Asian Journal of Information Technology 15 (22): 4500-4511, 2016
ISSN: 1682-3915

Mining Personalized E-learning System for Enhancing Learner Skills

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Abstract: In a traditional classroom when a good teacher observes that a particular student is finding some learning material to be hard to comprehend, he/she offers simpler materials and simpler explanations. The teacher comprehends the complexity levels of the available learning materials, customizes the set of materials offered to a student based on the classroom or homework performance of that student. In the age of open digital learning, available learning materials have grown by orders of magnitude. Also, the likelihood of a good human teacher paying direct attention to an average individual learner is very low now. Thus, it has become necessary to build automated systems that can comprehend the complexity levels of learning materials, so as to auto-select and auto-suggest suitable sets of learning materials for each individual learner. This study is an attempt to bring personalization into massive online learning by auto tagging the content of topics and courses and also auto-suggesting suitable materials based on the performance of the learner.

Key words: E-learning system, personalization, auto-tagging, ato-suggesting, individual learner, India

INTRODUCTION

These days, learners are frequently over powered with the expansive measure of learning materials accessible on the web. Notwithstanding spending time taking in the materials, learners are baited into investing more energy in perusing and separating to distinguish data that suits their necessities better either regarding information worth or inclinations. Restricted learning time can impede learners in finding valuable learning materials as frequently they may wind up getting unessential materials. One of the conceivable approaches to beat this issue is by utilizing recommender frameworks. A recommender framework is a product apparatus that backings clients in distinguishing fascinating things, particularly among extensive quantities of things. The prominent methodologies utilized as a part of recommender frameworks are community oriented separating, content based sifting and half and half separating. Communitarian sifting recognizes the fascinating things from other comparative client's assessments by ascertaining the closest neighbor (i.e., top N clients that have a comparative rating design) from a rating framework. New things that are important to the closest neighbor and that have not been appraised by the clients will be prescribed to them. Conversely, content based separating utilizes components of things to gather suggestions. Hence, forth things with comparable substance to the present survey thing will be prescribed to the dynamic client. Half and half sifting then again joins both substance based separating and cooperative separating strategies to deliver a proposal. Recommender frameworks in e learning can vary from various perspectives relying upon the sort of study to be prescribed, for example, course to select, learning materials, et cetera and whether the connection of learning is viewed as imperative while recommender frameworks have turned into a well known strategy for proposing things, communitarian and peer learning frameworks have additionally risen as a successful method for learning. Topping characterized peer learning as the procurement of information and ability through dynamic aiding and supporting among status parallels or coordinated mates. It includes individuals from comparative social groupings who are not proficient instructors helping each other to learn while learning themselves by so doing. Help and backing among associates can be exhibited from multiple points of view, for example, educating and/or sharing materials. Topping utilized the expression "peer partner" for somebody who is thought to be among the "best understudies" and who goes about as a surrogate instructor in a direct model of the transmission of information, from an educator to associate assistants to different learners.

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"Personalized e-learning system for enhancing learner skills" is a web application to provide virtual learning to the users. It provides flexible learning methodology where every learner can use the system round the clock, based on his/her interest. Personalization is provided here by considering two factors. First individual level of competence based on pre and post assessment tests. Second, technical and language based feedback taken from Learners on the provided material. Based on above analysis, this system will auto-suggest the relevant alternative documents with its level of complexity based on learners level. There by incremental learning is provided.

Literature review: The Personalized Instructing Recommendation System based on web mining (PIRS) system determines the sequence patterns from the web browsing history and different learning styles based on this result provide personalized recommendation to the web users by using an item based algorithm (Zhang *et al*., 2008). The SCORM standard is used to organize all the resources provided by the itinerary. It means detailed information about the resources and places it. This combination is used for teachers, experiments on learner behavior (Mor and Minguillon, 2004). To assist the auto recommendation for learners based on their navigation scheme (Wang, 2008). The usage of concept maps to identify the related information for the action (Nesbit *et al*., 2008). The learning is based on the summation of the user profiles and domain ontology. The association rules are playing major role in the selection of a course in a virtual environment (Guan *et al*., 2009). The concept maps and collaborative tagging algorithms are used to personalize their recommendation. Fuzzy theory and association and clustering techniques are applied to assess the supported learning materials in learning (Chen *et al*., 2004).

Serial Blog Article Composition PSO (SBACPSO) algorithm to provide most advantageous recommendations to users in blog assisted learning (Huang *et al*., 2009). To provide suggestions to the students by analyzing their test results and related concepts (Chu *et al*., 2006). Individualized learning paths are modeled by graph theory. The main problem is query and ranking problem, To enhance the personalized the tag recommendation using graph based ranking. Based the query results we ranking for the solutions and these solutions are suggest to the users (Guan *et al*., 2009). Compare the time complexity for pattern matching and the keyword tagging gradually it decreases (Kim *et al*., 2009). A document centered approaches are more proficient to prepare tag recommendations in an effective manner (Song *et al*., 2011). The sentiment based personalized system is used to address the problem in collaborative tagging (Xie *et al*., 2016).

In the material recommender system uses collaborative filtering with multi dimensional attributes. In sequential pattern mining method uses modified apriori is used to generate association rules and prefix span algorithms to find the pattern tree. Learner Preference Tree (LPT) is constructed based on the input taken from different learner's preferences and user rating for materials (Salehi and Kamalabad, 2013). The sequential based and ABR are combined with the cascade, mixed, weighted to generate final recommendation (Salehi *et al*., 2013). To improve the CF algorithm, so we work on genetic algorithm and K-NN and after evaluating the performance parameter are precision, recall are measured.

To avoid cold start and sparsity problems we introduce new similarly having two modules, the first module is represented about the weight of attributes are taken as chromosomes in a genetic algorithm for optimizing weights. This optimized weight is considered as learner's opinion according to the NNA. The second module deals about the preference matrix learner's interest based on explicit attributes of learning materials (Salehi *et al*., 2014). To analyze the Informatics course examination results using association rules, rank course topics following their importance for final course marks based on the strength of the association rules and which specific course topic should be improved to achieve higher student learning effectiveness and progress (Damasevicius, 2009). To make a realistic personalization of learning, data mining techniques were used which helps to manage big amounts of information mainly composed by contents, skills, tools, grades and students (Banu and Ravanan, 2011). It describes a hybrid approach which uses EDM and regression analysis to analyze Live Video Streaming (LVS) student's online learning behavior's and their performance in their courses. Student's participation and login frequency as well as the number of chat messages and questions that they submit to their instructors, were analyzed, along with student's final grades.

The data repository is collected from various resources such as log files, Quizzes interactive exercise, discussion forum, demographic data (gender, age and student's grades),student's behaviors, administrative data (school, teacher, region) and many other. In addition, these data have hierarchy level such as course, subject and topics. Time of access, time of observation (semester,

year), level (school, college), etc. This raw educational data needs to be converted into useful information. If handled very well, it will help the educational institute improve the teaching for both teachers and students. This systems can uses different recommendation techniques in order to suggest online learning activities or optimal browsing pathways to learners, based on their preferences, knowledge and the browsing history of other learners with similar characteristics. Their main objective is to adapt and personalize learning to the needs of each learner (Romero *et al*., 2007).

MATERIALS AND METHODS

Proposed work

Learner management module: In learner management module, learner performs the actions like registration/login, Course and topic selection,.

Registration and login: In order to use personalized e-learning System for enhancing Learner skills one should get registered if he is new by providing his details in order to provide authentication for learners. From subsequent usage learner can login with the details with which he already registered. Here we provide some security questions which are helpful to recover password when he/she forgot it.

Course selection: A set of courses are provided to the learners. They can select any of the course based on his interest. (Ex: C, Java)

Topic selection: After choosing the course, learner can select a topic which are disclosed. (Ex: if he/she chooses C, topics like Arrays, pointers, functions etc.,. are disclosed).

Assessing learner level: Firstly, select a topic in a course. learner takes the starter test which is treated as pre-assessment. Then a standard document will be provided for the learner. Once the document is gone through by learner, he takes post-assessment test. Also he provides feedback related to language and technical aspects for standard document. Pre-assessment, post-assessment and feedback of learner becomes the input for the Naïve Bayes classifier to assess learner level.

Document relevance: The keywords are will be like concept name, subject name, topic name, type for doc are given as input for the google engine and jaunt api is used to get the relevant links from the google. After extraction of all links documents will be downloaded to find relevance. Each document becomes the input for the cosine similarity calculation. This calculation creates a vector that represents a document in an n dimensional term space. The relevancy rankings between the documents are determined by measuring the angle between the vectors. The smaller the angle the higher the similarity values between the two documents. The items' similarity values are stored in the item similarity database. To find document relevance "Cosine Similarity measure" is considered. Cosine Similarity Measure is given by:

$$\text{similatrity} = \cos(\theta) = \frac{A.B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

By computing Tf-Idf in cosine similarity segregation of documents will be done as most relevant and moderately relevant.

RESULTS AND DISCUSSION

Complexity finder: Finding complexity for all relevance documents provided by the cosine similarity. For finding complexity of a particular document the following factors are considered Fig. 1-15 and Table 1.

These factors will focus on Publishing, Technical and English. By calculating syllables, Hard words, poly syllables, mono syllables, No.of sentences, No.of words, character count, Easy words, No.of letters from the document then the considered factors will be computed.

Auto-suggestion of Documents: Based on the learner level and complexity level of the documents, the system will auto-suggest the relevant materials.

Algorithm:

Step 1: Authenticating learner, by providing registration & login to the system.
Step 2: Offer subjects to the user. Based on his preference, he will select the subject.
Step 3: In this step, the learner will select the topic which he needs to study among the provided topics.

Table 1: Parameters to find complexity ofa document

Formula	Publishing	Technical	Language
Flash kinicaid	-	✓	✓
Flesch reading ease	✓	-	✓
Automated readabality index	-	✓	✓
Liensear write	-	✓	✓
Forcast	-	✓	✓
Smog	✓	-	✓
Coleman-liaue	✓	-	✓

Fig. 1: Login page

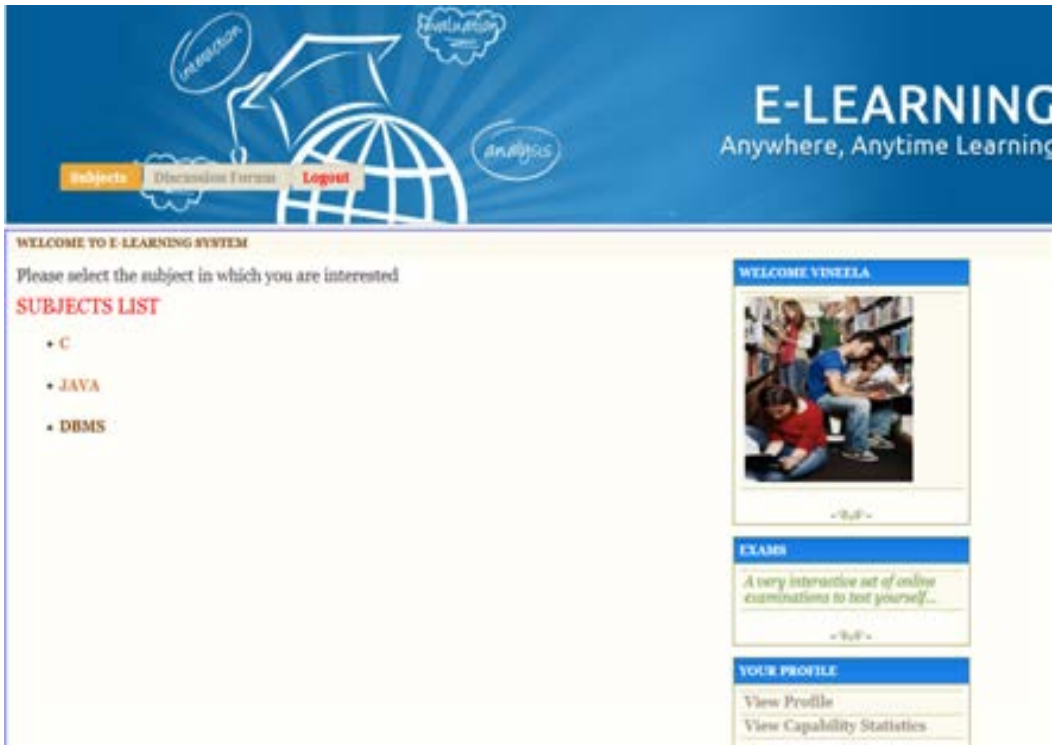

Fig. 2: Course selection

Fig. 3: Topic selection

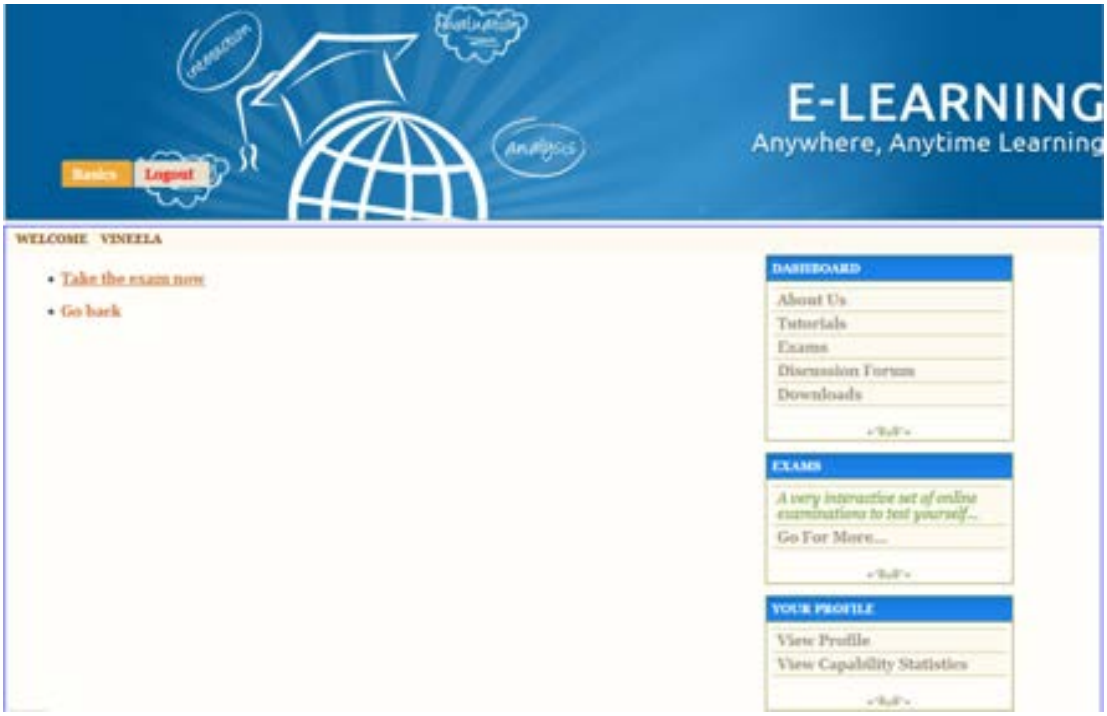

Fig. 4: Directed to pre-assessment test

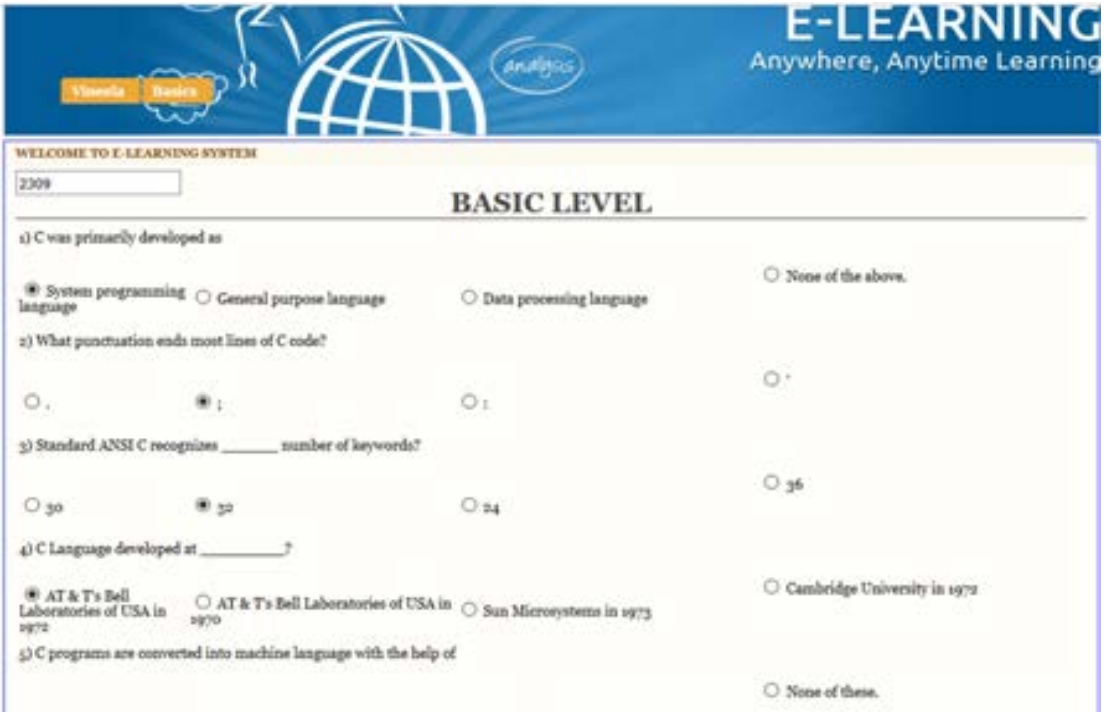

Fig. 5: Examination page

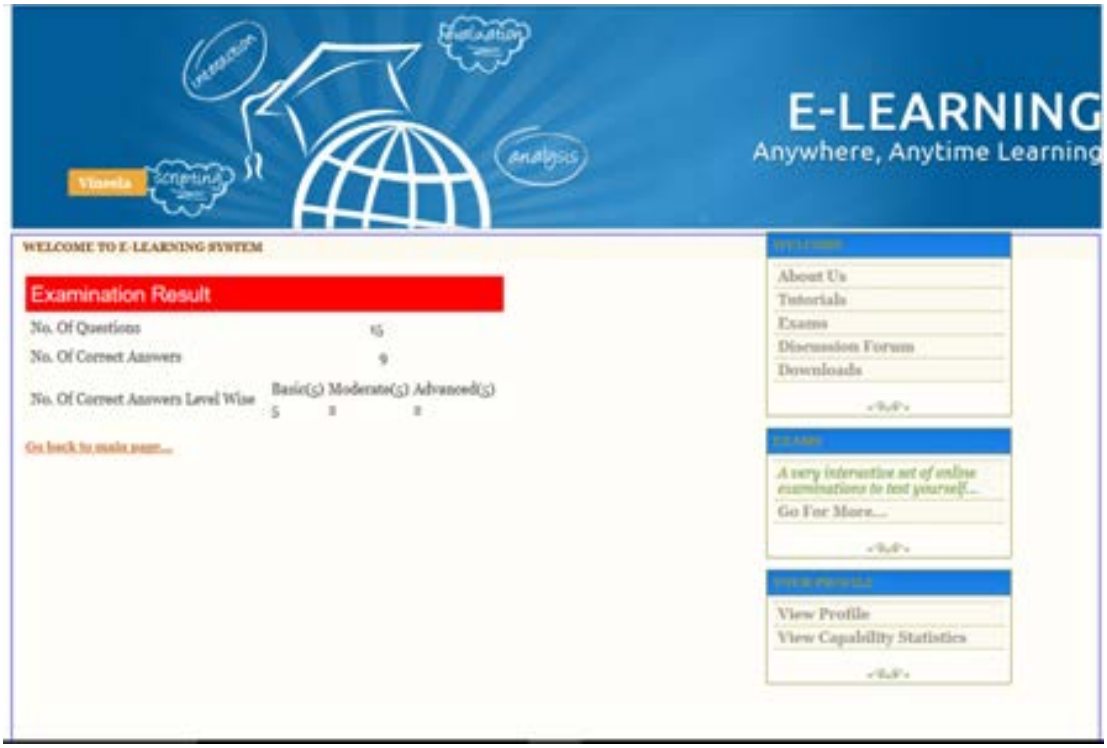

Fig. 6: Displays result for pre-assessment test

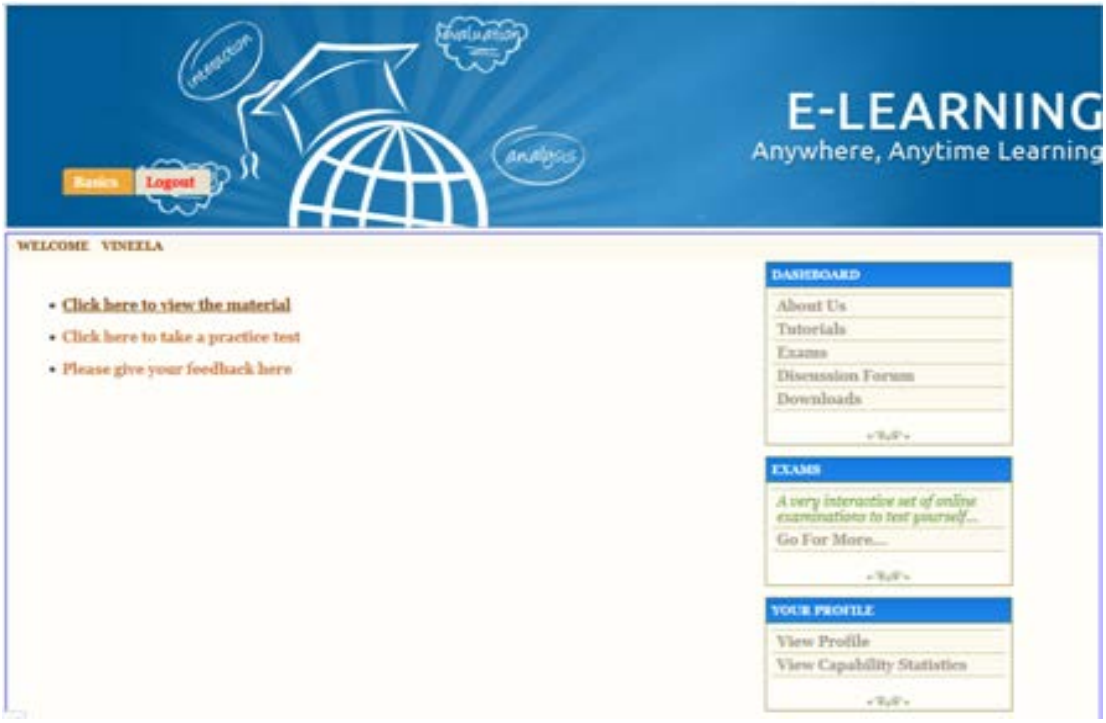

Fig. 7: Directed to standard document

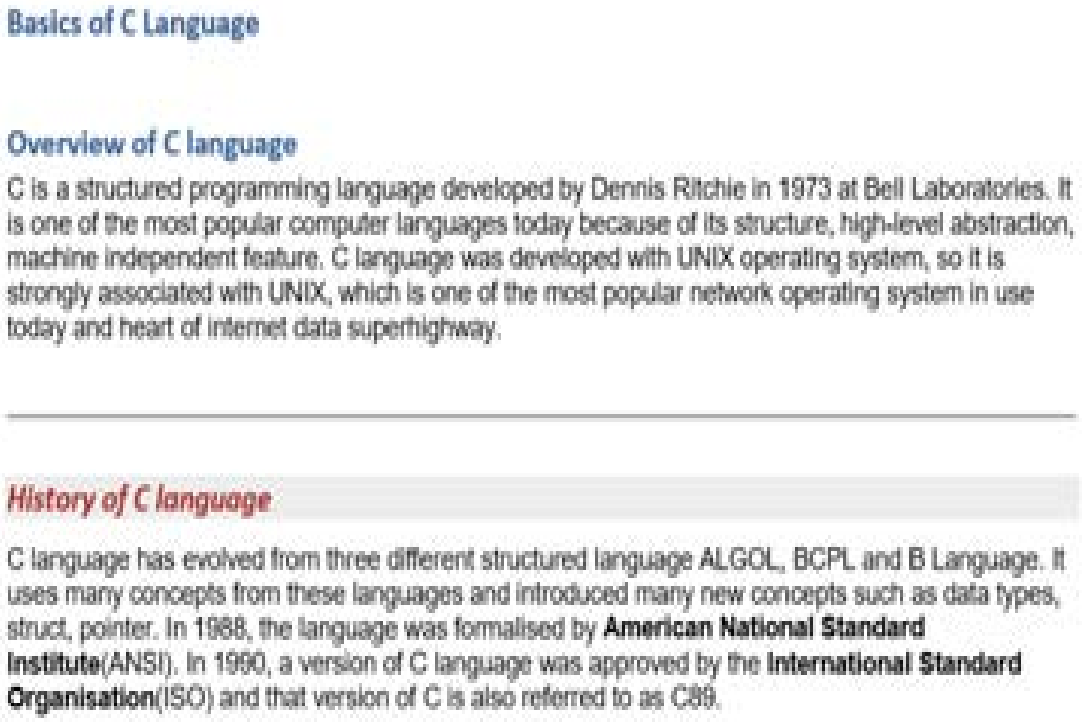

Fig. 8: Displays standard document

Fig. 9: Post-assessment examination page

Fig. 10: Displays result for post-assessment test

Fig. 11 : Feedback page

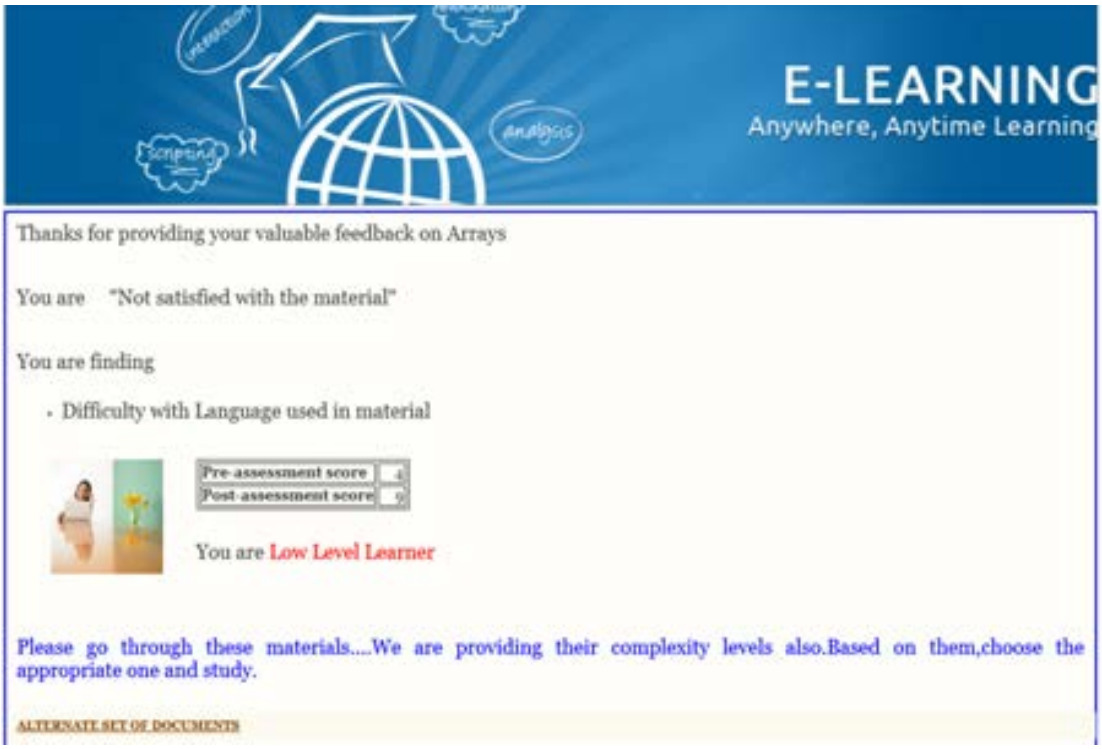

Fig. 12: Display learner level

Fig. 13: Auto suggest the documents

Fig. 14: Selection of alternative document

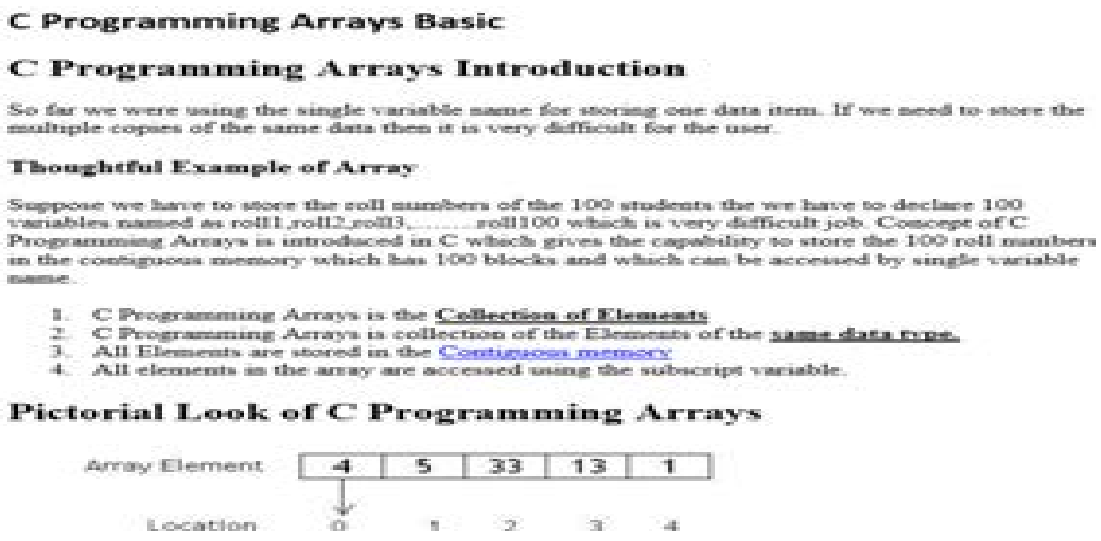

Fig. 15: Display material

Step 4 : For the first time, he needs to attend a pre-assessment test.
Step 5 : In this step, the learner is provided with a set of activities
Step 5.1 : Common material
Step 5.2 : Take post-assessment test
Step 5.3 : Provide feedback regarding Technical and Language aspects.
Step 6 : Now based on steps 4,5 the system will categorize the learner, by applying Naive Baye's Classifier algorithm.
Step 7 : Using Jaunt API, the documents relevant to selected topic are downloaded dynamically from the web into a specific user's folder.
Step 8 : From those documents, the system will segregate the most relevant documents by calculating similarity using cosine similarity measure.

$$\text{Similarity} = \text{Cos}(\theta) = \frac{AB}{\|A\|\|B\|}$$

$$= \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_t^2}\sqrt{\sum_{i=1}^{n} B_t^2}}$$

Step 9 : System will find the Technical and Language related complexity level for the documents obtained from Step8 based on some constraints like Flesch Reading ease, Flesch kincaid, Coleman-Liau, Automated Readability Index, Linsear Write, Forcast, Smog etc.
Step 10 : From Step 6 ,9 the alternate set of documents will be auto-suggested.

CONCLUSION

This study helps in auto-suggesting customized materials by assessing learner level, calculating complexity level of the documents.

RECOMMENDATIONS

Future research could access how our framework can be extended in including user interests into our document-centered approach and also to achieve more powerful predicative materials by using multimedia.

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