An Intelligent Assessment Mechanism of Asynchronous Discussion Posts

Chenn-Jung Huang, Shun-Chih Chang, Heng-Ming Chen, Chao-Yi Chen, Jhe-Hao Tseng, and Sheng-Yuan Chien

***Abstract*—In this work, an asynchronous learning platform that detects whether the learners address the expected discussion issues on asynchronous discussion boards is proposed. Concept maps related to the learning topics are first outlined by the instructor. After each learner presents a post on the asynchronous learning platform, a term weighting method is adopted to derive input parameters of a Support Vector Machines (SVMs) classifier. The classifier then determines if the learners' posts are related to the discussion topics. Notably, a peer review mechanism based on group intelligence is established in this work to improve the quality of the classifier. At the same time, a feedback module is used to issue feedback messages to the learners in cases where the proposed asynchronous discussion board detects that the learners have gone off on a tangent. The experimental results revealed that the 31 students in a junior high school participating in asynchronous online discussion activities related to natural science were benefited by the proposed learning assistance platform.**

***Index Terms*—Asynchronous discussion board, computer -supported collaborative learning, group intelligence, SVM classifier, text categorization.**

I. Introduction

Using the Internet as the transmission media, the development of an online discussion boards has its own distinctive characteristics. For example, students in lower learning achievement categories and learners with more passive learning styles can overcome their fear by participating in and discussing learning activities via using the online discussion boards. The instructor first specifies discussion topics, and then learners post their messages using the online discussion platform. In order to build up students' knowledge via the discussion, teachers have to examine whether the content of the students' posts is related to the learning topics. Accordingly, such an online platform cannot automatically assess the quality of the posts and the teaching load of the teachers is therefore not alleviated. Moreover, feedback to the students' posts cannot be provided until such time as the experts have finished their assessment.

According to Bandura's social learning theory [1], three elements, which are individual learners, peers, and learning situations, possibly affect individuals' learning performance. Furthermore, social learning emphasizes each individual's interaction with peers, as well as learning situations. Numerous web-based platforms have provided functionalities to promote learning interactions among online learners to obtain peers' support in web-based learning environments [2]. The popularity of social networking makes it possible to take advantage of asynchronous communication in the field of collaborative learning. Unlike face-to-face environments, when learners engage in social networking, they can take the time they need to reflect on their partners' contributions and think about their own posts before sending them off to their peers. For example, Nemec *et al.* [3] observed that a mixture of Facebook and applications whose features are like Facebook Groups or Chat could be a good supplemental tool in courses. Tu *et al*. [4] also conducted a case study of 36 college students to investigate the differences between face-to-face and Facebook friendship networks. Their findings indicate that gender gaps and peer group pressures are two significant differences between the two types of friendship networks.

Text categorization (TC), sometimes referred to as text classification or topic spotting, is the task of automatically classifying documents into categories from a predefined set. The content of a document is usually illustrated as a vector in the term space where terms consist of words, phrases, or any other indexing units used to define the contents of a text. A term weighting method represents how much a given term contributes to the semantics of a document, and is used to improve the effectiveness of TC. An inverse collection frequency factor is thus proposed in [5] to increase the term's discriminating power for TC purposes. A new and simple supervised term weighting method favoring high-frequency terms in the positive category was proposed in [6] to improve the terms' discriminating power for text categorization tasks. The experimental results showed that the new term weighting method consistently has better performance than traditional methods. Duan *et al.* [7] presented a supervised learning algorithm for TC based on a similarity search in the metric space of measure distributions in the dictionary, and verified the algorithm's effectiveness in the text categorization division of the 2012 Cybersecurity Data Mining Competition (CDMC'2012). Zheng *et al.* [8] proposed a method for TC based on a regularization extreme learning machine (RELM), where its weights can be obtained analytically.

We propose a tool which can effectively assist teachers by automatically examining whether students' posts address the learning topics according to diagnosis of students' posts. The learners' posts advanced during asynchronous learning activities were first processed via the post preprocessing unit and the term weighting computation module. Next, the extracted features were used as the inputs of a Support Vector Machine (SVM) classifier [9] to decide if some feedback messages with helpful suggestions should be given to the

Manuscript received June 13, 2014; revised August 21, 2014. This work was financially supported in part by the National Science Council of Taiwan under contract numbers NSC 99-2511-S-259-008-MY3 and 102-2511-S-259-010-MY3.

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learners. Next, we adopted SVM as our classifier because Sebastiani [9] proposed that SVM has better performance in the text categorization. Notably, a Facebook-like peer review approach was applied to improve the quality of the classifier, which is affected by the limitations of the term weighting method.

During the discussion, the proposed feedback module will show messages on the computer screen to prompt idle students, as well as those students whose discussion may not be related to the given topics. The design of the feedback module can guide those students whose posts are irrelevant to the given topics, in order to help them get on the right track and thus improves the classification accuracy. The experimental results showed the effectiveness of the application of text mining techniques, a SVM classifier, and the peer review approach to the implementation of an asynchronous discussion board used for a collaborative learning platform. In addition, this work can also alleviate the teaching load of teachers, and in doing so can allow them to spend more time and effort on designing teaching strategies.

The remainder of the paper is organized as follows. The details of the proposed asynchronous discussion board are presented in Section II. Section III reviews and discusses the experimental results. Conclusions and future work are described in Section IV.

II. Architecture of the Learning Assistance Platform for Asynchronous Discussion Board

A total of 31 junior high school students participated in asynchronous online discussion activities related to natural science. First, the course teacher introduced the principles of flying in a traditional teaching classroom, and then the students practiced folding flying paper airplanes according to three factors: how to fly straight, far, and stably. Before using the online learning assistant system, each student was asked to complete a pre-test to assess how many the students learned from the class and the practice activity. After that, the students were able to start to use the proposed learning assistance platform for asynchronous online discussion board to discuss how to make their paper airplanes fly straight, far, and stably. Finally, a post-test was administered to students to examine the performance of the proposed platform.

There are three purposes to this study, which examines the following research questions:

1) Does the proposed platform help increase students' learning performance with the assistance of the feedback module?
2) Do students learn after school with the assistance of the proposed asynchronous online discussion board?
3) Can students evaluate peers' posts with the design of the peer review module, based on the assumption that students can make correct assessments for peers?

As shown in Fig. 1, five major components are proposed in the proposed e-learning platform, including the curriculum support module, the post preprocessing unit, and term weighting computation, classification, and feedback modules. The keywords were first extracted by the platform from the students' posts after students posted their posts on the discussion board. Next, the extracted keywords were substituted by synonyms recorded in the keyword mapping table database. The term weighting computation module calculates the weights of the keywords, which are then used as the input vectors of a SVM classifier at the next stage. The SVM classifier detects whether a student's post is associated with the discussion topics given by the teacher, which are stored in the concept map records database in advance. Notably, it is possible for the classifier to misjudge a good post as a bad one if none of the keywords extracted from the student's post are found in the concept map records database. We thus adopt a peer review approach to evaluate each post and force the classifier to be retrained if the evaluation by peer review differs from that of the classifier. The feedback module will then determine if it is necessary to send a feedback message from the feedback message database to the student, according to the classification results. In addition, a teacher can check each student's post from the students' post records database whenever necessary.

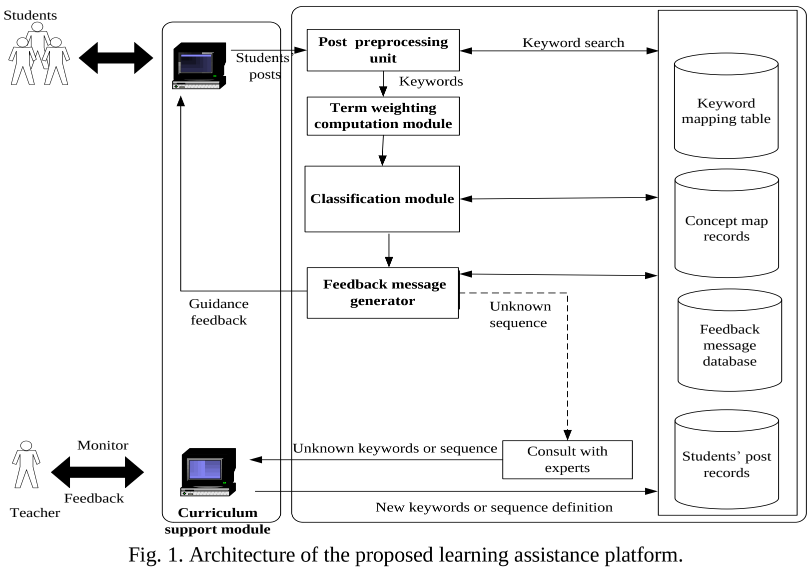

Fig. 1. Architecture of the proposed learning assistance platform.

A. Curriculum Support Module

The user script in the curriculum support module is shown in Fig. 2. Students can discuss the given topic in the discussion area in the left part of Fig. 2. Meanwhile, each user can choose one sentence and select which concept it relates to, including how to fly far, how to fly straight, and how to fly stably. Next, the user can determine the agreement scale of this selected sentence as any one of the following: “Agree”, “Strongly Agree”, “Disagree”, or “Strongly Disagree”. Notably, the curriculum support module not only supports teachers and students in collecting the supplementary learning materials, but also allows teachers to establish the discussion topics on the discussion board. Besides, a teacher can directly join into the discussion with students. Each student’s post and the messages of peer reviewers can be obtained from the system database by teachers. When the results from the SVM classifier and the peer review do not correspond to each other, a teacher will be asked to make the final decision.

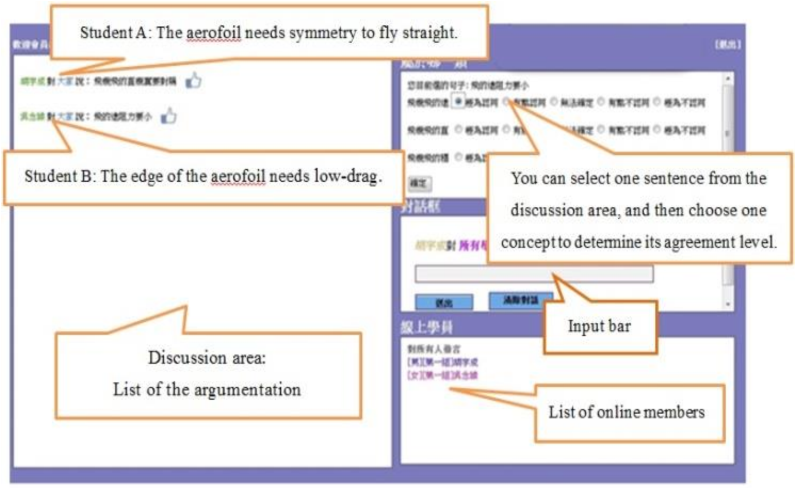

Fig. 2. Curriculum support module.

B. Post Preprocessing Unit

Learners may use different words or terms to represent the same meaning. For example, the noun “機翼” (aerofoil) or “飛機的翅膀” (wing unit) are all related to the meaning of “the wing of the airplane”. Therefore, it is necessary to build a Chinese synonym database. Before processing word segmentation, all synonyms are substituted by the unitary word to ease the complexity of the subsequent analysis.

Here, we adopted Chinese Knowledge and Information Processing (CKIP) system developed by Academia Sinica in Taiwan to construct the segmentation of Chinese words for further processing [10]. The pre-processed sentences will be uploaded to the website of CKIP system, and then the results of segmentation will be sent back to our proposed system. Then keywords were extracted by deleting stop words, i.e. words which are filtered out prior to, or after, processing of natural language data (text). These are some of the most common, short function words, like “這個” (this), “那個” (that), “是” (is), “在” (in, on, at), and “一” (one, a, an). We have to process this step because these stop words that are not directly related to the discussion topics appear frequently in the sentences.

C. Term Weighting Computation Module

Term weighting methods have been widely studied in text categorization (TC) to represent the importance of a term contributing to the semantics of a document. For example, a term weight computation method that prefers high-frequency terms in the positive category was proposed in [6] to improve the terms’ discriminating power of TC. The experimental results showed [11] that the new term weighting method achieves better performance than traditional ones. The weight of a specific term is calculated by multiplying the relevance frequency of a specific term with the number of this term’s occurrences in the documents, and the relevance frequency of a term is defined as,

$$RF = \log_2\left(2+\frac{p}{Max(1,n)}\right), \tag{1}$$

where p denotes the number of documents in the positive category that contain a specific term, and n represents the count of documents in the negative category that contain this term. Notably, a minimal denominator is used to avoid the occurrence of a zero divisor. Besides, two is placed as the first term on the right-hand side of the equation if there is no document in the positive category that contains this specific term.

In this work, each student’s post was graded by the course teacher during the training stage, and by another assistant Science teacher (who was also involved in the design and administration of the survey in this experiment) who graded the posts afterwards. These two teachers’ grades for each student corresponded with each other. The grading criteria were used to determine if a student’s post is related the topic or not, which means that it is not difficult to determine whether a student’s discussion is related to the main topic. The grading showed the degree of relevance between the posts and the expected discussion topics. To suit our needs, we revised the method presented in [6] to comprise four weighting levels transformed from the grades given by the teacher. The final weight of a specific term is then obtained by,

$$TW=\left(\sum_{i=1}^{p+n} WL_i \cdot TF_i\right)\cdot RF, \tag{2}$$

where p denotes the number of documents in the positive category that contain a specific term, and n represents the count of documents in the negative category that contain this term. WL_i stands for weighting level of the ith post graded by the teacher, and TF_i denotes the term occurrences of the ith post.

D. Classification Module

Similar to the approach taken in [6], the weights of the terms obtained from the term weighting computation method are fed into a SVM classifier during the training stage. The extracted features from the training sample posts as given in () were used to train the SVM classifier in turn. During the online discussion, each student's post will be fed into this SVM classifier to get an evaluation result.

As observed from sample posts, students' posts might include keywords that were not recorded in the sample database. In fact, this could very likely happen when the number of samples is limited. Accordingly, the weights obtained by using the term weighting computation method caused some misclassification in terms of results. Inspired by Facebook, we designed a Facebook-like peer review approach to adopt students' viewpoints into the decision making of the classification module. In the next sub-sections, we will describe the operations of the SVM classifier and the peer review module.

1) SVM classifier

SVMs have recently been gaining in popularity due to their numerous attractive features and impressive empirical performance [12]. The main difference between the SVMs and conventional regression techniques is that the former adopt the structural risk minimization (SRM) approach, as opposed to the empirical risk minimization (ERM) approach commonly used in statistical learning. The SRM tries to minimize an upper bound on the generalization rather than minimizing the training error, and is expected to perform better than the traditional ERM approach. Moreover, the SVM is a convex optimization, which ensures that the local minimization is the unique minimization.

2) Peer review module

In this work, the students in a class are assigned into groups. After a student posted an argument on the platform, the peers at the same group can press "Flag" button on the Facebook-like platform if the posted argument was related to discussion issues specified by the teacher. The peer review module then collected the peers' comments and made decision if the posted argument is indeed related to specific discussion issues. The peer review module is operated as follows.

Step 1: When the SVM classifier determines that a student's argument does not belong to the positive category that is related to the specified discussion issue, this module first decides if we should pay much attention to student's comments by using the following equation,

$$IF_H = \sum_l w_l - \sum_k w_k < \theta, \tag{3}$$

where the first item on the right hand side of () represents the total weights of the students that press the "Flag" button, and the second item denotes total weights of the students that press the "Flag" button. Notably, the weight of each student is given by,

$$w_i = \max\left(W_{i,o}, \rho \cdot \frac{Arg_i}{\sum_l Arg_l}\right), \tag{4}$$

where i denotes the index of the student, and ρ is a preset constant. The initial weight of each student, *Wi,o*, is provided by the teacher. Each student's weight can be dynamically adjusted in () based on Arg_i, which is the number of arguments and comments given by each student related to the discussion issues. The denominator of the second term inside the parenthesis presents the total counts of the arguments and comments given by each student related to the discussion issues.

Step 2: If $IF_H < \theta$, the peer review module will assume that the student's argument is not related to the discussion issues. The algorithm stops.

On the other hand, we will believe that the student's argument is related to the discussion issues if IF_H is larger than the threshold θ. They the algorithm computes the weight value that the argument belongs to category H by using the following equation,

$$\mathfrak{R}_{j,H} = \frac{\sum_i(\mathfrak{R}_{j,i,H} \times w_i)}{\sum_i w_i}, \tag{5}$$

where j is the index of the argument, w_i is the weight of student i that presses the "Flag" button. $\mathfrak{R}_{j,i,H}$ is provided by student i. It represents the extent of the jth argument that is related to the discussion issues in category H. Notably, this module will provide sample article to the students that press the "Flag" button. $\mathfrak{R}_{j,i,H}$ is then obtained by checking if the students press "Slightly Agree", "Agree", or "Strongly on the argument that they comment.

Step 3: If $\mathfrak{R}_{j,H} < 0.5$, we assume argument j does not belong to category H. This algorithm stops. Otherwise, the argument belongs to category H and its weight is $\mathfrak{R}_{j,H}$.

Step 4: We compute the weight vector of the new argument that falls into category H by using (), and then train the SVM classifier by using the derived weight vector as the inputs.

Step 5: Next we attempt to adjust the value of the parameter ρ to train our SVM classifier behaves consistently with the peers' comments given by (). ρ can be adjusted by,

$$\min_\rho \left\{\sum_{i=1}^{C} \sum_l \left(\mathrm{SVM}_i\left(TF_{l,term} \cdot RF_{term}\right) - \kappa_{l,i}\right)^2\right\}, \tag{6}$$

where C is the counts of the categories that the argument can fall into, SVM_i is the SVM classifier of the ith category. Notably, the output of SVM_i is one if the argument falls into the ith category, and zero vice versa. Besides, $\kappa_{l,i}$ is determined by,

$$\kappa_{l,i} = \begin{cases} 1, \text{ if } \mathfrak{R}_{l,i} > 0.5 \\ 0, \text{ otherwise} \end{cases}, \tag{7}$$

Step 6: The weight of each student as given in () is adjusted after ρ is obtained at Step 5.

Step 7: Equation () is computed to check if the new weights of the students fit the previous classification results. The threshold θ needs to be adjusted if the new classification results are inconsistent.

E. Feedback Module

During the discussion, students may be distracted by external factors, or the sentences they type may not be related to the given topics. Therefore, the proposed feedback module will show messages on the computer screen to prompt idle students who do not type any words for a pre-set default time, as well as showing messages to guide those students whose posts are irrelevant to the given topics, in order to help them get on the right track. First, the feedback module analyzes each student's posts after the students have posted their posts on the discussion board. Next, the feedback messages retrieved from the corresponding entries in the feedback message database are provided to the student immediately, if such feedback is determined to be necessary. Finally, if the feedback module finds that the message prompts given to the student on the screen did not have the effect of guiding the student to input sentences effectively related to the given topics as expected, the system would take action to inform the teacher of the need to provide an additional feedback message in person. These prompts automatically pop up in order to remind students to be attentive to details, as shown in Fig. 3.

Fig. 3. Example of hints in feedback messages for posts irrelevant to topics.

III. Experimental Results

To verify the effectiveness of the proposed computer-supported collaborative learning platform, 29 eighth grade students in a junior high school were chosen to use the platform. After the teacher of a Natural Science course gave a detailed description of how to build a toy plane during a traditional classroom teaching activity, the students were assigned into separated groups and then worked together to make paper airplanes using pieces of plain A4 size paper.

The students were asked to login to the platform after classroom teaching activities finished, and received feedback messages whenever the platform detected that the students' posts deviated from the expected topics, all of which revolved around design issues. A question of how to build an aircraft to fly for as long (time) and as far (distance) as possible using a plain piece of A4 size paper was given. The students were expected to focus on the discussion of three main learning topics, including how to fly far, how to fly straight, and how to fly stably. Under the subtopics, the related concepts included the airfoil size, the center of gravity, the throwing angle, the throwing strength, and the shape of the airplane's nose. As shown in Fig. 4, concept maps that address the above-mentioned designed issues were established beforehand by the teacher and were stored in the database. The platform retained students' posts in the database and examined whether the students' descriptions were related to the design issues. Each student was asked to take a pre-test and a post-test right before and after the online discussion, respectively.

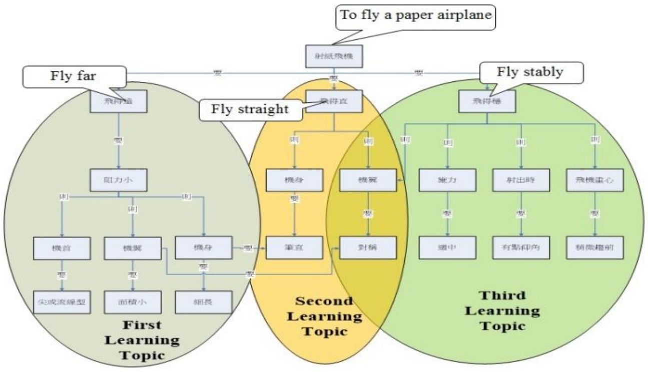

Fig. 4. Concept maps addressing the design issues.

384 sample posts, which were related to the learning topics were collected during the online discussion conducted via traditional classroom teaching and were used as the training samples for the SVM classifier. Notably, the evaluation results of the students' posts were also provided by the teacher after the experiment, and then were compared with the evaluation results given by the SVM classifier and the peer review module. Thirty-one students participated in the experiment and posted a combined total of 640 posts on the discussion boards. Table I and Table II show the confusion matrices of the SVM classifier and the peer review module; and Table III lists average successful recognition rates for the SVM classifier and the peer review module. We can observe that the classification rates for the SVM classifier and the peer review module can reach up to 97.66% and 98.91%, respectively. Notably, three posts that were incorrectly classified by the peer review module were correctly classified by the SVM classifier. In contrast, eleven posts that were incorrectly classified by the SVM classifier were correctly classified by the peer review module. Therefore, the effectiveness of the peer review module employed in this study is not only verified, but the overhead of the teacher or the teaching assistant resulting from the need for consultations at Step 8 of the peer review module was only slightly increased, because only 11 out of 384 posts needed to be arbitrated by the teacher or the teaching assistant. Furthermore, we analyzed the causes of incorrect evaluation given by the SVM classifier and observed that most instances of incorrect recognition resulted from students' typing errors. Since the platform issued annoying feedback messages owing to the incorrect recognition caused by the student's typing errors, we will attempt to avoid this where such messages are generated as a result of misspelling or mistakes in typing from happening in future work.

TABLE I: Confusion Matrix of the SVM Classifier

		Predicted class	
		Related to learning topics	Unrelated to learning topics
Actual class	Related to learning topics	114	6
	Unrelated to learning topics	5	259

TABLE II: Confusion Matrix of the Peer Review Module

		Predicted class	
		Related to learning topics	Unrelated to learning topics
Actual class	Related to learning topics	118	2
	Unrelated to learning topics	4	260

TABLE III: RECOGNITION RATE OF THE CLASSIFIER AND THE PEER REVIEW MODULE

	SVM	Peer review modification
Recognition rate	97.14%	98.44%

We then compare the students’ achievement before and after the online discussion. After examining each student’s pre-test and post-test, we found that there were three students whose grades were abnormal, due in part to these students not concentrating and being distracted by surfing other websites simultaneously with the exam or during the discussion. Therefore, we deleted these four data as outliers. The statistical results were obtained by running a *t*-test with the SPSS software package. As shown in Table IV, the average score received by the 29 pupils whose online discussion activity was supported by the proposed learning assistance platform is markedly demonstrably better than the average score received by pupils before using the platform. The evidence of highly significant correlation between the pretest and posttest listed in Table V and the high significance level as given by the results of the *t*-test in Table VI indicate that the learning effectiveness of the learners is indeed improved by the proposed learning assistance platform employed during the teaching activities.

TABLE IV: PAIRED SAMPLES STATISTICS

	Mean	Standard deviation	Standard error mean
Pre-test	52.42	15.66	3.24
Post-test	70.15	16.85	2.98

TABLE V: PAIRED SAMPLES CORRELATIONS

Correlation	Significance
0.432	0.018

TABLE VI: PAIRED SAMPLES TEST

Mean Difference	t	df	Sig.(2tailed)	95% C.I.	
				Lower	Upper
-17.73	-6.35	27	0.000	-27.52	-18.64

C.I= Confidence Interval, df= degrees of freedom

Notably, the teacher observed that the proportion of the students who were distracted from group discussion activity decreased substantially with the aid of the feedback module. Meanwhile, based on the teacher’s feedback, the proposed platform greatly reduced the teaching load of the teacher so that the teacher was able to spend more time giving individual guidance to the specific students that were falling behind or behaving inactively.

IV. CONCLUSION

Recently, cultivating the ability to construct posts through the practice of online discussion is an essential teaching activity in science education. To alleviate the teaching load of teachers, a learning assistance platform for asynchronous online discussion was proposed in this research, and therefore students can accomplish the online discussion task as their homework in the free time after school by any mobile device, like smart phones or tablet computers. The proposed work is able to automatically detect whether students addressed the related learning issues on a discussion board via the assistance of a SVM classifier and text mining techniques. Notably, a peer review algorithm is proposed to improve the performance of the SVM classifier. Once the system detects that students’ discussions strayed from the subjects in learning activities, a feedback rule construction mechanism provides timely hints or suggestions to the students to increasing the learning performance. The experimental results revealed that the proposed learning assistance platform proposed in this study effectively enhances the achievement of the sampled junior high school students participating in online discussion activities related to natural science.

82.76% of the students obtained better grades via the assistance of the proposed platform, while the other 17.24% of students’ post-test grades were not better than their pre-test grades. However, since the participants are junior high school students, it might be inferred that some of them are intellectually immature or otherwise not interested in learning. Some students showed passivity, and were behind their peers in terms of the learning activities. As for the students whose post-test grades were not better than the pre-test ones, we have to develop and enhance the functionality of the proposed system with an effective feedback mechanism to help students concentrate more diligently on learning and maintain a positive attitude.

In future work, we will consider combining students’ learning styles during the online discussion in order to provide adaptive feedback tailored for students with different learning styles. According to Grasha-Riechmann students Learning Style Scales (GRSLSS), learners are classified into six learning styles, including Independent, Dependent, Competitive, Collaborative, Avoidant and Participant. Alison and Lynn’s [13] study illustrated that working with others is important, and working with people from different backgrounds helps students to realize their own learning styles. In their experiment on group selection by learning style, the results demonstrated that the performance of the groups formed on the basis of balancing members’ learning styles, *i.e.* heterogeneous grouping, is much better than the performance of self-selecting groups. Huang’s studies [14] [15] also showed that groups being composed of members with all kinds of learning styles increases performance and effectiveness in terms of learning.

In addition, we will consider testing Latent Semantic Analysis in comparison with the proposed SVM classifier, and we would like to compare traditional teaching with the e-learning approach, as well. Next, we will also enhance the functionality of the peer review module, such as to add the function that students can evaluate their posts among peers, and not just determine if the discussion is related to the topic. A further research related to the improvement of increasing the quality of posts will be processed in future work.

Besides, we only used t-test to analyze students' achievement before and after the conducted online discussion activity, and we will add more participants engaging in online discussion activity to explore the factors which may affect the learning performance via our proposed e-learning assistant platform in future work. One limitation of this study is that the 31 students participated in this experiment to assess their learning performance before and after using the proposed system for a period lasting only one-month, due to the limitation of course time. In addition, pre-existing personal friendships between the participants and how these relationships might affect learners' social interactions have not been discussed in this study. Thus, further exploration of the impacts of social network interaction on enhancing online discussion, collaboration, and learning performance will be needed and considered in future work, as well.

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