Machine Learning Based Improved Recommendation Model for E-learning

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***Abstract* - E-learning has gained importance due to the need of re-skilling, up-skilling, augmenting normal education system by providing knowledge delivery in virtual environment. A good E-learning system needs to have a customizable process, initiated by learner profile and dependent on training requirements. It can deliver desired results when it is integrated into day-to-day learning patterns providing a clear competitive edge for e-learning platforms. Learning needs to be relevant to the context of the concept. Learners in any learning environment differ in their learning style, level of knowledge, preferences, and attempts in solving and addressing problems when their expectations are not met. The current study illustrates and discusses a framework how machine learning (ML) technologies can be applied to e-learning systems to help the learner in selecting an appropriate learning course. Courses that require special privileges to be accessed can be handled according to the learner profile and learner's categories. In this paper, we present a comprehensive survey of current e-learning systems. Further an intelligent e-learning framework has been presented. The authors have applied 2 machine learning methods to the proposed framework and outcomes are discussed.**

Key Words - E-learning system, Learner profile, Learner category, Machine learning.

I. INTRODUCTION

The main purpose of e-learning is accessibility to users around the world in anywhere and anytime mode, and ability to find and select the appropriate courses with less efforts and minimum time. E-learning systems often suffer from a paucity of information, which can exceedingly obstruct the accomplishment of recommendation strategies. When a student searches the web as an attempt to solve a problem, he suffers from the large number of resources which are, in most cases, not related to his "needs", or may be related but complex and advance. The result of his search might make him more confused, scattered and finally result in wasting his time which -in some cases- may have negative effects on his achievements. In the current paper the authors review the evolution of e-learning approach. The concept of adaptive e-learning is discussed in section 2. An e-learning platform with intelligent recommendation approach has been proposed in section 3. This has been tested using K-means and Naïve-Bayes. In section 4, the results are analyzed and presented.

II. LITERATURE REVIEW

2.1 E-learning a personalized approach:

The conventional pattern "one size fits all" is unacceptable and inapplicable to all students. As suggested by Twyman, & Janet S. in 2014 [1] it conflicts with the emerging more convenient long-term learning styles and approaches of "competency based education".

Klašnja-Milićević, Aleksandra, et al. in 2011 [2] have studied the learners' learning styles in combination with mining the frequent sequences in the Web logs using AprioriAll algorithm. They suggest that if used in collaborative filtering approach, it has the potential to improve quality of e-learning system.

Collaborative learning using computer-based technology has been surveyed by Shawky, Doaa, et al. in 2014 [3]. For their effectiveness. They have suggested use of diverse technologies to provide personalized experience to learner. However, it is also noted that certain social characteristics of learners are missing in these technologies.

A learner based recommendation for e-learning is proposed [4] by Wan, Shanshan, and ZhendongNiu in 2016. To enhance the variety within a learner oriented recommendation system, immune-algorithm and multi-feature learner models are used by applying "mixed concept mapping", which is essential to obtain the learners' characteristics.

Generally, the concept of personalized-learning is viewed as the subjective education and assistance recommended to the learners that refers to blended learning scenario based on conjunction of many web-based techniques by McCarthy, B., and K. Schauer in 2017 [5].

An extensive review of methodologies to build "automatic tutoring system" based on learner profiling has been presented by Chrysafiadi, Konstantina, and Maria Virvou. 2015 [6].

The authors Garrido, Antonio, Lluvia Morales, and Ivan Serina in 2016 [7] present a method to generate sequent of e-learning paths that is built on "case-base planning techniques" using the compiled historical information.

2.2 Estimating and adapting to personalized style:

The authors Ouf, Shimaa, et al.in 2017 [8] suggest framework based on ontology to deduce the learner's model. Their model involves four layers to personalize the learning process based on behaviors and rational-controlled effects.

Some approaches are proposed to obtain the classification information immediately. The authors Zapata, Alfredo, et al. in 2015 [9] have used collaborative filtering methods within e-learning systems, considering the long-practiced and well situated learning platforms. The classification information can be acquired from the interacting rating enrollments. To acquire the learners' score and items, they have added "voting functionality".

The authors Dwivedi, Pragya, and Kamal K. Bharadwaj in 2013 [10] suggested a trust aware framework to identify learners which have more knowledge as well as similar learning styles like active learner as dependable learners. They have major weight regarding recommendation approach. The model as achieved by them depends on a “learners rating matrix".

Chen . Wei et al in 2012 [11] had suggested a hybrid method of item-based collaborative filtering and sequential pattern mining (SPM) algorithm for recommending useful learning items to users in a centralized and a Peer to Peer (P2P) online learning systems.

In 2018, Tarus, John K., ZhendongNiu, and Dorothy Kalui in their paper [12] suggested several combinations of “learner’s context awareness”, mining “sequential access patterns” with collaborative filtering algorithms to improve accuracy and personalized recommendation over traditional recommender systems that simply use content based and collaborative filtering (CF) with content features for similarity ratings.

“Collaborative tagging techniques” are implemented within a methodology proposed by Klašnja-Milićević, Aleksandra, BobanVesin, and Mirjana Ivanović in 2018 [13] to achieve online tutoring model.

2.3 Use of soft Computing methods in adapting E-learning:

An adaptive e-learning system is proposed by Awoyelu, I. O., O. A. Awosan, and E. R. Adagunodo in 2016 [14], using the “K-Mean algorithm” in the decision layer to select the course from collected data of student’s profile, performance and knowledge domain. The material is dynamically chosen in relation to the student's ability to understand the set of materials, and then according to the student's performance, the model changes the study manner automatically.

The proposed system by Vaishali, Fulpagare, et al. in 2016 [15] is considered as a new method of “fuzzy tree matching” depend on “ontology, M-tree creation, fuzzy logic, Pearson's correlation” in order to scrutinize the individual learner's needs more semantically. Moreover, they used a hybrid recommendation based on collaborative filtering is supported with “Pearson correlation” and “content-based recommendation” to introduce more recommended meaningful resource for the learner with high-precision outcomes. This algorithm is used which based on “Fuzzy Tree” to accommodate the desired learning since the massive amount of materials cause problem for varies system in their learning pattern.

A hybrid recommendation methodologies have been proposed by Wan, Shanshan, and ZhendongNiu in 2019 to personalize long-term learning experience in [16]. They apply varied e-learning recommendations for improving the satisfactions of learner, using an influence based learner model, which is independent of “rating information”. They have used the “self-organization theory” to generate the clusters of learners depend on the information propagation which effects on their dynamic interaction and collaborative behaviors. Moreover, the learners have different natures with respect to the uncertainty characteristics. Therefore, “Intuitionistic fuzzy logic” has been used to optimize their model.

A new method is applied to achieve the personalization in e-learning based on setting the correspond grade of the learning objects related to the learner's learning pattern by Christudas, Beulah ChristalinLatha, E. Kirubakaran, and P. RanjitJebaThangaia in 2018 [17]. They propose a new way using an adjusted model of “genetic algorithm” named as “Compatible Genetic Algorithm (CGA)”, which involves on the corresponding grade of the "learning objects”, which is related to the learner's knowledge level and measuring his/her interaction, and hence, a promising satisfaction score of learners is achieved during the learning process. The compatibility level of the learning objects is tuned with respect to the learning style of the learners' feedback. Since the “complexity level tuning” helps the e-contents instructors to design the adequate class of learning materials that fit the learners.

The authors Shawky, Doaa, and Ashraf Badawi [18] have suggested a framework to personalize an e-learning system. They use “reinforcement learning algorithm” to enhance the dynamic modeling, to account for the “continuously-changing students’ states”. It is more useful in this work to combine some procedures to optimize each “student-state pair", considering the taking a large number of “state-action” values in a way which doesn't reflect complication problems, as well as the advantage of applying the recursive training online.

There are many uncertainty behaviors of the learner which are complicated to analyze them entirely. A fuzzy methodology has been used to deduce uncertainty behaviors of the learner [19]. It has been found suitable to efficiently overcome deep-seated ambiguity, uncertainty, and individual character of the process of decision making.

“Fuzzy set theory” is applied in e-learning systems to address the fuzzy characteristics such as the uncertain feedback of learners, including the linking between individual learners' needs and groups of e-learning sources [20] despite the learner's intuitive way to selecting the materials as well as complexed and multi-dimensional.

III. PROPOSED SYSTEM

Deducing convenient preferences for a learner from a huge number of diverse knowledge resources is a complicated and strenuous task. This type of learning is based on the principle that each student is unique and has different background, knowledge level, learning needs, and learning outcomes than others. From here comes the need for an intelligent learning system that can guide students based on their needs. This study represents an intelligent educational recommender model for web-based learning environment which can provide meaningful recommendations for the most interested and relevant learning materials suitable to the students’ needs based on their profile.

A virtual learning platform is different from others domains. It has many peculiarities with overmuch technical combination, with each side supporting the other. The learner’s desire to try multidimensional learning must be considered in this environment, including knowledge successive and time continuation.

3.1 Learner Profile for Educational Objects Adaptive Model:

A student profile can reflect his active courses, achieved learning score and his level of knowledge. This can be obtained by using intelligent methods and via accessing students' history as well as similar students' experiences. For a satisfactory user's experience learning processes need to be fast and just-in-time. Speed is required to process large amount of student's data to select suitable content of the learning material (highly specified, not too general). Also, powerful intelligent mechanism needs to be executed for automatic matching such material with learner's category within reasonable time. These contributes to solve the problem of losing time finding the individual needs of materials from the huge of contents inside e-learning environments which will help students to stay focused.

An appropriate learning material differ from learner to another with respect to his/her cognitive level that is, efficiency status as well as capability to obtain the knowledge. To achieve the impact during the learning process, educational content must be selected in an adaptive manner, which is based on the individual features or the behavior of each learner. Also considering the similarity between many learners using the particular patterns may be useful.

3.2 The Proposed Learning Materials Adaptive-Selection Model:

This study proposes a model for selecting appropriate educational materials to learners. Learner's behavior can be facilely observed on the web, and be very expressive, and reflects the traits of the learners. For example, persons surfing Python-programing books section of a website are mostly linked to Software-Concept. The learner's profile is related to his/her actions on the web. Learner profiling is the process of identifying your learner to reach them by achieving more levels of diversity in the e-learning environment, and to know their target and why they are in your website. Learner's profile is a set of information about a specific learner. The learner model is the most important component in an adaptive e-learning system, because of its ability to represent the characteristics of the learner according to which the learning system provides recommendations.

To develop a model that can learn how provide services need to reflect the reality accurately, each learner is linked to a set of concepts. This process can be done using a history of the learner, individual information, preferences and the learning styles. Many methods have been presented earlier in the field of learner profiling.

AI can be suitably applied to build this profile in an implicit way. We can find a student profile and categorize the students in a way that helps us to detect the kind of student interaction with the study materials and the activities according to their groups, or to suggest the students are less interactive in order to help them understand the material and find out their problems. (Figure 1) shows this architecture.

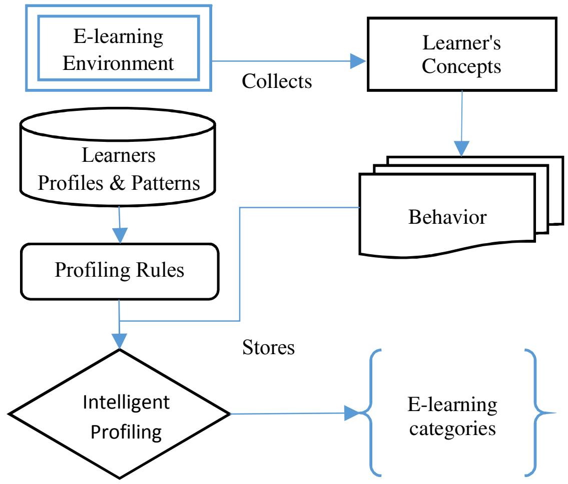

Figure 1 Structure of Automatic Profiling

It becomes necessary to facilitate the retrieval of resources through their indexing in order to meet the individual requirement of the students. Presently there are several ways to index the e-learning contents which hold a standard structure of metadata such as SCORM standard [21].

As for SCORM standard file content; all files are stored in html format, each html file is stripped to extract the text inside it, there is a relation between the location of each word and the its importance inside the document, but clearly that some kind of semantics are reflected through html tags. Considering this matter, the path of each word is considered to determine the weight of the word inside the document along with the frequency of its occurrence, i.e.: when the word appears in the title it is considered more important than when it appears in the body of the text. Some tags like the <TITLE> tag increase the importance of its children, whereas other tags like the <P> tag may reduce the importance of its children. HTML tags can be nested, each tag is related to a weight that it passes it to the descendants.

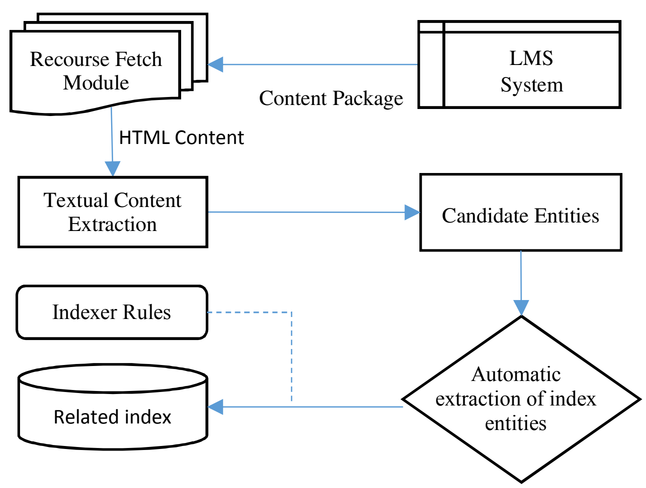

Figure 2 Structure of Indexing Content

It is clear that the weight of the word is linked to the weights of all the tags which included it, starting from root tag down to the direct parent of the word. We collect the content from as many sources as available in e-learning system, extract the importance of each word in each document, and index this content in our system which store these document and entities. Then these entities are linked to categories. Figure 2 illustrates the structure described. The content is collected from several sources available in e-learning system, and the importance of each word in each document is extracted, and this content is indexed in our system which store these documents and entities. Then these entities are linked to categories of learners.

3.3 Proposed Machine Learning Approach:

The model is based on the interests of the learner and semantic analysis of learning materials. The content of each learning material is processed, specifically the textual content is searched for entities and terms $\{t_1, t_2,\ldots,t_k\}$; we have selected 12 terms (scientific concepts). According to the framework in Figure-3, our objective is to apply a suitable machine learning algorithm to match the e-learning category to the e-learning content and to create a recommendation about the individual needs of a learner. In this work we have implemented two ML methods namely Naive Bays Classifier and K-Means Clustering. This whole experiment is done in Python environment using the Scikit Learn package.

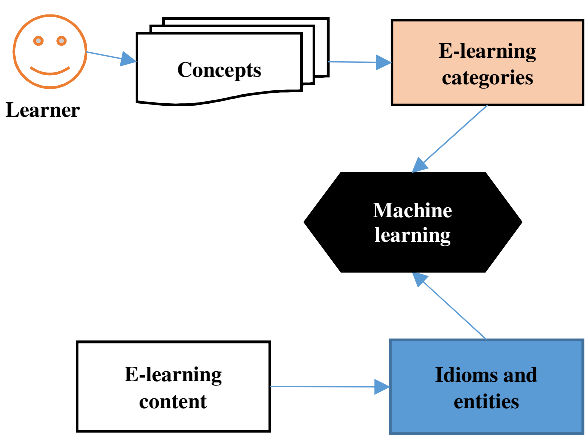

***Figure 3** AI-Based E-Learning Model*

To implement and evaluate the model, we have used a customized dataset which we have generated through taking user survey data. We have used a google form in order to carry out the survey. Where, each learner is linked to a set of concepts. A total of 96 materials (mi) from several scientific concepts based on recommendation from 90 learners in our college that we have collected, which reflects the actual needs of a real learner. The learners are supposed to provide their choices in terms of text entries. Finally, a dataset is collected having 12 columns and 1500 rows. Where, the column values are meant to capture the data regarding frequency of the material selected by a learner from a particular concept. e.g. Material = {Web application, C-Programming, Python Programming, Java …etc.}, categories = {Software, Networks, Multi-media, Artificial Intelligence…. etc.}. For a single category, a number of materials are available. A learner has to choose how many materials which associates the category.

Some sort of preprocessing as well as cleaning is applied on the dataset. As the data is text, it has to be converted into numerical form. The same data has been used for building the machine learning (ML) model, but preprocessed separately for which Python libraries are employed.

For Naïve Bayes (NB) model; we calculate whether the terms and materials are associated or not. To convert data set into numerical, we have used the function "LabelEncoder().fit_transform()" , which allows to convert string into numeric mode in order to be in machine-readable form. Then (NB) model will choose the best representation for data set. For example: we have used the function "datafram['Term']=number.fit_transform(datafram['Term'])" that represents the term "Software" with the number "10", "Multimedia" with the number "8" and so on. In the current problem context, we apply Bayes theorem to calculate posterior probability $P(c|x)$ of class (content, category), as follows:

$$P(c|x) = \frac{P(x|c)\,P(c)}{P(x)} \quad (1)$$

Where, P(c) denotes the prior probability of content, P(x) denotes the predictor prior probability of category and P(x|c) denotes the likelihood of the class. From history of the data we compute the conditional probability between the categories and the content.

To illustrate the use of Naive Bayes algorithm to our current problem of matching the user categories to the content groups, we give an example; we have part of data set of categories and corresponding target variable 'content' (suggesting possibilities of content). Now, to perform it we define the association of e-learning categories and content groups as shown in Table I:

TABLE I. E-LEARNING CATEGORIES/CONTENT GROUPS

E-learning categories	Content groups
(A) Software Engineering.	(G_1) learning c-programing.
(B) Mathematics.	(G_2) Coursera - Software Modelling.
(C) Programing.	(G_3) NPTEL - Graph Theory.
	(G_4) NPTEL - Probability & Statistics.

To classify the learners' category, we choose the base data as shown in Table II.

TABLE II. BASE DATA OF CATEGORY/CONTENT

Category	A	A	B	C	B	A	B	C	A	B	B	C
Content	G_1	G_2	G_3	G_1	G_4	G_1	G_3	G_1	G_4	G_3	G_3	G_1

Then we convert this data set into a frequency table and create likelihood table by finding the probabilities in Table III. Thereafter, we use the Naive Bayesian equation, as in (1), to calculate the posterior probability for each class:

$P(G_1|A) = P(A|G_1) * P(G_1) / P(A) = 0.4 * 0.35 / 0.33= 0.42$

$P(G_1|B) = P(B|G_1) * P(G_1) / P(B) = 0.0 * 0.35 / 0.41 = 0.00$

(In this case "Zero Frequency", we can use the smoothing technique such as Laplace estimation)

$P(G_1|C) = P(C|G_1) * P(G_1) / P(C) = 0.6 * 0.35 / 0.25 = 0.84$

TABLE III. FREQUENCY/LIKELIHOOD TABLE

Frequency /Likelihood Table					
Learners' Category	**Content Groups**				
	G_1	G_2	G_3	G_4	**Probability**
A	2	1		1	0.33
B			4	1	0.41
C	3				0.25
Grand Total	5	1	4	2	
Probability	0.35	0.08	0.33	0.16	

The class with the highest posterior probability is the outcome of prediction. We note that the score of the third content is the largest, so the learner will receive the third content as it can fit his interests more likely.

In K-Means model; we have 12 Terms and 96 materials. Each material has to finds out which center it is closest to. Assumes terms and materials are real-valued vectors. Clusters based on centroids of points in a cluster, c. Reassignment of materials to clusters is based on distance to the current cluster centroids. Or one can equivalently phrase it in terms of similarities. We select K random terms $\{t_1, t_2 \ldots t_k\}$ as seeds. Until centroid positions don't change and a fixed number of iterations. For each material (m_i):

- Assign mi to the nearest Term t_j (cluster) such that distance (m_i, t_j) is minimal. Next, update the seeds to the centroid of each cluster.
- For each cluster t_j , $t_j = \mu(m_j)$

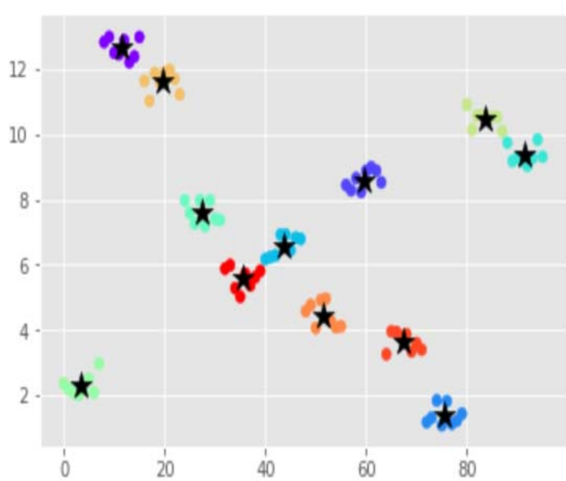

***Figure 4** K-Means Clustering Allocated to the Instances*

As it is illustrated earlier, we have 12 terms, where each one represents as a cluster and each cluster has 8 materials. To convert data set into numerical mode for using it as an input to our model, we have used function "random.uniform()" which allows us to generate random numbers (in our case 8 numbers for each cluster thus we have 96 materials for all clusters) in a range between 0 and 1, then we add a specific number. For example: we have used the function "data['Software']= np.random.uniform(0,1,8)+2". Figure-4 shows a graphical plot of the clusters that were allocated by the k-means clustering algorithm for learning material adaptability model.

Exceptional cases may arise when new user profiles category or new content group it introduced. In such case, the frequency table database can be adaptively updated for the new entries. Over time the model will be able to predict the desired content to a user profile with lesser error.

IV. RESULTS AND DISCUSSIONS:

In this proposed system we start with significant amount of past data of user profile category and content group usage. By using the above methodology, the frequency tables are updated. Once the learning phase of the Naive Bayes probability model stabilizes new and current user profile can be associated with content using the frequency table database. From the simulation results, the accuracy obtained for NB model is 80% and the accuracy for the same data set in case of k-means algorithm is coming around 91%. But it can be observed that, the testing time for K-Means is much more than that of NB model. This is due to the inherent characteristics of K-Means algorithm, which is known as a lazy learner as compare to NB. Table IV presents the accuracy got on test instances which are averaged on 10 iterations. Figure-5 represents the accuracy percentage obtained by both the model while tested on the same dataset.

TABLE IV. THE EXPERIMENTAL RESULTS

Average Accuracy% over 10 iterations for K-Means	Average Accuracy% over 10 iterations for Naïve Bayes
0.6666666667	0.619230769
0.70	0.722637363
0.8333333333	0.729615385
0.9166666667	0.730296703
0.9166666667	0.769318681
0.9166666667	0.789395604

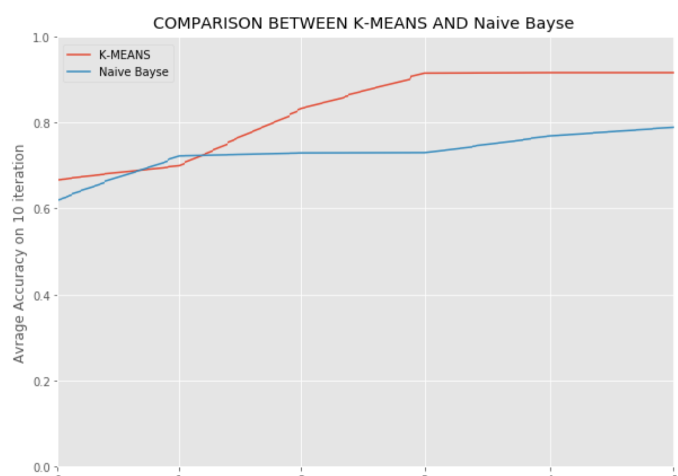

***Figure 5** Graphical Plot the accuracy for both Models*

Table-V demonstrates the values of testing time for new instances, which clearly shows the variation among two models. The graph for the same is provided as Figure-6.

TABLE V. TIME TESTING

Time testing in seconds	
Naïve Bayes model	**K-Means model**
0.4840207099914551	1.9674813747406006

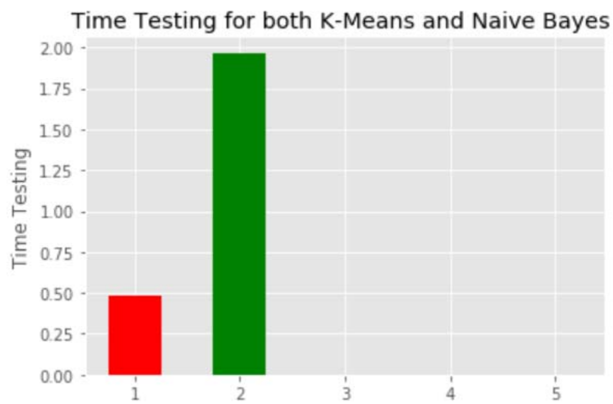

***Figure 6** Performance Evaluation of the Time Testing*

V. CONCLUSION

This paper presents an AI based E-learning system by incorporating intelligent support systems. Based on the need and aptitude of the student the learning materials could be chosen which will help both the students and the teachers to enhance the learning outcome as a whole. This work provided a means of providing a learning material adaptability model using Naïve Bayes classifier and K-Means clustering algorithm, which associates a user profile to a content group. The system learns in an unsupervised as well as in supervised mode by using the past data. We aim to show the benefits and results from the process of automatic student profiling, so that we can support current e-learning systems by adding new intelligent support systems that can provide improved association with the contents.

In future we will work on adapting a hybrid model to carry out our work for getting even promising results. We will also try to enrich our dataset to have a more adaptive model.

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