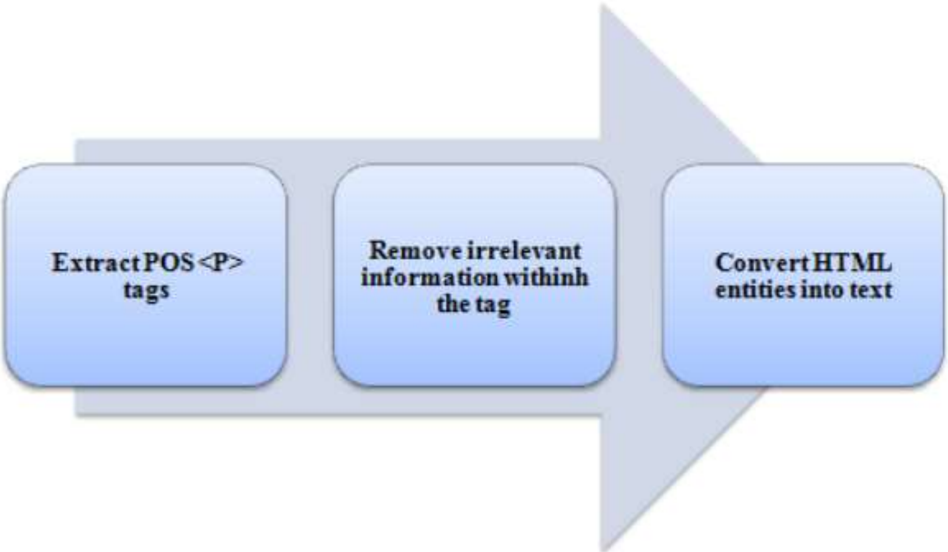

Figure 2: Steps involved in the extraction of texts from a web page

In UQR algorithm, the irrelevant information is removed. The text that is attained after this reduction provides the same prediction of the decision feature as that of the actual required features that is enclosed in the Part of Speech (POS) tags. Feature selection is included in this algorithm. The UQR algorithm is attempted to calculate a reduct without entirely creating all the probable subset of features. This begins with a null set R and adds the subset x with those features. These results in a major growth on the rough set dependency metrical using the equation 1, until a maximum value of one is produced. The dependency degree function is mathematically represented as below.

$$\gamma_{RU(x)}(y) = \frac{|POS_{RU(x)}(y)|}{|U|} \tag{1}$$

Figure 3 exhibits the steps that are used in the execution of the UQR algorithm. In this algorithm, C is the set of the entire conditional features and R denotes the reduced attributes or the set of decision features.

$R \leftarrow \{\}$
do
$T \leftarrow R$
$\forall x \in (C - R), \forall y \in C$
$\gamma_{RU(x)}(y) = \frac{|POS_{RU(x)}(y)|}{|U|}$
If $\overline{\gamma_{RU(X)}(y)} > \overline{\gamma_C(y)}$
$T \leftarrow RU\{x\}$
$R \leftarrow T$
Until $\overline{\gamma_{RU(x)}(y)} = \overline{\gamma_C(y)}$
Return R

Figure 3: UQR algorithm

3.3 Summarizing

After the needed information is extracted, it is summarized. A summary is generally a brief version of the original text. It must also be noted that a summary is a compressed version of the main document that contains all the relevant and important information. Summarization should be made in a perfect manner in order that the multiple-choice questions (MCQs) are correctly framed from the summary. If the summary is not generated in a proper manner, then the system performance will be affected as a whole.

In the proposed system, the summarization indicates the compilation of sentence which can be created as MCQs utilizing the preference learning with the aid of MSO. The MSO augments the relevancy score and computation cost of the text summarization process. The usage of optimization is informative because the questions must be created from the significant part of the domain. In addition to this, the sentence must have sufficient information to generate the possible key (answer) of blank place in the question.

The MSO algorithm starts with the initialization of the requisite parameters. The text document is the input for this algorithm. The output is the summarized document. The algorithm initially checks that if a query is existent or not. If a query is detected from the domain, then each query is processed. The position and the velocity of the query are updated as those 2 variables are the indispensable parameters of this algorithm.

The updated values are used to generate the updated solution. The best value is selected by performing multiple iterations. The algorithm stops when no more queries are there to be processed. The summary is generated in a proficient and quick manner. Fig 4 proffers a detailed notion of the MSO algorithm.

Input: Initialization of the text document t_d

Output: Summarized document s_d

Begin

  if a query is detected in the domain, **then**

    f**or** each query i in the domain c

    do $pbest_i = p_i$

    end for

  else

    for each i in the domain

    do

    Update the query velocity and position

    $p_i(t+1) = p_i(t) + v_i(t+1)$

    $v_i(t+1) = wv_i + c_1 r_1(pbest_i - p_i(t)) + c_1 r_1(pbest_i - p_i(t))$

    Update $pbest_i$

    for each domain c **do**

      if $difference(p_i, cbest_c) < r$ **then**

      if $f(p_i) > f(cbest_c)$ **then**

      $cbest_c = p_i$

      End if

       Reinitialize query i

      End if

      $cbest_{domain} = \arg\max_{pi \in domain}(f(p_i))$

    End for

    End for

  End if

End

Figure 4: MSO Algorithm

3.5 Creation of Blank and key

The creation of a key denotes the generation of an answer to the existent questions and it is performed utilizing an SP. It must be feasible to find the key utilizing the residual portion of the sentence. The key must be generated in such a manner that it is not easy for the students to guess it. The POS <P> tag represents that each sentence in the summary is a question. It contains nouns, proposition, and adjectives. The blank spaces in the sentences have to be replaced with proper nouns, adjectives or common nouns at the start or end of the sentences. This task is carried out by the SP algorithm. The input to this algorithm is the questions and the output of this algorithm is the key for blank space.

$$\overline{X}^{(i)} = \frac{1}{M_i}\sum_{j=1}^{M_i} x_j^{(i)} \tag{1}$$

Where M_i is defined as the total count of words in the i^{th} summary. $x_j^{(i)}$ is defined as the word vector length. $\overline{X}^{(i)}$ is defined as $N \times 1$a vector. Similarly, a K sentence is defined by $N \times 1$a vector as given below.

$$\overline{X} = \frac{1}{K}\sum_{i=1}^{K} \overline{X}^{(i)} \tag{2}$$

All the words that are considered are taken as a column that is defined over $N \times (\sum_{i=1}^{K} M_i)$ matrix V :

$$V = [c_1 x_1^{(1)},\ldots., c_1 x_{M_1}^{(1)}, c_2 x_1^{(2)},\ldots, c_2 x_{M_2}^{(2)},\ldots c_K x_1^{(K)},\ldots, c_K x_{M_K}^{(K)} \tag{3}$$

Where, c_1, signifies the similarity factor that lies betwixt 0 and 1. The correlation matrix forms the key (answer) to the question. It is denoted as R for all the words existent in the sentence that is defined with $(\sum_{i=1}^{K} M_i) \times (\sum_{i=1}^{K} M_i)$

$$R = V^T V \tag{4}$$

Correlation matrix betwixt words of a i^{th} summary is provided here.

$$R^{(i)} = V^{(i)^T} V^{(i)} \tag{5}$$

The subsequent steps are formulated for the augmentation of the algorithm. These steps are utilized to discover the distracters of the question. The covariance matrix is symbolized with other opinions S utilizing $(\sum_{i=1}^{K} M_i) \times (\sum_{i=1}^{K} M_i)$ matrix.

$$S = W^T W \tag{6}$$

Where W indicates a column vector. The mean values of the vectors of words are subtracted as proffered below.

$$\Delta = \overline{X}^1 - \overline{X}^2 \tag{7}$$

$$S_1 = \sum_{i=1}^{K} P_i [\overline{X}^i - \overline{X}]^T [\overline{X}^i - \overline{X}] \tag{8}$$

$$S_2 = \sum_{j=1}^{M} [X_j^i - \overline{X}^i]^T [X_j^i - \overline{X}^i] \tag{9}$$

Where S_1 and S_2 represent the other choices that must be similar to the key. The second and third preferences of the blank in the question which are closer to the key are given as the above equations. The proposed work focuses on increasing the speed of the search space and extorts information as of the web page by utilizing UQR algorithm. Then, the extorted features are summarized using MSO for creating the MCQs effectively. SP is used for creating the choices of the question for enhancing the knowledge of the users.

4. EXPERIMENTAL RESULTS

The proposed MSO based automated ontology for e-assessment is employed in the working platform of JAVA. The machine configuration is:

Processor: Intel i5/core i7
CPU Speed: 3.20GHz
OS: Windows 7
RAM: 4GB

4.1 Performance Analysis

Automated ontology was developed from a user required domain in the context of e-learning and assessment. The proposed method overcomes the challenges in the context of e-learning and assessment. Initially, the extracted information from the web page is taken. Then it is summarized. Then the formation of a question with blank and key is carried out. The proposed system is implemented utilizing the i) myCBSE guide and ii) MCQ quizzes databases. The experiential analysis is made by contrasting the parameters like accuracy, error rate, precision, and recall. The question creation satisfies the following properties.

- A sentence is associated to the user's domain
- A high standard question should be created
- All the questions have blank in a relevant location.
- A distracter is extremely nearer to the key.

a) Accuracy: It implies the percentage of precisely classified instances. It is the base metrics for performance and it ascertains how precise the classification prototype is in evaluating all classes.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{10}$$

b) Precision: It indicates the number of exactly classified positive instances divided with the count of examples that labeled as positive using the system.

$$precision = \frac{TP}{TP + FP} \tag{11}$$

Where, TP indicates the 'true positive', TN symbolizes 'true negative', FP implies 'false positive' and FN indicates 'false negative'.

c) Recall: It is computed by the division of the number of precisely classified positive examples and the count of positive examples in the data.

$$recall = \frac{TP}{TP + FN} \tag{12}$$

d) Mean Squared Error (MSE): It gauges the average squared error of predictions.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \tag{13}$$

Where, y_i is the actual expected output and $\hat{y}_i$ is the model prediction.

The following table evinces the performance metrics of the 3 disparate algorithms that are utilized in the proposed system. They are UQR, MSO, and the SP.

Table 1: Analysis of the performance metrics of the UQR, MSO, and SP

Metrics	**Extraction (UQR)**	**Summarize (MSO)**	**Key creation (SP)**
Accuracy	97.7	96.2	94.7
Precision	94.3	93.9	95.2
Sensitivity	95.8	95.3	94.3
Specificity	96.2	94.5	93.6

The tabulated values are plotted as a graph for better visualization and understanding. For the graph, it can be analyzed that the UQR has a propitious result as the performance measures are seen to generate elevated values. From table.1, the proposed system has 97.7% accuracy in extraction level, whereas, 96.2% accuracy in summarize level and 94.7% accuracy in key creation level. For all performance metrics, the proposed system produced good results. Figure 5 gives the graphical interpretation of the performance metrics utilized in the proposed system.

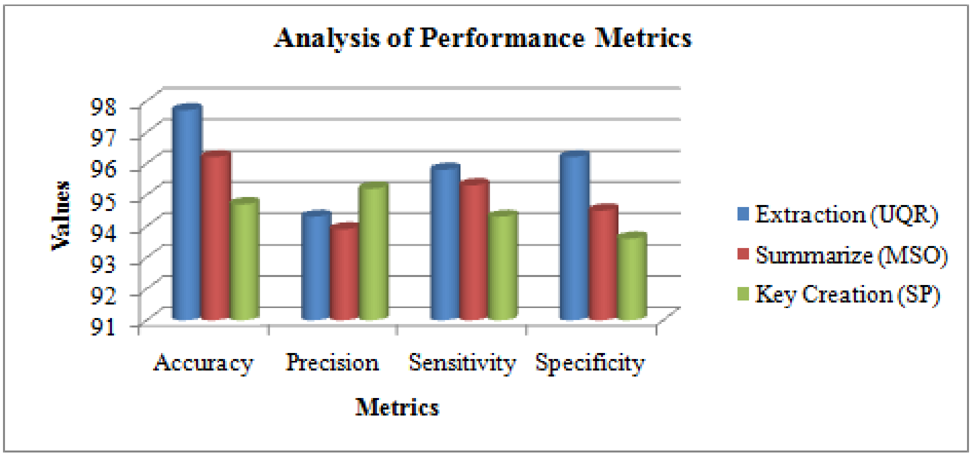

Figure 5: Graph showing the analysis of the performance metrics

The error rates have to be low for an effectual algorithm. The different categories of errors that are utilized in the analysis are the MSE, Relative Square Error (RSE) and the Relative Absolute Error (RAE). MSE measures the average of the squares of the errors. RSE is the absolute error divided by the exact magnitude. RAE is the average of the actual error values. The following table.2 delineates the error rates for the various algorithms that are utilized in the proposed system. From this table, it is obvious that, extraction UQR attains 17.9 MSE, summarize attains 19.7 MSE and key creation attains 20.2 MSE.

Table 2: Error rates for the algorithms used in the proposed system

Error rates	Extraction (UQR)	Summarize (MSO)	Key creation (SP)
MSE	17.9	19.7	20.2
RSE	21.4	20.3	22.8
RAE	23.7	24.5	26.3

Figure 6 delineates the graph that represents the various error rates in the algorithms that are utilized in the extraction of text, summarization, and key creation. The error rate is higher all along the generation of the key/answer.

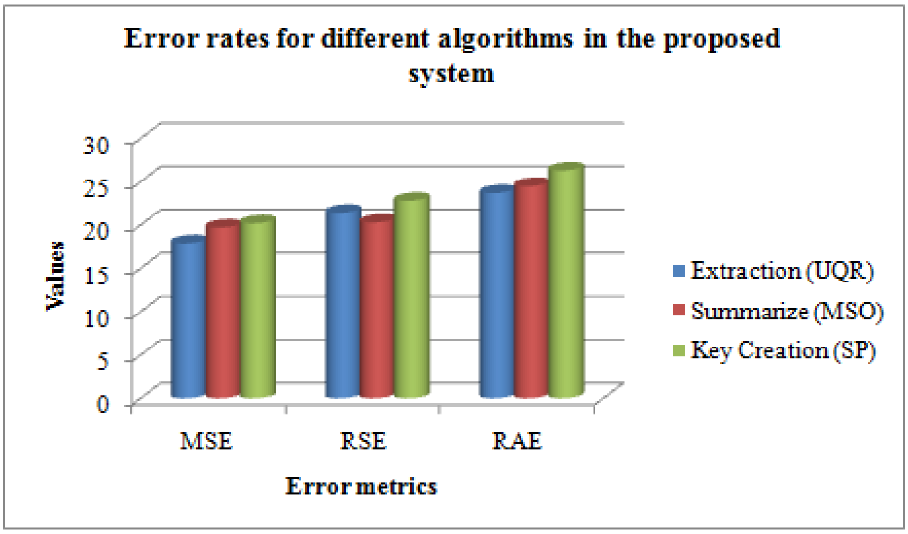

Figure 6: Graph depicting the error rates for different algorithms in the proposed system.

4.2 Comparative Analysis

Here, the proposed system is contrasted to various other prevailing algorithms. For this, the performance metrics like precision, sensitivity, accuracy, and specificity were computed. The algorithms that are taken for this analysis are the proposed MSO, Firefly along with Particle Swarm Optimization (PSO) algorithms. Table 3 delineates this analysis.

Table 3: Comparative analysis of the performance metrics

Matrix	MSO	Firefly	PSO
Accuracy	96.2	94.2	89.7
Precision	93.9	92.0	90.2
Sensitivity	95.3	92.8	87.9
Specificity	94.5	91.6	90.8

From the above table.3, it is evident that the MSO has superior performance when contrasted to the other 2 algorithms say Firefly and PSO. It is also perceived that the values of precision, sensitivity, accuracy, and specificity are the highest when contrasted to the other optimization algorithms. The proposed MSO evinces 96.2% accuracy. The subsequent figure delineates the above-tabulated values in the form of a graph.

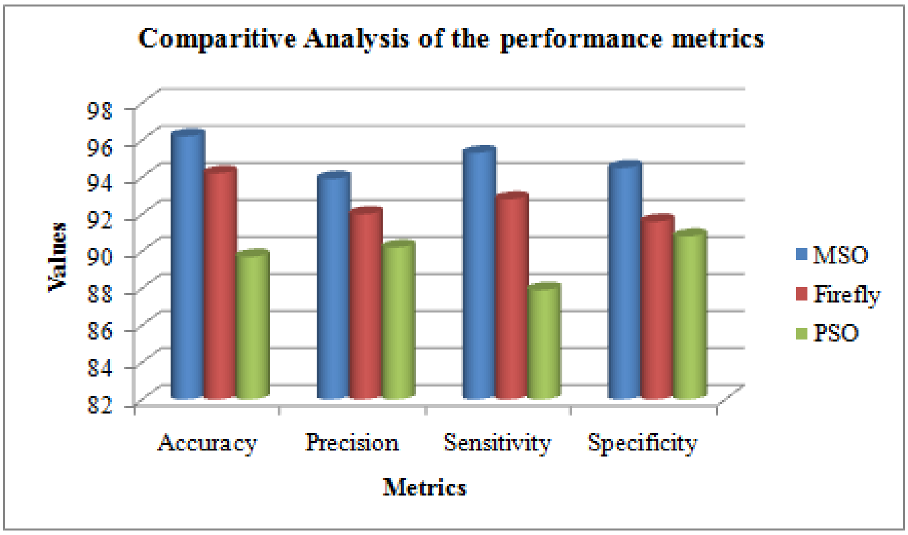

Figure 7: Comparative Analysis of the performance metrics

The error rates such as MSE, RSE, and RAE is computed for the proposed MSO and it is compared with two existing algorithms like the Firefly and the PSO algorithms. It was perceived that the MSE is less when contrasted to the other 2 algorithms.

The lower values of error rates in the proposed system bring elevation in the system's performance. Thereby, when the error rate is less, the performance is augmented. The error rate of the PSO is the highest when contrasted to the proposed system and the Firefly algorithm. This confirms that the proposed one has enhanced the level of performance when contrasted to the prevailing works.

Table 4: Comparative analysis of error rates

Error Rates	MSO	Firefly	PSO
MSE	19.7	20.9	22.4
RSE	20.3	21.7	23.9
RAE	24.5	25.9	29.1

The above table is formulated as a graph which is evinced in figure 8. From the figure, it is confirmed that the MSE of the proposed MSO is 19.7 whereas it is 20.9 and 22.4 for Firefly and PSO respectively. The RSE values of the 3 algorithms that are taken for comparison exhibit slight variations. The least value 20.3 of RSE is observed utilizing the MSO. The RAE values are computed and contrasted to the prevailing works. It was perceived that even RAE parameter was the least on contrasting to the other algorithms. All those factors justify the fact that the proposed system has propitious results and better performance when weighed against other related works.

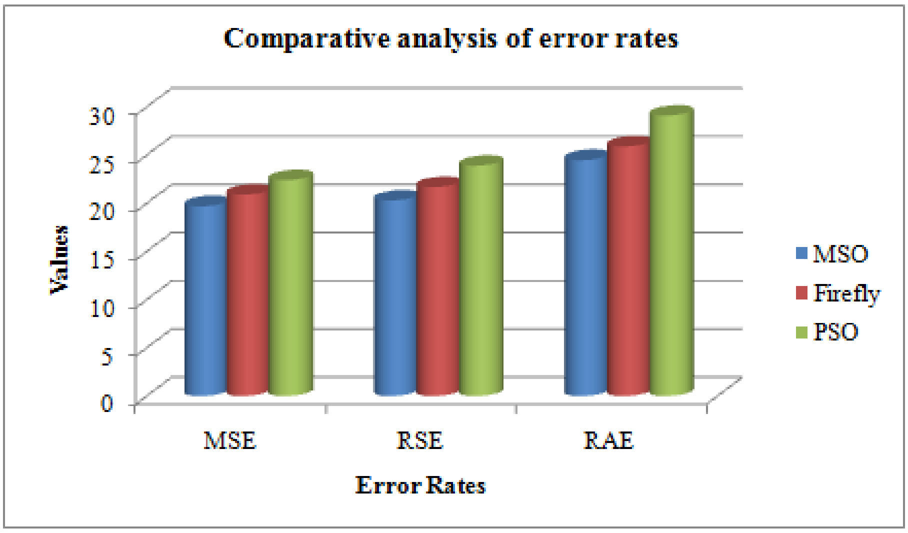

Figure 8: Graph showing the comparative Analysis of error rates

5. CONCLUSION

In this paper, automatic ontology is generated for e-assessment systems. The UQR algorithm was used for extracting texts from the web page. Summarization of texts was done using MSO algorithm. The key generation process was done using SP. The performance of the proposed algorithms was contrasted to the other prevailing works. From the experiential results, it is deduced that the proposed algorithms made the system more effectual. The performance metrics that are taken for the analysis are the error rate, precision, accuracy and recall and the attained results are compared. In error rate level, the proposed MSO has the least error of 19.7, which is better when contrasted to the PSO and firefly algorithm. Also, the proposed MSO attains 96.2% accuracy, but firefly attains 94.2% accuracy, and PSO achieves 89.7% accuracy. This work could be further extended with more enhancements in optimization.

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