

Retraction

Retracted: Sentiment Analysis in British and American Literature Teaching under Formative Assessment and Machine Learning

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] Y. Jin, "Sentiment Analysis in British and American Literature Teaching under Formative Assessment and Machine Learning," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 7954166, 9 pages, 2022.

Research Article

Sentiment Analysis in British and American Literature Teaching under Formative Assessment and Machine Learning

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In English education, British and American literature is a new type of course. The teaching of British and American literature has also undergone many reforms. In the practice of teaching reform, artificial intelligence- (AI-) assisted teaching such as machine learning (ML) has a long history. The performance is continuously improved by studying the mechanism of computer simulation of the human brain learning British and American literature. Then, computer intelligence can be realized. Based on this, this paper mainly discusses two aspects. One is the sentiment tendency analysis method based on the sentiment dictionary, and the other is the sentiment tendency analysis method based on ML. It mainly introduces the judgment of different emotional tendencies by the sentiment analysis model, which is an automatic review analysis and ensemble classification approach. The improvement of sentiment analysis improves the recognition range of text sentiment words in British and American literature teaching to optimize the process of text analysis. Its main feature is that the sentiment analysis of text directly acts on the tendency of words, with fine granularity and accurate analysis. Finally, it is concluded that the maximum value of the algorithm proposed here is 0.9, which has higher accuracy than the maximum value of 0.81 of other analysis models. The results indicate that the integrated classification model combining British and American literature teaching with the dimensions hidden Markov model has relatively reasonable text analysis and high sentiment classification accuracy. In terms of British and American literature teaching, using ML algorithms can effectively help teachers teach British and American literature through sentiment analysis.

1. Introduction

In recent years, artificial intelligence (AI) technology has developed extremely fast. AI is the basic way to realize computer intelligence. How to cultivate students' ability to analyze and solve practical problems has become the core of machine learning (ML) courses [1]. Meanwhile, ML also has obvious advantages in AI. In the teaching process of British and American literature courses, the derivation of theoretical knowledge and the cultivation of students' practical programming abilities are conducive to the integration of the content of computer majors with British and American literature courses [2]. Students must master knowledge and techniques related to ML, so they can break through in AI and information technology. In this context, ML-based sentiment analysis research has emerged, which is aimed at ana-

lyzing people's emotions in British and American literature teaching [3]. Sentiment analysis on English and American literature teaching is the only way to improve British and American literature teaching.

In recent years, scholars have studied sentiment analysis based on formative assessment. They explored it in many aspects through ML methods, including the exploration of British and American literature teaching [4]. The methods of feature selection and representation of different emotions are analyzed, and experimental comparisons are made when texts are classified. It is found that the support vector machine (SVM) method has the best classification effect using bigrams feature representation and selection for information gain under the condition of selecting appropriate features and training sets [5]. As a result, ML-based sentiment analysis research is a current research hotspot, and

these studies can improve the teaching of British and American literature. It is urgent to conduct sentiment analysis on British and American literature teaching.

Based on this situation, sentiment analysis is carried out in the teaching of English and American literature to improve the teaching of British and American literature. This paper mainly discusses two aspects. One is the sentiment tendency analysis method based on the sentiment dictionary, which mainly includes the establishment of the sentiment dictionary and the calculation method of sentiment weight. The second is the sentiment analysis method based on ML, which mainly introduces the judgment of different sentiment tendencies by the sentiment analysis model, which is an automatic review analysis and ensemble classification approach (ARAEC). The improvement of sentiment analysis improves the recognition range of text sentiment words in British and American literature teaching to optimize the process of text analysis. In short, this paper expounds that the integrated classification model that combines British and American literature teaching with the dimensions hidden Markov model (DHMM) has reasonable text analysis and high sentiment classification accuracy. The use of ML algorithms can more effectively help teachers teach British and American literature through sentiment analysis.

1.1. Literature Review. Chan et al. (2020) examined the limitations and advantages of ML techniques. Emotional design-related big data could be captured from social media, so the prospects and challenges of using big data to enhance emotional design were discussed. So far, limited research had been attempted [6]. Li et al. (2018) investigated an ML-based dynamic mapping method for emotion design to overcome these challenges. It extensively collected the emotional responses of consumers [7]. Järvelä et al. (2020) found that collaborative learning could be a powerful method for sharing understanding among learners. What matters was not just the individual but the shared process of the group. Therefore, group-level supervision was critical to learning success. Technological solutions and digital tools available would help individual, peer, and group learning today and in the future from multidisciplinary perspectives [8]. Liaqat et al. (2021) proposed a classifier based on ML (SVM, logistic regression, decision trees, naive Bayes, random forests, linear discrete analysis, and quadratic discrete analysis) and a new hybrid method of deep learning (DL) classifiers (one-dimensional convolutional neural network (CNN) and two-dimensional CNN) for recognition pose detection. The proposed hybrid approach used predictions from ML and DL to improve their performance. The experiments were carried out on a wide range of benchmark datasets, and the accuracy of the results reached more than 98% [9].

2. Materials and Methods

2.1. ML Theory. ML is to enable computers to simulate human learning behaviors, cultivate automatic acquisition of knowledge and skills, and continuously improve human capabilities [10]. Machines acquire new knowledge and skills

by recognizing and using existing knowledge. Currently, ML is divided into supervised learning and semisupervised learning. Supervised learning is mainly applied to classification and prediction. The given training dataset is set to [11]

$$\mathcal{X} = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}. \quad (1)$$

In Equation (1), $X_i \in X, Y_i \in Y, i = 1, 2, \dots, n$.

2.2. ML Model. In statistical learning, the maximum likelihood estimation method is usually used to solve the learning problem. The known sample information is used to find a set of parameters to maximize the probability of the sample data under this set of parameters. A likelihood function needs to be constructed before maximum likelihood estimation [12]. The known probability mass function is shown in Equation (2). The maximum likelihood function is shown in Equation (3) assuming that all samples satisfy the independent and identical distribution [13].

$$P(y|x; w) = (h_w(x))^y (1 - h_w(x))^{1-y}, \quad (2)$$

$$L(w) = \prod_{i=1}^m P(y_i|x_i; w) = \prod_{i=1}^m (h_w(x_i))^{y_i} (1 - h_w(x_i))^{1-y_i}. \quad (3)$$

The log-likelihood loss on the entire dataset is averaged, and the maximum likelihood function of logistic regression (LR) is brought into Equation (4). Then, the logarithmic loss function $J(w)$ of LR is obtained, also known as the cross-entropy loss function, as shown in Equation (5) [14].

$$J(w) = -\frac{1}{N} \ln L(w), \quad (4)$$

$$J(w) = -\frac{1}{m} \sum_{i=1}^m y_i (w \bullet x_i) - \ln(1 + e^{(w \bullet x_i)}). \quad (5)$$

The parameter update method of stochastic gradient descent is used to minimize the loss function of the LR model after the loss function is clarified to make the model have good performance [15]. The optimal values of the model parameters can be acquired [16]. The update parameters are adjusted to iterate, and the optimal solution is continuously approached, so the value of the loss function is minimized. The update method is revealed in the following equations [17].

$$g_i = \frac{\alpha J(w)}{\alpha w_i} = (h_w(x_i) - y_i) \bullet x_i, \quad (6)$$

$$w_i^{k+1} = w_i^k - \alpha g_i. \quad (7)$$

In Equations (6) and (7), k is the number of iterations required, and α is the learning rate of the model. Each time, an appropriate learning rate is set. The value of $\|J(w^{k+1}) - J(w^k)\|$ can be compared after the parameters are iteratively updated. If the comparison result is less than the set

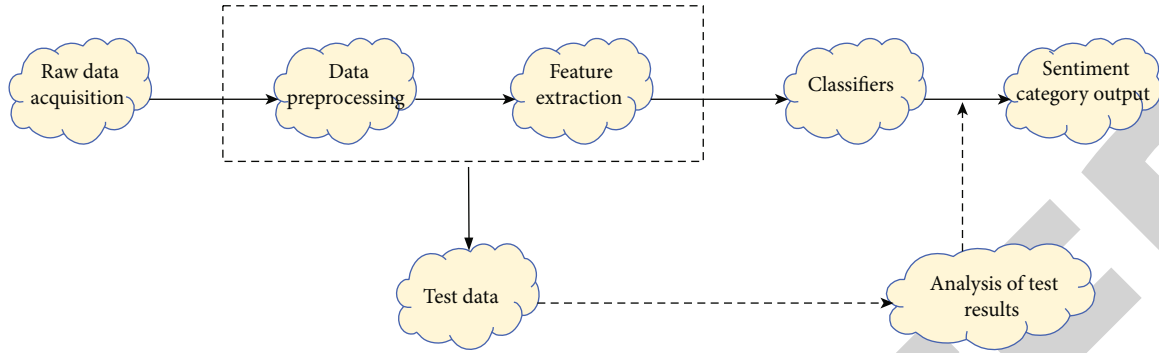


FIGURE 1: Text sentiment analysis flowchart.

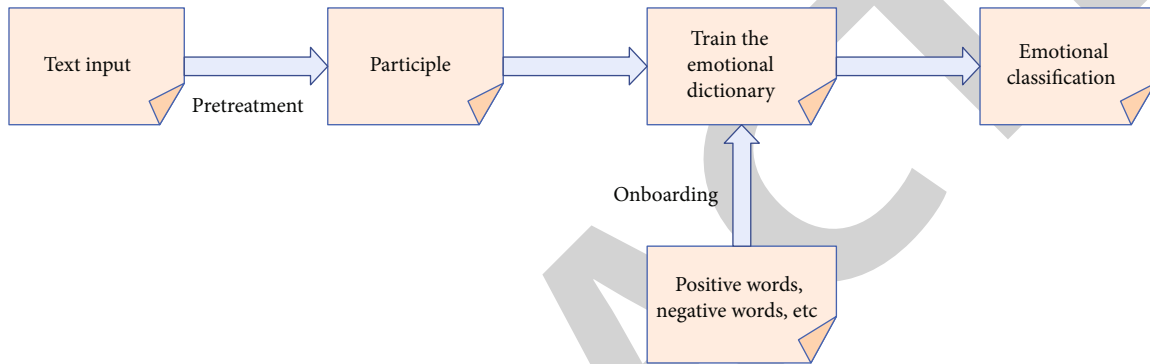


FIGURE 2: Diagram of the dictionary-based sentiment analysis method.

threshold or reaches the maximum number of updates, the optimal model parameters are found, and the parameter update is stopped [18].

2.3. Text Sentiment Analysis. Text sentiment analysis is to analyze subjective texts with emotional colors, mine emotional tendencies, and classify emotional attitudes [19]. The process of text sentiment analysis includes raw data acquisition, data preprocessing, feature extraction, classifier, and sentiment category output [20], as shown in Figure 1 [21].

The first step is usually to collect the original text before text sentiment analysis. Then, preprocessing operations such as filtering, word segmentation, and denoising are performed on the text to further obtain subjective texts. The sentiment dictionary is used as an important reference, and the criteria or rules for judgment are formulated according to the research content. Specifically, the polarity of adjectives or emotionally colored phrases in the text to be classified is determined, and a polarity value is assigned. The total sentiment tendency of text is the sum of all polarity values [22], as manifested in Figure 2.

In the experimental context, qualified texts are made as training samples. Then, the text features are extracted, and the feature weights are calculated. The constructed classifier can judge the sentiment category of the text. Among many ML methods, information gain, chi-square test, and word frequency-inverse text frequency are commonly used feature selection methods. The commonly used classification methods include SVM, naive Bayes algorithm, and maximum entropy [23].

2.4. Sentiment Analysis Research Methods

- (1) Back Propagation (BP) Neural Network. Artificial neural network (ANN) was first proposed by Rumelhart and McClelland. Imitation of the neural structure and function of the biological brain is the basis of ANN. Its imitation plays a powerful role in complex, multifactor, nonlinear, and other problems. This is why it is widely used in computers, communication, biology, social science, and other fields. The combination of BP neural network evaluation teaching quality and college evaluation index system can ensure the true objectivity of evaluation. The index system should include many specific evaluation items. The evaluation scores are usually homogenized before being fed into the network, and the homogenization formula is as follows [24].

$$X = \frac{I - I_{\min}}{I_{\max} - I_{\min}}. \quad (8)$$

In Equation (8), X is the normalized input value. I is the input value I_{\max} and I_{\min} to be processed, which are the maximum and minimum values of the input quantity, respectively.

Generally speaking, the number of evaluation indicators for the number of neurons in the input layer (generally referred to as secondary evaluation indicators) is equal. The difficulty of model application is the determination of

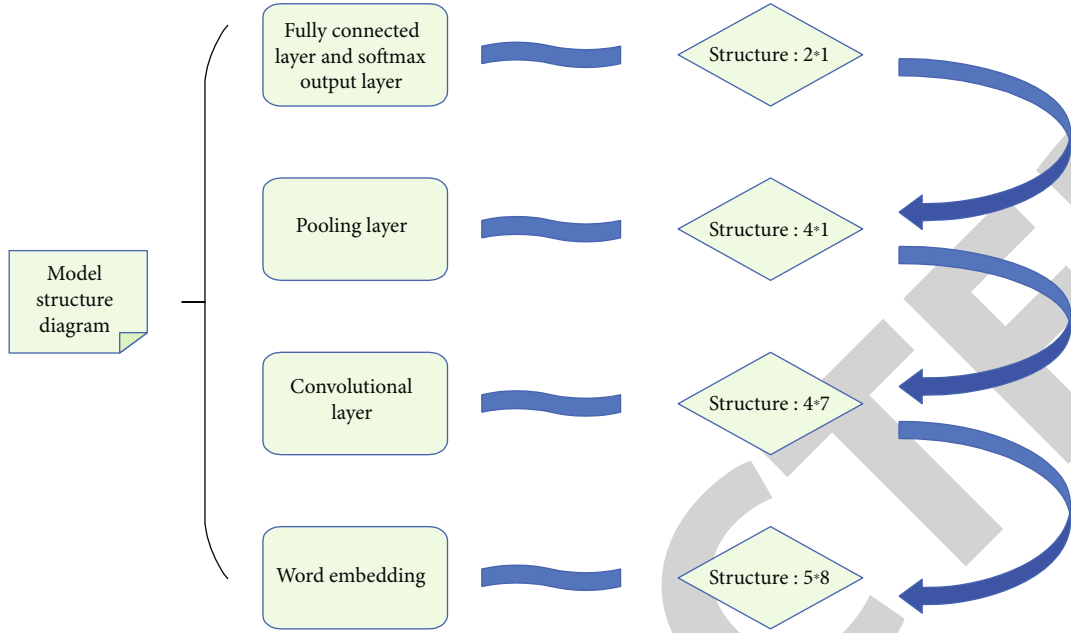


FIGURE 3: CNN model structure diagram.

the hidden layer structure. Studies have shown that a three-layer BP neural network with a hidden layer can approximate any continuous function. According to the actual situation, the number of hidden layer neurons is usually determined by trial and error [25].

$$m = \sqrt{n+1} + \alpha; m = \log_2 n; m = \sqrt{nl}. \quad (9)$$

In Equation (9), m , n , and l are number of neurons in the hidden, input, and output layers, respectively. α is a constant from one to ten. The transfer function should be properly selected when the BP neural network model is applied. The input layer neurons generally use linear functions. Hidden layer neurons generally use saturated nonlinear hyperbolic tangent purelin linear function, which is usually the output function of the model. The final set model is a model with high prediction accuracy and generalization ability after repeated training on the selected training samples. It can further evaluate the quality of teaching.

- (2) CNN. The CNN used by many scholars is a common ML model. For CNN, its nonlinear properties and region-learning embedding capabilities are particularly prominent. Embedding, convolutional, pooling, and output layers make up a CNN. In the embedding layer, the word level is embedded in each paragraph of the text, which is represented as a matrix. In the convolutional layer, the dimension of the word vector is fixed to the width of the filter. This captures the relationship between adjacent words. In the pooling layer, the maximum value corresponding to each feature map is extracted to let it operate the pooling over the maximum time. Extracting features is implemented on the output layer, and the proba-

bility distribution on the output is implemented through a fully connected layer. It is found that the character deep CNN in text classification performs well through the research of Yang Rui et al. on the text classification method of CNN. As a result, CNN models are inseparable from many tasks [26]. Local n -gram features are extracted from text through a CNN. The disadvantage is that long-range dependencies may not be captured. Modeling the long short-term memory (LSTM) order of text can address this shortcoming. Typically, CNN and recurrent neural network (RNN) are combined with both sequence or tree-based models. Experimental studies have shown that the advantages of CNN are that it can overcome the large computational burden of neural networks. Its shortcomings are also obvious, requiring more training time than other methods. The structure of the convolutional layer is demonstrated in Figure 3.

The convolutional layer extracts local features from the trained word vectors through convolution kernels of different sizes and extracts different features of the text. The pooling layer is a further feature sampling from the feature map output by the convolutional layer. It filters some redundant text features after the convolution layer and extracts the most useful information in the text. Using a pooling layer can increase the computational speed of the model and prevent the model from overfitting. The pooling layer is mainly divided into max pooling and average pooling. Each neuron in a fully connected layer connects all neurons in the previous layer. It acts as a "classifier" throughout CNN. The fully connected layer can integrate all local information with the categories in the volume layer or pool layer.

TABLE 1: Experimental environment.

Environment	Hardware environment	Operating system	Development platform	Development language	Libraries used
Configuration	Intel i7CPU, 8 G memory, 512 G hard drive	Windows10 64 bit	PyCharm Community Edition 2020	Python language	Python3.6, TensorFlow, Jieba, NumPy, Gensim, SciPy

(3) The third is RNN. RNN applies the same set of weights recursively on a directed acyclic network. Language-driven CNN models explore tree structures and try to learn complex compositional semantics, so input segments are tree structures. The selection tree and the dependency tree constitute the tree structure of the RNN. First, leaf nodes represent words, internal nodes represent phrases, and root nodes represent entire sentences in a selection tree. Second, each node can represent a word in the dependency tree. The word is connected to other nodes through dependencies. In RNN, what is computed from all its children using a weight matrix is a vector representation of each node [27].

(4) The fourth is the SVM. As a supervised learning model that can effectively analyze data, the basic theory of SVM comes from the linearly separable case. (a) Assuming that the sample set is $(x_i, y_i), x \in R^n, y \in \{-1, +1\}$, an optimal classification surface is defined in the space of dimension n . The data is categorized, and the points in training are the furthest from the hyperplane. The discriminant function is $g(x) = wx + b$, and the hyperplane equation is $wx + b = 0$. (b) After normalization, all samples satisfy $y_i[(w \cdot x_i) + b] \geq 1, i = 1, \dots, n$. The classification interval is now equal to $2/\|w\|$. Therefore, the training point in condition (a) is the furthest away from the recruit plane, which is equivalent to $\|w\|^2$ minimum. (c) The optimal classification surface problem can be expressed as the following constrained optimization problem [28].

$$\min \frac{1}{2} \|w\|^2 = \frac{1}{2} (w \cdot w); \text{ s.t. } y_i[(w \cdot x_i) + b] \geq 1, i = 1, \dots, n. \quad (10)$$

In Equation (10), $(w \cdot w)$ denotes the inner product of the optimal hyperplane normal vectors. For linear inseparable problems, the usual approach is to introduce slack variables $\xi_i \geq 0, i = 1, \dots, n$. Besides, $C > 0$ is defined as a penalty factor to penalize misclassification. At this time, the constrained optimization problem is transformed into

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i; \text{ s.t. } y_i[(w \cdot x_i) + b] \geq 1 + \xi_i, \xi_i \geq 0, i = 1, \dots, n \quad (11)$$

The above problem can be transformed into a dual problem after the Lagrange function is introduced.

TABLE 2: BiLSTM model experimental parameters.

Parameter name	Learning rate	Batch size	Number of hidden layer units	Dropout	Epochs
Parameter value	0.001	64	128	0.5	10

$$W(\alpha) = \sum_i^n \alpha_i - \frac{1}{2} \sum_i^n \sum_j^n y_i y_j \alpha_i \alpha_j (x_i \cdot x_j). \quad (12)$$

Only the dot product operation $(x_i \cdot x_j)$ is involved in the sample. At this time, the decision function is the SVM, which is widely used in the evaluation of college teaching quality because of its strict mathematical theory support and its excellent performance in dealing with complex multifactor variables. The basic path of evaluation is as follows: (1) The samples are divided into learning samples and prediction samples. (2) The samples are normalized. (3) SVM performs self-learning and seeks optimal parameters. (4) The test sample is texted. (5) The test results are evaluated [29].

(5) The fifth is the transformer-based bidirectional encoder characterization technique. The following introduces a natural language preprocessing technology based on the neural network, which is Bidirectional Encoder Representations from Transformer (BERT). It can fine-tune BERT models by leveraging input and output layers to create models for various text analysis tasks. Transformer technology is the core of BERT, and it has many advantages. It is very suitable for processing natural language tasks based on encoder-decoder models and attention mechanisms. It is found that BERT can perform well compared with the SVM model when the amount of data is large, and its processing performance will be significantly improved. Experimental research shows that BERT's excellent feature extraction ability can help further improve the performance and stability of sentiment classification, thereby further accelerating the speed of convergence. It is also possible to use BERT for sentiment analysis under the three language conditions of the same text.

2.5. Experimental Environment. PyCharm is used for the experiments, and the development environment configuration is shown in Table 1.

The development language of the experiments is the Python language. Python is a scripting language that

TABLE 3: CNN model experimental parameters.

Parameter name	Learning rate	Batch size	Dropout	Epochs	Convolution kernel length	The number of convolution kernels
Parameter value	0.001	64	0.2	15	256	2, 3, and 4

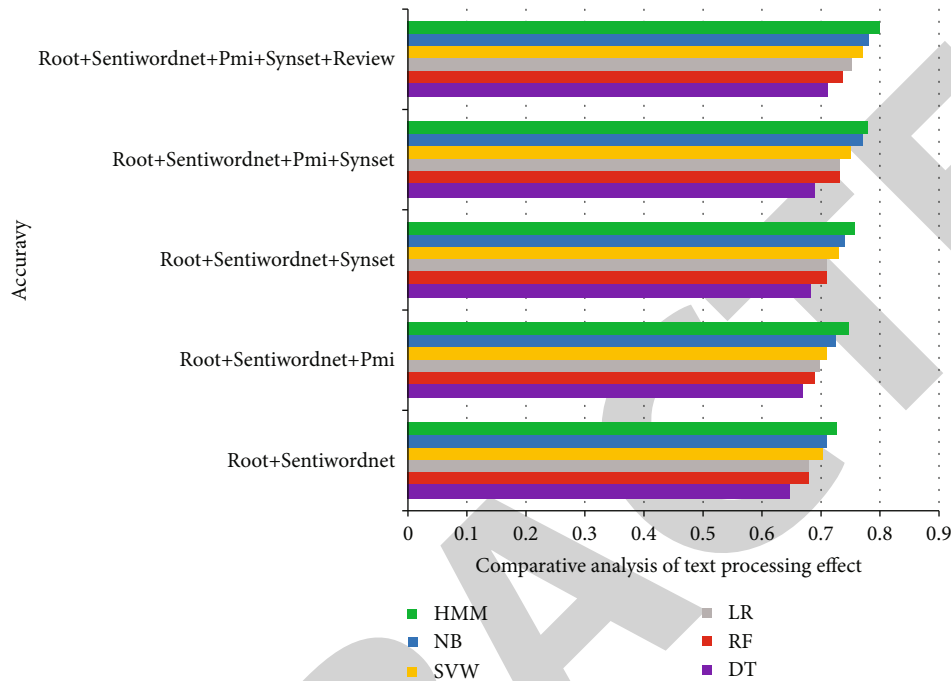


FIGURE 4: Comparison of text processing effects.

combines compiled, interactive, interpreted, and object-oriented. Python has strong portability and an extensive standard library, and it is easy to read and maintain. The standard libraries used here mainly include TensorFlow, Jieba, NumPy, Gensim, and SciPy. Among them, Jieba is used for word segmentation. TensorFlow supports building neural network models and is an open-source ML framework.

2.6. Data Preprocessing. Filtering, removing duplicate comments, and word segmentation are performed on the acquired experimental data. Each dataset is marked separately. Then, the marked data is compared. The majority rule is adopted. The same label for the same piece of data is used as this data label. After preprocessing, it can meet the basic requirements of sentiment analysis in British and American literature teaching. The training word vector file here uses the teaching dataset, and the size is 0.736. The Ngram2vec is used, and the Skip-gram model is adopted for training. The parameters to be set are as follows. The window size is five. The minimum word frequency is ten. The sample size is $1e-5$. Negative sampling is five. The output word vector has a dimension of 3,000.

2.7. Parameter Settings. The main hyperparameters and parameter values of the experiments are shown in Tables 2 and 3.

3. Results and Discussion

3.1. ML Experiment Results. This paper applies decision tree (DT), LR, random forest (RF), SVM, hidden Markov model (HMM), and naive Bayes model (NBM) for the classification of all data. Tenfold cross-validation is used, and the accuracy value is for comparison. Root represents the unreferenced text analysis link. SentiWordNet represents a textual analysis of citations. Synset represents a textual synset. Pmi stands for mutual information detection. Review means to implement the follow-up/original review analysis mechanism.

From Figure 4, Root, Sentiwordnet, Synset, Pmi, and Review have reached the maximum value of 0.8 in the tenfold cross-validation, and the smallest DT has also reached 0.7. This shows that the extension of sentiment analysis and text features are continuously optimized. This verifies that the extension based on sentiment analysis is beneficial to the sentiment classification process based on ML.

Here, three volunteers manually mark the comment text on 1,000 randomly selected training data according to the requirements of the “big five” British and American teaching sentiment analysis. The traditional ML algorithm is selected for training, and the results are compared with the rule-based personality analysis method. Figure 5 shows the details.

From Figure 5, the rule-based personality prediction accuracy rate of SVM is mostly around 0.5. Most of NB’s rule-based personality prediction accuracy is around 0.4. Therefore, SVM has obvious recognition accuracy relative

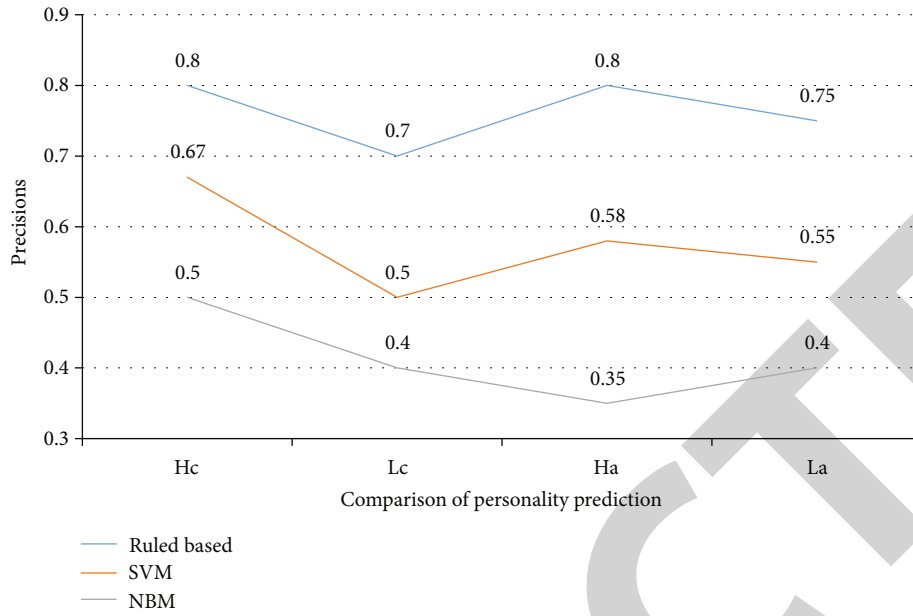


FIGURE 5: Comparison of personality predictions.

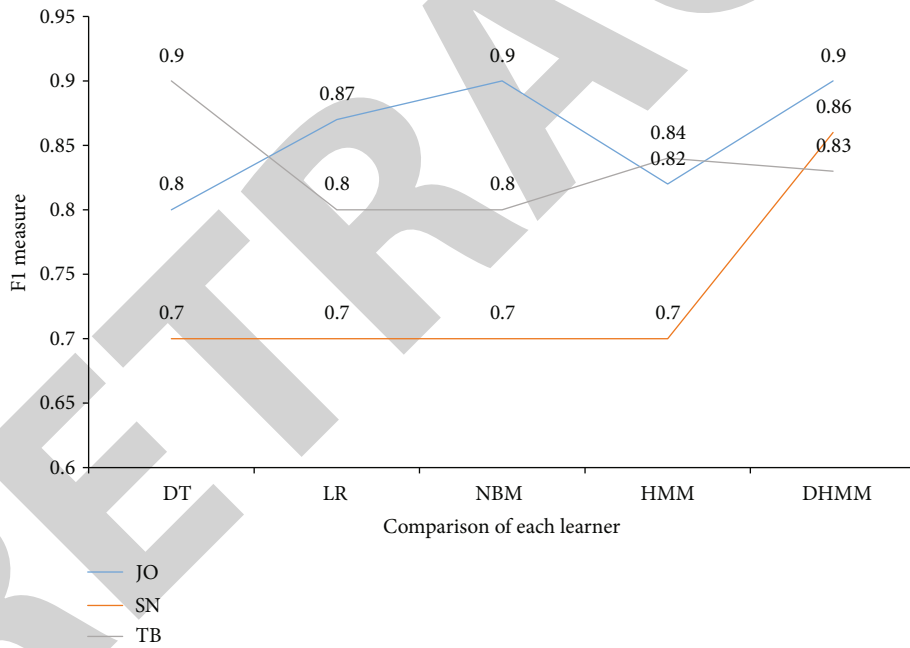


FIGURE 6: ARAEC model integration of each learner comparison.

to NB. The effect of the ML algorithm on the personality analysis of comment text is not obvious. There are few emotional words showing personality in the comment text, so it is difficult to predict the user’s personality with high precision only through the text.

For control experiments, the meta-classifier uniformly uses SVM for classification. The DT, RF, LR, NBM, HMM, and the improved DHMM are compared, respectively. The experimental results are revealed in Figure 6.

From Figure 6, different ML models have good results in ARAEC. The model using the DHMM ML algorithm has a

better classification effect and generalization effect than other models.

In addition, this paper selects the sentiment analysis methods (models) proposed in recent years for simulation comparison, which are the ACAEC model, Sosml model, and WebIS model. These mainstream sentiment analysis models are all based on English text analysis. This paper adjusts the text processing method during simulation. The analysis process of these three models is shown in Figure 7.

From Figure 7, the algorithm proposed here has a maximum value of 0.9, which has a higher *F1* value than the

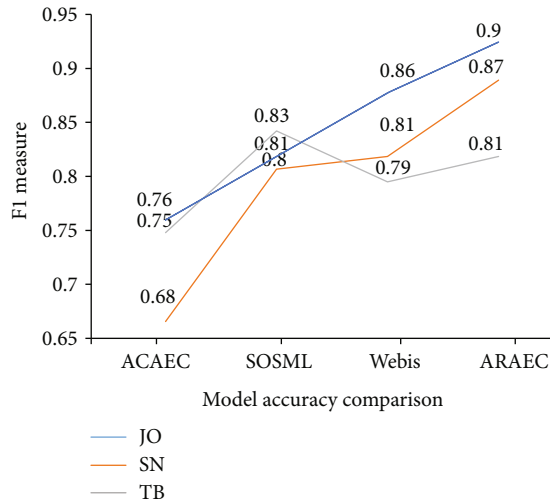


FIGURE 7: Accuracy comparison of ensemble classification models.

maximum value of 0.81 for other analysis models. The reason is that the analysis of British and American literature teaching texts here is more comprehensive than in other integrated learning models. It is proved that the ensemble classification model combining English and American literature teaching and the DHMM has reasonable text analysis and high sentiment classification accuracy.

SVM and NB have an obvious recognition accuracy rate compared with the ML-based algorithm of Kamble et al. (2021) in electroencephalogram-based emotion recognition [30], the five ensemble learning-based exact maximum likelihood algorithms, and the five traditional coupled map lattices algorithms. It shows that the integrated classification model combining British and American literature teaching has reasonable text analysis and high sentiment classification accuracy.

4. Conclusion

This paper mainly discusses two aspects. One is the sentiment tendency analysis method based on the sentiment dictionary, which mainly includes the establishment of the sentiment dictionary and the calculation method of sentiment weight. The second is the sentiment analysis method based on ML, which mainly introduces the judgment of different sentiment tendencies by the sentiment analysis model, which is ARAEC. The improvement of sentiment analysis improves the recognition range of text sentiment words in British and American literature teaching to optimize the process of text analysis. The main feature is that the sentiment analysis of text directly acts on the tendency of words, with fine granularity and accurate analysis. For example, the rule-based personality prediction accuracy of SVM is mostly around 0.5. Most of NB's rule-based personality prediction accuracy is around 0.4. Therefore, SVM has obvious recognition accuracy relative to NB. The sentiment analysis method based on ML has very high requirements on the training dataset. The text analysis simulation comparison between the Sosml model and the Webis model is mostly around 0.8. In conclusion, this paper has a reasonable text analysis

and high sentiment classification accuracy in combining British and American literature teaching with the integrated classification model based on the DHMM. The use of ML algorithms can effectively help teachers teach British and American literature through sentiment analysis. However, there are some difficulties at present, which provide potential research value for future work in this field. First, the diversity of samples will lead to the unsustainable accuracy of data processing. Datasets in different languages may make the same method behave differently. Second, the data analysis of a single algorithm cannot achieve ideal results. How to combine different algorithms to improve processing efficiency is the key research content in sentiment analysis in the future. Research on these aspects can be continued in the future.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declared no conflicts of interest.

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