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## Exploring the Reform of English Informatization Teaching and Micro-Class Teaching Mode in College Based on SVM Model in the Background of Big Data

Wen Sun<sup>1</sup>

### **Abstract**

*This research introduces the SVM model to examine the reform direction in order to increase the effectiveness of English informatics education reform in colleges and universities. Firstly, the optimal hyperplane is defined in the process of constructing support vector machines, and LS-SVM and BT-SVM algorithms are introduced. The kernel function of SVM is sorted out to determine its operation conditions, and thus the BT-SVM algorithm flow is obtained to facilitate the full-text algorithm work. The algorithm model simulation experiments are carried out to confirm the method's viability after outlining the technological methods. In order to further investigate the microlearning and informatization of English instruction in colleges and universities, the simulation experiment findings are employed. The results show that the average score of students' evaluation of teaching content is 90.8, teaching method is 88.5, teaching attitude is 85.7, and the average score of teaching result is 84.5, which is in a satisfactory state in general. The BT-SVM algorithm's accuracy rate in teaching processing is 98.72%, which contributes to increasing the effectiveness of the entire teaching evaluation process. Thus, it is clear that both the computation of teaching evaluation indexes and the efficiency of teaching processing are accurately and efficiently handled by the method presented in this study.*

**Keywords:** big data, SVM model, support vector machine, college English, microlearning model

### **Introduction**

In colleges and universities, English instruction is getting more and more attention. The single indoctrination teaching method, where the teacher is the center of the classroom and students can only passively rely on him or her for learning, has a number of drawbacks, including the gradual loss of students' own initiative and ability to think for themselves, which makes the absence of constructive communication between teachers and students problematic (Guo, 2021). Therefore, urgent reform of the outdated and boring English teaching methodology is required in the big data era.

The "micro era" was ushered in by the growth of Internet technology and the acceptance of mobile smart devices, so that the audience's access to information is no longer restricted by time and place, and micro lessons have emerged. According to the literature (Wang, 2022) (An, 2022), the micro-

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<sup>1</sup> Lyceum of the Philippines University, Manila, 0090, Philippines.

Corresponding author: Wen Sun ([sunwendaisy@163.com](mailto:sunwendaisy@163.com))

class teaching approach has given colleges and universities a direction for changing how they teach English hearing, speaking, reading, writing, and translation. The vast amount of information resources on the Internet can help students find the micro-lesson videos that fit their learning habits, thus increasing their enthusiasm for practicing speaking and getting rid of the traditional "high score and low ability, dumb English" teaching disadvantages.

The advent of "college English instructors" emphasizes how important it is for teachers to build their information literacy in the context of information technology, and the emergence of MOOCs and other teaching tools offers fresh suggestions for microcourses at colleges and universities. The initial sources of courses are also university-level courses offered by prestigious universities. As a result, the impact of MOOCs on higher education has become an important area of research. The literature (Li & Li, 2022) affirms the value of MOOCs in terms of technological development, high tuition fees for students in brick-and-mortar schools, funding crisis, and government policy guidance, and points out various challenges faced by traditional universities through comparison. The emergence of the flipped classroom has led to a new climax in the development of microlearning. The literature (Kong, 2014) indicates that the flipped classroom has become popular and is widely used in K-12 education and higher education, involving a wide variety of subject types, not only in "STEM" type teaching, humanities teaching, but also in English language teaching, language teaching. According to the literature (Hung, 2018), cooperative learning, inquiry-based learning, mastery learning, game-based learning, and other techniques are frequently utilized in the teaching of English as a second language. The features of active learning are reflected in all teaching strategies, notwithstanding their differences. The literature (Alsowat, 2016) states that research on information-based teaching should focus on whether its teaching methods significantly improve students' performance, engagement, satisfaction, and promote advanced thinking as well as independent learning ability. Studies in the literature (Chuang, Weng, & Chen, 2018) demonstrate that a student's gender, age, linguistic background, amount of desire, and starting English ability may all have a big influence on how well they ultimately learn. According to the literature (Abeyssekera & Dawson, 2015), learner satisfaction, which is described as students' attitudes or feelings toward learning activities, is one of the key criteria for determining how effective a teacher is and how well a course is being taught. It also implies students' motivation, expectations, and behavioral outcomes of learning activities. Microlearning transforms the way that English is taught through reading in colleges and universities by breaking up the most important and challenging passages into brief videos that teachers can use to explain further and break down the problems one at a time. This not only encourages students to think for themselves but also fosters positive classroom interaction (Teng, Lian, & Jiang, 2021). The SVM model is often used to explore the quality of teaching evaluation and its construction process. In three sections, this work imaginatively proposes to integrate the SVM model into the reform of college English teaching and the investigation of micro-course mode to examine the outcomes of micro-course teaching mode in the setting of big data.

The first part constructs the support vector machine, introduces the LS-SVM and BT-SVM algorithms and sorts out their algorithm principles respectively. The second part conducts the simulation experiments of the algorithms in this paper to check whether they are applicable to this study. The final section examines reform tendencies and evaluates the outcomes of microcourses and English informatization in colleges and universities.

## Support Vector Institution Building

### Optimal hyperplane

The support vector machine approach evolved from the linearly divisible case, and in this paper the concept of optimal hyperplane is illustrated with the two classification problem (Dinh, Nguyen, Tran, & Hoang, 2021). The difference between multiclassification and two-classification is that multiclassification can take more than one value, while the two-classification output has only two values.

Assumption

$$T = \{(x_1, y_1), (x_2, y_2), \dots, (x_l, y_l)\}, x_i \in R^n, y_i = \{-1, 1\}, i = 1, 2, \dots, l$$

where  $n$  is the spatial dimension and  $l$  is the number of samples. Finding a function that divides the sample into two groups is the goal of SVM training, which in a multidimensional space, we image as a classification hyperplane, can be described in mathematical language in the following form:

$$\omega \cdot x + b = 0 \quad (1)$$

Following categorization, the outcome is:

$$\omega \cdot x + b \geq 0, \quad y_i = 1 \quad (2)$$

$$\omega \cdot x + b < 0, \quad y_i = -1 \quad (3)$$

where  $\omega$  is the normal vector of the classification hyperplane and  $b$  is a threshold value.

In this case, the hyperplane may not be unique, and the classified hyperplane is shown schematically in Figure 1.

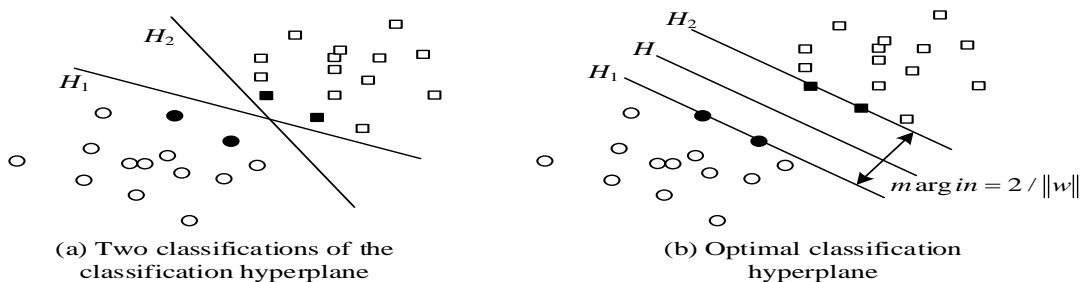


Figure 1: Schematic diagram of classification hyperplane

As can be seen from the figure, there is more than one hyperplane to achieve error-free classification, but among the many classification hyperplanes, SVM needs to find the closest point in the two classes of data with the largest distance to the hyperplane.

So that the obtained hyperplane has better generalization and generalization ability, and can ensure the minimum empirical risk, then the hyperplane that satisfies the above conditions is called the optimal classification hyperplane.

In Figure 1(b),  $H$  is one of the many classification hyperplanes,  $H_1, H_2$  is the closest classification hyperplane in the two spatial classes, they are parallel to  $H$ ,  $H$  is also closest to  $H_1, H_2$ , then the classification hyperplane  $H$  satisfying the above conditions is the optimal classification hyperplane we are looking for, the classification interval is defined as the space between points  $H_1, H_2$ . The mathematical expressions of  $H, H_1, H_2$  are:

$$H : \omega g x + b = 0 \quad (4)$$

$$H_1 : \omega g x + b = 1 \quad (5)$$

$$H_2 : \omega g x + b = -1 \quad (6)$$

Since the distance from  $H_1$  and  $H_2$  to  $H$  is  $1/\|\omega\|$ ,  $margin = 2/\|\omega\|$ .

### LS-SVM algorithm

Searching the hyperplane of the maximal boundary is the objective of a linear support vector machine, also known as a maximum boundary classifier. The decision boundary of the linear classifier can be expressed in the form of  $\omega g x + b = 0$  for training sample  $T = \{(x_1, y_1), (x_2, y_2), \dots, (x_l, y_l)\}$ ,  $x_i \in R^n$ ,  $y_i = \{-1, 1\}$ ,  $i = 1, 2, \dots, l$ , which in the two classification problem divides the training samples into two and classifies them into their respective classes. If there exist two samples  $x_1, x_2$  lying on the decision boundary, they satisfy:

$$\omega g x_1 + b = 0 \quad (7)$$

$$\omega g x_2 + b = 0 \quad (8)$$

The result of subtracting the two is:

$$\omega g (x_2 - x_1) = 0 \quad (9)$$

From the knowledge of spatial vectors, it is clear that vector  $x_2 - x_1$  must be parallel to the decision

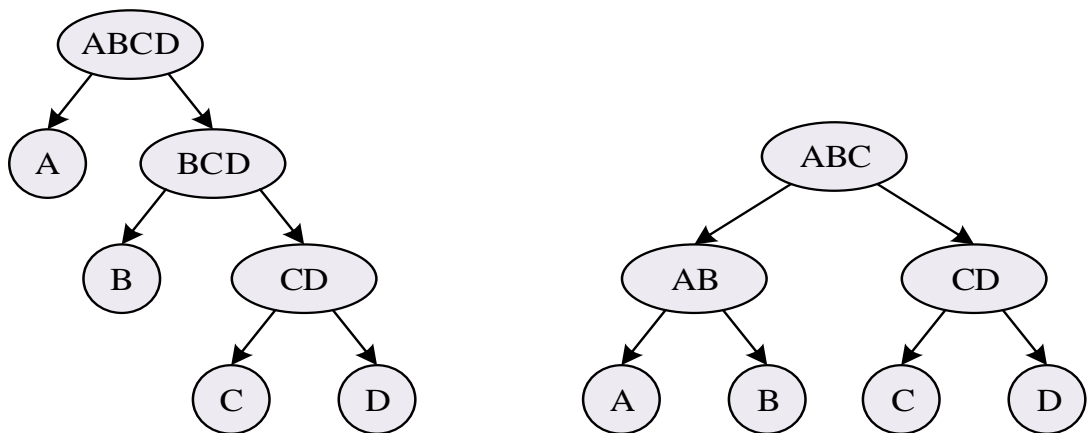
boundary in the direction of  $x_1$  to  $x_2$ . From Equation (9), it is clear that the dot product of vector  $\omega$  and  $x_2 - x_1$  results in zero, and the direction of  $\omega$  is perpendicular to the decision boundary. By defining the class label above the decision boundary as +1 and the class label below the boundary as -1, the classification label  $y$  of any training sample  $x$  can be predicted.

**BT-SVM algorithm**

The main idea of the BT-SVM multiclassification algorithm is: First, all the categories are divided into two subcategories then the subcategories are further divided into two subcategories, and so on until all the nodes contain only one category for this purpose, and then a binary SVM classifier is trained at each non-leaf node, and The binary tree's structure will be best for both training speed and classification accuracy when it is near to normal (Lou, 2022) (Wu, Zhou, & Xing, 2021). Figure 2 depicts the composition of a popular binomial classification tree.

When the binomial classification tree tends to have a regular structure, it leads to the phenomenon of "error accumulation", i.e., once a misclassification occurs at the upper node, the error will be passed on to make the subsequent nodes lose the meaning of classification, i.e., the subclassifiers that have a greater impact on the overall performance of the BT-SVM method are located at the upper nodes.

Therefore, in the process of generating the binary classification tree, the principle of easy to difficult should be followed, and the easiest separated classes should be partitioned out first, then the more difficult classes, so that the classification errors are as far away from the root node as possible.



**Figure 2:** Common binary classification tree structure

The algorithm's basic idea is as follows:

Let  $X$  be the sample set containing  $k$  classes and  $x_i$  be the training set for class  $i$ , then:

The sample center of class  $i$  is:

$$c_i = \frac{1}{n_i} \sum_{x \in X_i} x \quad (10)$$

Where,  $i = 1, 2, \dots, k$ ,  $n_i$  is the sample size of category  $i$ .

If  $c_i, c_j$  is the sample center of class  $i$  and class  $j$  respectively, then the Euclidean distance between class  $i$  and class  $j$  is:

$$d_{ij} = \|c_i - c_j\| \quad (11)$$

Minimum hypersphere radius for class  $i$ :

$$R_i = \max \{\|c_i - x_i\|\} \quad (12)$$

Where,  $x_i$  is the sample of category  $i$ .

If the minimum hypersphere radius of class  $i$  and class  $j$  are each  $R_i, R_j$  and the Euclidean distance between them is  $d_{ij}$ , then the relative distance between classes  $i$  and  $j$  is:

$$D_{ij} = \frac{d_{ij}}{R_i + R_j} \quad (13)$$

### Kernel function of SVM

The kernel function is one of the most critical techniques for support vector machines. Through the nonlinear transformation of the SVM kernel function, Without worrying about the specifics of the nonlinear transformation, random vectors in low-dimensional space can be mapped into high-dimensional feature space, and avoids the calculation of the high-dimensional space by just performing the inner product operation between training samples. The Mercer condition must be satisfied as one of the criteria for selecting the kernel function to perform the inner product.

Mercer's theorem: If function  $K$  maps on  $\mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$ , that is, maps from two n-dimensional vectors to a real number field, then if  $K$  is a valid kernel function, then the associated kernel function matrix is symmetric if and only if for training sample  $T = \{(x_1, y_1), (x_2, y_2), \dots, (x_l, y_l)\}, x_i \in \mathbb{R}^n, y_i = \{-1, 1\}, i = 1, 2, \dots, l$ .

The Gauss radial basis functions, Sigmoid functions, linear kernel functions, polynomial functions, and others are often used kernel functions to satisfy Mercer's requirements. The kernel functions used in differentiating between support vector machines.

***Polynomial kernel function***

$$K(x, y) = [(xgy) + 1]^d \quad (14)$$

The discriminant function for constructing a support vector machine is:

$$f(X) = \text{sign} \left\{ \sum_{i=1}^s \alpha_i y_i (X \cdot X_i + 1)^d - b \right\} \quad (15)$$

where the letters  $s, d$  stand for the quantity of support vectors and the kernel function's maximum power, respectively.

***Gauss radial basis function***

The most popular kernel function for SVMs is the Gauss radial basis function, which has been demonstrated to be linearly separable for finite samples in the feature space:

$$K(X, X_i) = \exp \left( -\frac{|X - X_i|^2}{\sigma^2} \right) \quad (16)$$

The discriminant function for the support vector machine that was created is:

$$f(X) = \text{sign} \left\{ \sum_{i=1}^s \exp \left( -\frac{|X - X_i|^2}{\sigma^2} \right) - b \right\} \quad (17)$$

(3) Sigmoid function

$$K(X, X_i) = \tanh [v(X, X_i) + a] \quad (18)$$

The corresponding constructive SVM discriminant function is:

$$f(X) = \text{sign} \left\{ \sum_{i=1}^s \alpha_i \tanh [v(X, X_i) + a] - b \right\} \quad (19)$$

It should be added that the Sigmoid function hyperbolic tangent function, equation (18) can satisfy the Mercer condition only if  $v$  and  $a$  take appropriate values.

***BT-SVM algorithm flow***

Test phase: If  $D_1(x) > 0$ , it enters the root node left subtree, calculates the decision function  $D_2(x)$ , which continues onto its left subtree for judgment and is still larger than 0. If not, it enters its right subtree and continues cycling until it reaches the leaf node, at which point it outputs the category label to which the unknown sample belongs, that is, the category label that is stored at the leaf

node. Figure 3 displays the algorithm's flowchart.

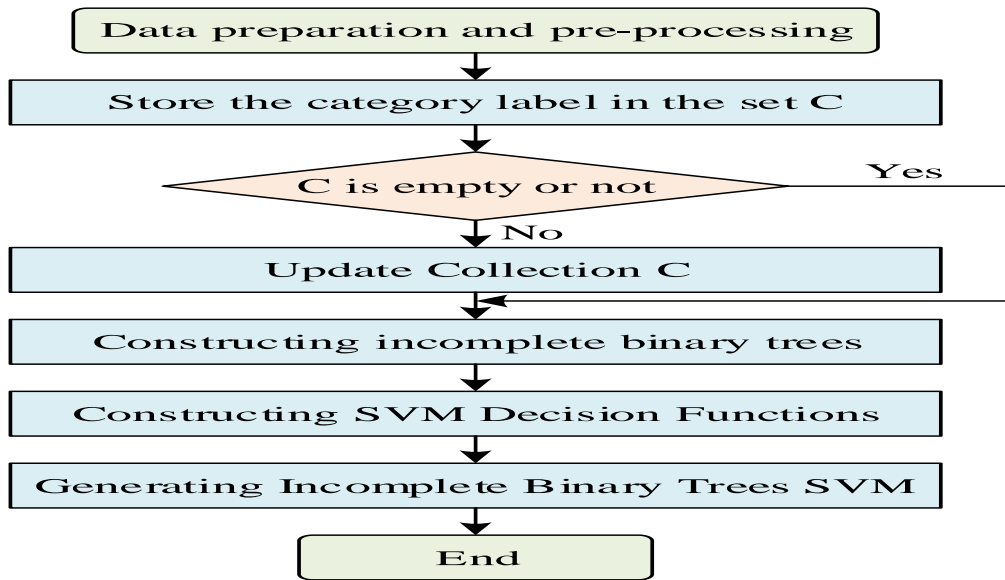


Figure 3: Flow chart of algorithm

## Experimental Analysis of SVM Model Simulation

### Experimental data sources

To confirm the complete effectiveness of the enhanced imperfect BT-SVM multi-classification method in this paper, four data sets, Glass Identification and Vowel data sets from UCI data, and Letter and Satimage data sets from Statlog database, were selected for experiments (Ghaedi & Soleimani, 2022) (Rezvani & Wang, 2022). The information of the simulated experimental data is shown in Table 1, Before the classification operation, these data sets are normalized in this paper so that they take values in the range of [-1,1].

Table 1: Simulation Experiment Data In formation

Data set	Number of categories	Number of attributes	Number of samples	Number of tests
Glass	5	8	106	100
Vowel	13	17	589	259
Letter	24	14	14450	3100
Satimage	8	24	4520	2000

### Experimental methods

The experiments in this paper are written in C++ and Microsoft Visual Studio 2016 is used as the development platform. The specific environment of the experiment: Processor: AMD A6-4400M



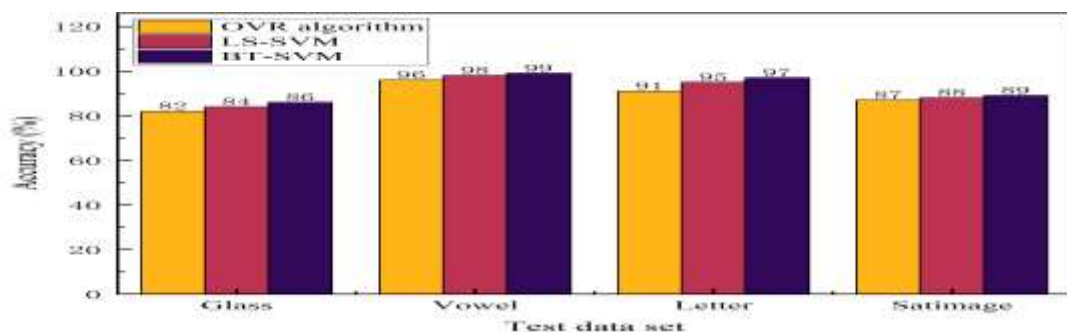
APU with Radenon (tm) HD Graphics 2.70Ghz, Memory: 8G, OS: Windows 8.

The incomplete binomial tree support vector multiclassification algorithm with relative distance is performed as follows: firstly, the multiclass classification problem is divided into several subproblems with two classifications, and then a classifier is constructed for each subproblem using the SVM method and then these classifiers are combined using the binomial tree structure to achieve the purpose of solving the multiclass classification problem. The algorithm is implemented based on the LIBSVM toolbox developed by Prof. Chih-Jen Lin at National Taiwan University with corresponding modifications.

### ***Experimental results validation***

This research conducted eight tests using the OVR method, the linearly separable support vector machine (LS-SVM), and the modified BT-SVM algorithm on the chosen four datasets, respectively, to make the experimental findings more illustrative, and recorded the split-time accuracy of the experiments to calculate the mean of the results of the eight experiments, and Figure 4 displays the efficacy of the three support vector machine classification techniques.

The OVR algorithm averages an accuracy rate of 89%, the LS-SVM method an accuracy rate of 91.25%, and the BT-SVM algorithm an accuracy rate of 92.75%. By contrasting the three algorithms, it can be seen that the BT-SVM algorithm put forth by this party performs better than the OVR and LS-SVM algorithms in terms of accuracy, and can be used to provide precise technical support for the construction of micro-course teaching modes in colleges and universities as well as the reform of the teaching of information technology.



**Figure 4:** Accuracy of three support vector machine classification algorithms

One of the most crucial metrics for assessing the overall effectiveness of the algorithms in the classification problem is classification time, and one of the most crucial indicators is training time. In order to better compare these three algorithms, the training time and testing time of them are counted separately in this simulation experiment, and the training time comparison of the three classification algorithms is shown in Figure 5. The volume of computation over classification grows as the quantity of training texts does, which makes the training time and testing time of the sub-

algorithms longer, and the LS-SVM algorithm takes the shortest time in the testing phase, followed by the BT-SVM. The average time taken by the three algorithms is 73 s for OVR, 61 s for BT-SVM, and 57.75 s for LS-SVM. Due to the difference in sample sizes and the various classifier algorithms used in solving, the three techniques differ in the solution process. In addition, since the multiclassification technique for support vector machines based on relative distance using incomplete binomial trees needs to calculate the relative distance between each two categories while LS-SVM does not, it takes longer time than LS-SVM method in the training phase but less than OVR method. The partial BT-SVM technique based on relative distances reduces the amount of time required for classification and increases the precision of the findings, it demonstrates the algorithm's effectiveness and viability and demonstrates its suitability for the development and investigation of the micro-course teaching mode and English informatization teaching reform in colleges and universities.

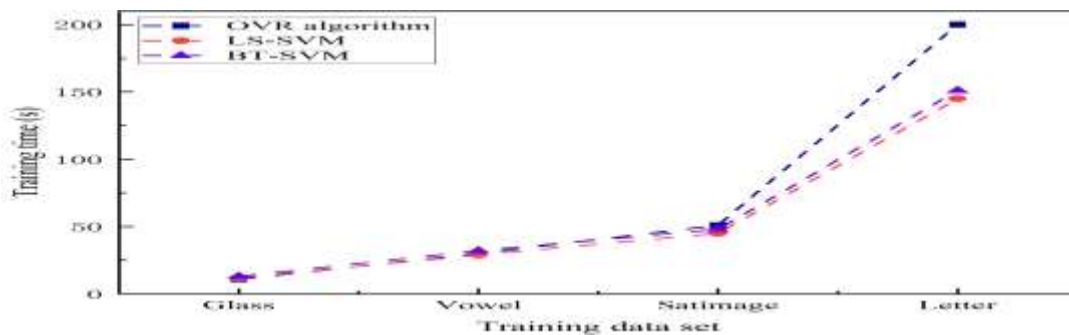


Figure 5: Training time comparison of three classification algorithms

## Under the Influence of Big Data, the English Language is Being Taught in an Increasingly Digital Style at Colleges and Institutions

### *College English informatization teaching*

A current teaching strategy that uses information technology is known as "informatization teaching." The importance of teaching English through informatization is that, in the first place, it allows for the innovation and transformation of the conventional English classroom teaching model. Additionally, the idea of contemporary education technology may be used to curriculum instruction, relying on information technology to support English teaching, boosting students' interest in learning English from a fresh angle by introducing dynamic, visual content into the English classroom. Second, we employ information technology to provide more practical teaching scenarios, design a setting that is easily adaptable to students' requirements, and enhance students' proficiency in using English as a second language. To create a practical learning environment and enhance the teaching effect, for instance, one could take into account the preferences and cognitive traits of the students and play video materials for them in the classroom that match the teaching requirements, are appropriate for the students' learning, and can effectively depict real-life scenes

of people in English-speaking nations. Thirdly, current educational technology with highly deep information storage is used in the process of teaching English through informatization, which efficiently integrates graphics, sound, and images, saving teachers' board time when compared to the conventional English teaching mode, while also emphasizing key concepts and challenging concepts, and enhancing the classroom learning materials, thereby increasing the effectiveness of English teaching.

***BT-SVM Evaluation of English Informatization Teaching Quality in Colleges and Universities***

A significant factor in determining the effectiveness of university instruction is student evaluation, and the most crucial step in that evaluation is the establishment of an index system. Table 2 displays the evaluation metrics for the effectiveness of informative English instruction.

**Table 2:** Evaluation Indicators of Informatization Teaching Quality

Level	Secondary evaluation index	Code	
I evaluation index			
	Information based teaching content setting	1. The concepts and principles are described accurately, with prominent emphasis and difficulties properly handled	Content1
		2. Integrate theory with practice	
	3. Clear teaching objectives and clear teaching ideas		
Teaching attitude	1. Attend and leave classes on time without missing	Attitude2	
	2. Carefully plan classes, check and remark on students' homework promptly		
	3. Strict scholarship, teaching and educating, caring for students		
Information based teaching methods	1. Use micro classes, MOOC and other teaching platforms to assist teaching	Method 3	
	2. Use modern educational technologies such as multimedia		
Information based teaching achievements	1. Improve students' English thinking ability	Effect 4	
	2. Students' English scores improved		

According to the content of Table 2, the evaluation indices for the effectiveness of English informatization teaching are quantified in order to study the whole scores of each indicator and examine the benefits and drawbacks of English informatization teaching in colleges and universities

from the viewpoint of the students, and Figure 6 displays a quantitative examination of the effectiveness of English informatization education.

The four indexes scored from highest to lowest are: teaching content evaluation average score of 90.8, teaching method average score of 88.5, teaching attitude evaluation average score of 85.7, and teaching achievement evaluation average score of 84.5. Students have the highest evaluation scores for teaching content, believing that informatized English teaching brings diversification of English content, and diverse and rich English materials open up English horizons. Secondly, teaching methods, big data informatization teaching means not only the simple expansion of teaching materials, but also the novel change of teaching forms, such as the continuous integration of learning pass, know-to, MOOC, flipped classroom and other teaching methods, which can promote the excitement for English study and raise classroom interest in English.

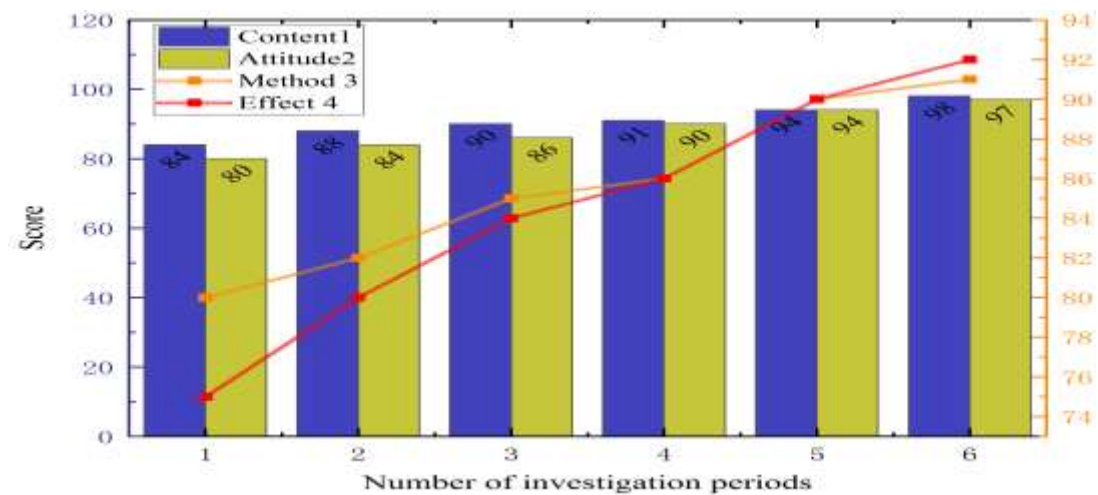


Figure 6: Quantitative Analysis of English Informatization Teaching Quality

***BT-SVM English teaching quality evaluation treatment efficiency test***

The evaluation processing efficiency was verified according to the quantitative results of 4.1.1 English informatics teaching in colleges and universities. In Table 3, the classification outcomes of the two binomial tree multi-classification methods are compared. The numbers in the table represent the average of the data from six studies, and they primarily measure how much time and how well these two algorithms classify data when processing teacher evaluations.

These two methods take approximately the same amount of time to complete the classification procedure, the reason the difference in classification time between the two methods is negligible is mostly due to the fact that the experimental data categories and numbers are modest and the calculation is not as intensive, but when the amount of evaluation data grows, the BT-SVM algorithm will advance more quickly, and the time gap between the two methods will widen. By using the relative distance between categories as a parameter for choosing which categories should

be segmented out first, the revised BT-SVM method in this study lowers the accumulation of mistakes caused by the binary tree structure, resulting in a reasonably high classification accuracy. Given that the BT-SVM multi-categorization algorithm is practicable and has a high processing efficiency, it can be used to evaluate the effectiveness of teaching in colleges and universities. This simplifies the process of reforming English teaching in colleges and universities through the use of technology.

**Table 3:** Comparison of two binary tree multi categorization algorithms' classification outcomes

Algorithm	Training time(ms)	Test time (ms)	Accuracy(%)
Partial binary algorithm	22.7	7.3	96.30
BT-SVM algorithm	23.8	6.4	98.72

## Microlearning mode

### *Micro-classroom*

A micro-lesson is a brief and comprehensive teaching exercise centered around a knowledge point or teaching link that is thoughtfully created in the form of streaming media for the optimal outcomes of students' independent learning.

Micro-lessons only change the presentation and delivery of content, not the properties of the content, thus improving the learning effect. In a word, micro-lesson is a customized learning resource for students, courseware is the core element of micro-lesson (content design), explanation is the dynamic realization of micro-lesson (interactive interpretation), and video is the perfect combination of the two (bearing method), the introduction of microlessons offers a fresh approach to teaching college English. The micro-lesson is a short presentation of the learning content of knowledge points with video as the carrier, and its characteristics are as follows: Firstly, it is short, usually in 5-10 minutes.

Secondly, the teaching content is small, different from the amount of knowledge presented in the classroom, only around the important and difficult content, so it is also suitable for students to review and knowledge review after class, and assist pupils in quickly resolving issues with learning. Finally, in the Internet environment, mobile smart devices are easy to carry around, so students can use fragments of time to absorb and consolidate their knowledge.

### *LS-SVM English microlearning effectiveness test*

To ensure the effectiveness of the microteaching format, a test of microteaching results was conducted. Firstly, we ensured that the English level of the selected student performance control class and the experimental class were comparable, and then a pre-test analysis of English level was conducted on the English performance of the students in both classes for the semester. Table 4 displays an example t-test for the college English microcourse pre-test results.

The results indicated that the experimental class had an average score of 72.58 while the control

class had an average score of 72.62. i.e., prior to the start of the experiment, the average results of the two classes of pupils differed by 0.04 points, demonstrating that their levels of English proficiency were essentially equal.

**Table 4:** Sample t-test of college English pre micro class scores

Sample inspection		Test of mean t						
		F	Sig	t	Mean difference	Standard error	95% confidence interval	
						upper limit	lower limit	
English scores	Assume equality	3.450	0.567	-1.035	-2.208	2.140	-6.438	2.024
	Assume unequal	—	—	-1.050	-2.208	2.115	-6.365	1.970

The sample t-test for the post-test scores of college English micro-lessons is shown in Table 5. The experimental class scored higher at the conclusion of the micro-course in English than the control class, according to the findings of the test for the difference between the post-test scores of the two classes. The experimental class had a mean score of 74.65 while the control class's mean score was 72.83, a difference of 1.82 points. Last but not least, the outcomes of an independent sample t-test on post-test scores for college English revealed that Sig=0.510, which is larger than 0.05 chi-square, and F=0.0475, which is less than 0.05, demonstrating that the experimental class's overall results were considerably higher than the control class's scores. This demonstrates that from a broad viewpoint, the practical application impact of creating English micro-class teaching mode has a considerable advantage over the traditional classroom teaching effect when it comes to the process of teaching English at colleges.

**Table 5:** Sample t-test of college English micro class scores

Sample inspection		Test of mean t						
		F	Sig	t	Mean difference	Standard error	95% confidence interval	
						upper limit	lower limit	
English scores	Assume equality	0.475	0.510	-2.275	-3.088	1.510	-6.079	-0.113
	Assume unequal	—	—	-2.074	-3.094	1.487	-6.070	-0.126

**College English informatization teaching reform and micro-course construction**

*Reforming the way that English is taught at colleges and universities*

### Increase training and improve teachers' informatization teaching level

In the big data era, adopting an online teaching approach is both a required practice and a future trend for schools and institutions. Therefore, instructors must first possess the informatization teaching level in order to effectively use the informatization teaching technique. There are a lot of elderly professors in colleges and universities. Because their educational environment was different from the social environment of today, despite their knowledge and strength, they do not fully understand the informatization teaching mode and, given the option, would prefer the traditional teaching mode.

Despite the fact that the informatization teaching mode differs from the traditional teaching mode, instructors are still the primary educators and the creators of the curriculum in this setting. Additionally, because the use of new media necessitates greater proficiency in the use of informatization, a number of factors have led universities to adopt effective informatization new media education; therefore, it is essential to improve teacher preparation. Teachers should be given the opportunity to use new media tools to advance their understanding of computer technology, master office suites, and raise their level of software usage. Teachers should be trained in various forms of multimedia teaching in order to enhance their lesson plans and increase student interest in learning, which will enhance the overall effectiveness of the teaching process. This is due to the variety of informatization teaching methods currently being used.

### Utilize information technology to enhance the way English is taught at colleges and institutions

While the new information technology can assist colleges in maximizing the teaching mode and raising the teaching standard, the old teaching method has numerous drawbacks. When using the information-based teaching style, teachers can create their course materials on a computer, which can help them save time and energy while teaching and give them more time to assist students with their queries.

At the same time, English instruction in colleges and universities may be diversified with the aid of the information-based teaching approach. Teachers will not be limited to the lectures in the classroom, but can also use the platform to carry out diversified teaching activities and create a lot of opportunities for students to practice language, which can deepen their understanding of the teaching content effectively and realize the breakthrough of the important and difficult points of teaching.

### ***College English micro-course teaching model building***

#### ***Pre-course video release***

Teachers can utilize the university English micro-lesson teaching method to supplement classroom instruction after creating the micro-video by fully using the MOOC course development idea.

Prior to the start of class, the video is uploaded to the server, which then calls a streaming video



converter to convert it into a streaming video file to increase the network's video transmission's efficiency.

The students' "classroom learning" then starts when the teacher adds written materials, post-lesson links, and class exam questions at the bottom of the video. Students can access the English microlearning system through their computers or mobile terminals, log in to their accounts, and learn from the uploaded videos in a variety of ways, including mobile learning and online learning, according to their specific conditions. Students can watch the video content multiple times to make sure they "understand" the lesson material, follow the hard-to-read words and phrases at any time, study the hard-to-understand words and phrases multiple times while using the translation materials, fully express their opinions when faced with questions, and communicate with teachers and other students in-depth online about particular issues. Students might get better knowledge of their own language after the exchange. Following the exchange, students can work on their pronunciation in accordance with their individual learning needs and level of prior information acquisition.

### ***Classroom teaching***

Teachers do not lecture students in the conventional sense in the classroom, and students are not just passive consumers of the original knowledge and information, nonetheless, on the basis of rearranging the information covered in the knowledge points recounted in the micro-video shown prior to the class, enhancing additional learning materials like board books and electronic documents to fulfill the diverse learning needs of students, it centralized comments from students in the network to describe the issues collectively to remove the majority of On the basis of the students' input from the network, the teacher will also give a group explanation, clearing up the majority of the students' questions and concerns.

Following that, teachers set aside more time for interaction, allowing students to break up into small groups to analyze, discuss, and exchange issues with word and sentence pronunciation, translation practice, and grammar that come up during the learning process in order to better understand these issues and internalize their knowledge. At the same time, teachers must improve the planning and direction of student group discussions, gradually broaden students' cognitive structures in accordance with the material covered in micro-video learning, encourage knowledge transfer while completing knowledge learning, and recognize the development of students' critical thinking and problem-solving skills.

### ***Micro-lesson teaching combined with flipped classroom***

Microlessons can be used in English classes as an adjunct teaching technique by teachers to help students become more motivated and laser-focused on learning the language. Teachers can use the content and various expressions of micro-lessons to attract students' attention and create an active and healthy classroom atmosphere to help teaching.



In the process of content design, teachers need to divide teaching knowledge into different levels and classify and design thematic teaching, so that students can realize the classification and innovation of thinking and establish a complete knowledge structure in the transmission of thematic teaching content. Teachers should also reasonably control the degree of micro-lessons, avoid over-reliance on micro-lessons and neglect the goal of teaching, and carry out teaching according to the principle of knowledge transfer so that teaching can be carried out smoothly and with better effect. At the same time, they should also ensure the correlation between micro-lesson teaching mode and flipped classroom teaching mode, find the interface between these two teaching modes, to prevent the issues with college English micro-lesson teaching, optimize and innovate the college English micro-lesson teaching model in accordance with the flipped classroom model. The goal of this study is to demonstrate the relationship between the flipped classroom and the college English microcourse delivery method in order to enhance the innovative effect of the latter.

### Conclusion

This research aims to bring the SVM model into the reform of English informatization in colleges and universities to investigate the new opportunities of teaching in micro-lesson mode. The key findings of this work are as follows. By constructing a support vector machine, LS-SVM and BT-SVM algorithms are presented to examine the teaching outcomes of college informatization and the efficacy of micro-course teaching:

In teaching processing, the BT-SVM algorithm's accuracy rate was 98.72%. The average score for teaching content was 90.8 on the evaluation of teaching quality, while the average score for teaching manner was 88.5. The average scores for the control class and experimental class on the test of teaching results for the micro-class were 72.83 and 74.65, respectively, with a difference of 1.82 points between them.

This shows that the application of informative teaching makes the overall college English performance at a high level, which indicates that informative English teaching combined with micro-classes can improve the quality of college English teaching.

In order to improve teachers' information-based teaching levels and the overall effectiveness of instruction, it is necessary to foster teachers' information-based teaching levels.

In order to implement the optimization and innovation of the college English microcourse teaching mode, the flipped classroom model is used in the innovation of teaching methods. By doing this, the problems associated with college English microcourse teaching are avoided, and the innovation effect of the college English microcourse teaching mode is strengthened.



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