Retraction

Retracted: Evaluation Method of Writing Fluency Based on Machine Learning Method

Mathematical Problems in Engineering

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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.

References

[1] S. Gao, "Evaluation Method of Writing Fluency Based on Machine Learning Method," *Mathematical Problems in Engineering*, vol. 2022, Article ID 1253614, 12 pages, 2022.

Hindawi

Research Article

Evaluation Method of Writing Fluency Based on Machine Learning Method

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In light of society's rapid advancement, more and more people worldwide are placing importance on education. There are several domains in China where the importance of writing exceeds the importance of reading, listening, or speaking. It has been shown that many Chinese students commit grammar problems if they are writing an article. Several researchers attempted to determine students' writing talents in terms of amount and complexity, on the one side, and then also focused on identifying conclusions on the accuracy, the organization of ideas, and the barriers to fluent writing via qualitative data gathering approaches. This research uses a machine learning technique to measure students' writing fluency. Writing fluency capabilities can be predicted using a novel adaptive generative adversarial network-based deep support vector machine (AGAN-DSVM) technique. The trace-oriented approach can be used to examine the features like accuracy, syntactic complexity, and organization of ideas aspects. The prediction rate of lexical complexity and sentence complexity of our proposed method achieves 90 and 95%, respectively. Plots created with origin's graphing tool display the results of a comparison between the proposed approach and several other ways already in use. The proposed method is evaluated and compared using several different metrics, including the accuracy dimension, syntactic complexity dimension, organization of ideas dimension, distributions of the mistakes in the text, lexical complexity, sentence complexity, essay particularities, and comparison of accuracy, F1 score, and syntactic complexity.

1. Introduction

People throughout the world are paying more attention to education as society develops rapidly (de Wit and Altbach [1]). For an individual to attain fluency in English, they must master four language skills: hearing, speaking, reading, and writing (Abrejo et al. [2] and Mody and Bhoosreddy [3]). Writing, on the other hand, appears to be the most difficult and unappealing skill to master. Since it demands a lot of time and careful feedback, which is essential to the growth of writing, teachers find it the most difficult to teach (Altnmakas and Bayyurt [4]).

A well-expressed piece of art possesses a specific set of traits. Furthermore, their ideas are organized logically and cohesively, which includes proper grammar and spelling, punctuation, and syntax standards (Wang and Fan [5]). The author employs a wide range of complex phrase structures and language, all while keeping the text intelligible. It is not difficult for someone with good writing skills to organize their material, and they do not waste a lot of time on the task of putting together coherent ideas. The more a person's writing ability increases, the better he or she can meet the needs of written expression (Mkandawire et al. [6]). As a result, writing is so highly valued in China that in some disciplines, it may even be more valuable than reading, listening, or even speaking.

To begin with, grammar is an inherent aspect of writing in the English language. Studies by Song [7] show that many Chinese students make grammatical errors when they write academic articles. For example, a sentence may have two verbs, the writers may not have understood what the pronoun "it" meant, or a sentence may be written without a subject. These types of errors can be seen in the writing of Chinese students of any grade level.

Figure 1 depicts a lesson plan for improving students' academic writing skills. According to the figure, teachers

Figure 1: Cycle of implementation of pedagogy to improve students' academic writing.

critiqued the students' opinion essay draughts, followed by a class discussion. They were asked to self-evaluate their work. Once they have done that, they will be asked to write a reflection journal entry in which they may share their thoughts on their performance, what they have learned, and their mistakes. This was followed by a class discussion in which the teacher addressed the points raised by the students. The pupils then worked in pairs to correct each other's work. They once again evaluate and provide feedback. Another reflective diary entry from each student provided the teacher with topics for a second whole-class discussion and explanation.

A clear focus will make our writing's goal more understandable and make it easier for readers to follow our logic. By structuring our body paragraphs, we make sure that both we and our readers maintain focus on and make connections with our thesis statement. A solid organizational structure enables us to express, evaluate, and make sense of our ideas. The notion represented in the main phrase is supported, explained, illustrated, or supported by evidence in the supporting sentences, which are also known as the paragraph's body. Additionally, elaboration provides more information to clarify what has already been presented. By mastering grammar, you will have the opportunity to choose your style nuances and make your writing more readable and understandable. Style affects the reader's perception of the material itself by serving as the container for the text's meaning. Chinese college graduates are increasing annually, and as English has become the de facto language of academia, they must be able to write in it for academic purposes (MacDonald [8] and Ahmed and Ali [9]). This study makes an effort to develop a system that is based on machine learning to analyze the writing fluency of students. This is necessary because manually evaluating students' writing fluency is a difficult task. The following are the contributions made by the study.

(i) To predict the writing fluency capabilities, a novel adaptive generative adversarial network-based

deep support vector machine (GAN-DSVM) technique is used.

(ii) The trace-oriented approach can be used to examine the features.

The remaining parts of the research were organized in the following way: the relevant works are illustrated in Section 2, the proposed technique is illustrated in Section 3, the findings and discussion are illustrated in Section 4, and the conclusion is illustrated in Section 5.

2. Literature Survey

The use of automated writing evaluation (AWE) in second language writing schools has become more popular in recent years. While the technology is focused on lower-level (LL) abilities, like grammar, instructors believe AWE may help by enabling them to focus more on higher-level (HL) writing skills like content and structure. This may have a favorable effect on student revisions. There is, however, a lack of data to back up these assertions, raising doubts about AWE's influence on classroom instruction. To test these claims, Link et al. [10]compared two second language writing courses allocated to either an AWE + teacher feedback or a teacher-only feedback condition. Geng and Razali [11] provide a comprehensive evaluation of the research into the usefulness of automated feedback. Analytical synthesis includes eleven publications published in the last five years that met the inclusion and exclusion criteria. Analysis of prior research gaps in automated feedback, such as lack of design for delayed post-tests, student writing performance, and students' writing techniques concerning the AWE program, is shown through a literature review matrix for synthesis. In China, "Automated Writing Evaluation (AWE)" has been extensively used in computer-assisted language acquisition. Research on what motivates students to utilize AWE is limited. To this goal, Garg et al. [12] and Li et al. [13] surveyed 245 Chinese college students and used their responses to evaluate several suggested hypotheses utilizing two external variables (i.e., computer self-efficacy and computer fear) added to the technology acceptance model (TAM). Perceived usefulness, attitude toward usage, and computer self-efficacy were shown to have a direct impact on learners' behavioral intention to use AWE, whereas perceived ease of use and computer self-efficacy had an indirect effect. Alobaid [14] and Shahabaz and Afzal [15] emphasize and use YouTube's online English learning materials as an example of a smart learning environment. This study hypothesizes that learners who utilize online language resources may improve their writing fluency over time. Salihuand and Zayyanu [16] and Zedelius et al. [17] explored whether human judgments of short story originality can be predicted by creativity metrics and linguistic analysis. College students (with and without creative writing expertise) composed short tales based on a prompt. The rubric assessments corresponded with existing creativity measures. Two computerized text analysis methods were used to examine the short tales' linguistic properties. Even though Frankenberg-Garcia points out that automated

writing assessment software has garnered a lot of attention in the CALL literature, there is a paucity of empirical research on predictive text and smart writing aids. To fill this knowledge vacuum, Dizon and Gayed [18] and Li [19] looked at the influence of Grammarly, an intelligent writing helper that uses predictive text technology to improve the quality of mobile writing produced by Japanese L2 English students in the USA. China's English-language colleges often use the AI-based writing assessment system. Using Juku "Automated Writing Evaluation (AWE)", Lu [20] found that AWE is effective in helping students with their English writing; both teachers and students have a positive attitude toward the use of Juku AWE in terms of immediate and clear feedback, time savings, and awakening interest in English writing.

To begin, a cross-sectional methodology looks at the variables of AWE adoption after a period that may have had some unavoidable and prospective effects on individual aspects of learners due to the long-term exposure to AWE. The longitudinal and comparative validity of results for the rapidly evolving context of AWE usage is still an open question. The research did not check for the moderating impacts of key variables like gender and other demographics. Students' preoccupation with correctness rather than flow in their writing was a significant obstacle. Therefore, students were reassured that making mistakes is not a "sign of inhibition" that must be eliminated, but rather a strategy for learning and an entirely normal part of picking up a second language. Learners, however, would be reminded of the need of achieving a happy medium between correctness and flow in both their formal and casual writing. The New Media Consortium's 2016 Horizon Report for Higher Education highlights the difficulty of customized learning, which includes the restriction of having to create learning environments that are flexible and responsive to unique learners in specific scenarios. Specifically, the issue of "one size fits all" arises when students are offered a choice between two or three episodes of the YouTube BBC language program as the focus of the next class; inevitability, a small number of students will choose the episode that the majority of their peers have chosen. When this happens, teachers will take note of the student's preferences and propose those subjects to other courses so that students have access to a wide range of information. Fortunately, the smart learning environment was able to assist with these difficulties, thanks to the many features and benefits that have since become standard in this kind of learning environment, as well as the proliferation of individualized learning opportunities. To investigate these issues, the present research develops an AGAN-DSVM.

3. Proposed Methodology

In this section, we will go into further detail on the machine learning technique to evaluate writing fluency. Figure 2 represents the suggested approach flow. Data collection tools were first used to acquire participant samples. After that, a normalization technique was used to preprocess the acquired data. Trace-oriented feature analysis is used to examine the data's features. Then to estimate the writing fluency skills, a unique adaptive generative adversarial network-based deep support vector machine (AGAN-DSVM) approach is applied.

3.1. Samples of Participants. 74 first-year English majors from two courses at a local university in southwest China participated in this study, with only eight of them being male, which is typical for majors like English. Most of them had been studying English since junior high school for at least six years and were proficient in the language (Yang 2020). Participants had to produce an essay expressing their viewpoints.

3.2. Data Collection Tools. The qualitative and quantitative aspects of fluent writing were measured using both qualitative and quantitative data gathering methods. The data collection tools listed below were used to gather student writings and their data.

(i) Writing Quantity Formula—A more objective metric for assessing writing output is the number of syllables written per minute, which may be calculated as an average of all words written in a given period.

(ii) Language Accuracy Holistic Scale—Accuracy was evaluated using the "Language Accuracy Holistic Scale." From 0 to 9, there are ten possible outcomes on this scale. From 0 to 10, each category ranks the writer's use of spelling, punctuation, and grammar accuracy.

(iii) Lexical Diversity Formula—Before figuring out lexical diversity, the total number of words and the number of different words were counted. In this study, unlike the others, polysemy was taken into account when figuring out how many different words there were. However, it was not taken into account when trying to figure out what kind of difference there would be when polysemy was taken into account and when it was not.

$$\text{Lexical diversity} = \frac{\text{Different no of words}}{\text{total no of words}} \times 100. \quad (1)$$

(iv) Lexical Density Formula—Students' texts were counted, and their lexical density was calculated by subtracting the terms on this list from the total number of words in each text.

$$\text{Lexical density} = \frac{\text{No of content words}}{\text{total number of words}} \times 100. \quad (2)$$

(v) Syntactic Complexity Scale—The method that the researcher used to determine the level of syntactic complexity involved looking at the grammatical structure of the sentence as well as the components that contributed to the sentence's meaning.

3.3. Preprocessing Using Normalization. A common preprocessing step in most data mining systems is data
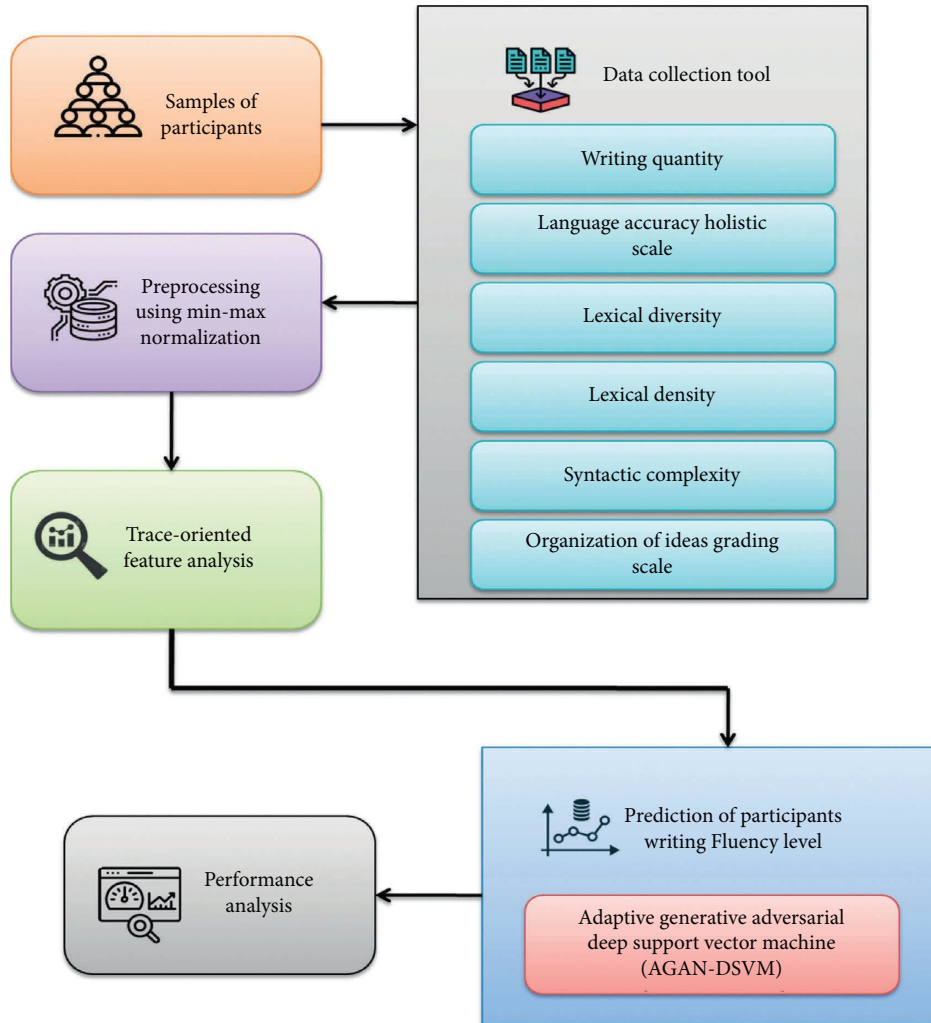
Figure 2: Flow diagram of the suggested approach.

normalization. When it comes to data cleansing, there are several methods at our disposal. We have chosen to employ z-score normalization because it is quick and easy.

3.3.1. Z-Score Normalization.

By taking the mean and standard deviation of each feature throughout a training dataset and dividing it by the dataset's size, Z-score normalization, also known as zero-mean normalization, normalizes each input feature vector. Each attribute's average and standard deviation are calculated. The transformation is required, as mentioned in the general formula.

$$n' = \frac{(n - \mu)}{\sigma}. \tag{3}$$

The discussed attribute n has a mean of μ and a standard deviation of σ. Every feature in the dataset is subjected to z-score normalization before training can commence. Once training data have been obtained, the standard deviation and mean of each feature should be stored for use as algorithm weights.

3.4. Trace-Oriented Feature Analysis (TOFA).

TOFA is used to analyze the features of the student's writing after it has been preprocessed. Finding a suitable projection matrix $U \in C^{o \times l}$ for linearly projecting $t_b = U^Y Z_b \in C^l$, $b = 1, 2, \ldots, j$ to lower the text vector dimension from to l, where $l \ll o$ is the goal of the linear feature extraction (FE) issue. The optimal projection matrix U is obtained from a set of text data Z by maximizing an objective function $N(U)$ under the restriction that $U \in M_{va}$ where $M_{va} = \{U \in C^{o \times l} | U^Y U = B\}$ is the solution space of the FE issue. The matrices $B \in C^{l \times l}$ are identical in this case. M_{va} is a continuous solution space because W can be any real value. Any FE algorithm's objective function, denoted by $N_{va}(U)$, can be expressed as follows:

$$U^* = \arg \max_{U \in M_{va}} N_{va}(U). \tag{4}$$

PCA, MMC, and OCA are three of the most often used feature extraction techniques that can be evaluated using the optimization framework outlined in [4].

3.4.1. Principal Component Analysis.

We can discover a p-dimensional subspace that has basic vector oriented in directions that have substantial variations with the use of PCA, which is an unsupervised FE technique. In this example, the covariance matrix of all the text documents is $R = \sum_{b=1}^{j} (z_b - H)(z_b - H)^Y / j$, where $h = \sum_{b=1}^{j} z_b / j$ is the mean of the text documents. There are a few ways to express the PCA's objective function in terms of the matrix trace, such as $N_{\text{LRE}}(U) = yc\{U^Y R U\}$ where $yc\{R\} = \sum_{b=1}^{j} R_{bb}$. Singular value decomposition (SVD), which has a time complexity, is the main source of PCA's computational burden. Thus, PCA's answer is

$$U^* = \arg\max_{U \in M_{va}} N_{\text{LRE}}(U). \tag{5}$$

3.4.2. Maximum Margin Criterion.

The maximum margin criterion is a new supervised method that has been suggested. There may be s classes of data in the collection; the number of classes is given by the symbol z_b and j_n, which is equal to 1, 2, ..s, etc. The vector of the centroid for the next class is given by

$$h_n = \frac{\sum_{z_b \in s_n} z_b}{j_n}. \tag{6}$$

The objective function of MMC is similar to that of LDA in that it utilizes an inter-class scatter matrix

$$K_i = \sum_{b=1}^{s} \frac{j_b}{j} (h_b - h)(h_b - h)^Y, \tag{7}$$

and an intra-class scatter matrix.

$$K_u = \sum_{b=1}^{s} \frac{j_b}{j} z_b \in s_n^A \{(z_b - h_n)(z_b - h_n)^Y\}. \tag{8}$$

To maximize the distance between documents of various classes and the proximity of documents of a similar class in the low-dimensional space being projected, MMC employs many techniques. To solve MMC, the objective function is $N_{\text{HHR}}(U) = yc\{U^Y(K_i - K_u)U\}$, and hence the solution is

$$U^* = \arg\max_{U \in M_{va}} N_{\text{HHR}}(U). \tag{9}$$

3.4.3. Orthogonal Centroid Algorithm.

The orthogonal centroid algorithm (OCA) is a supervised algorithm, too. A GC matrix decomposition test proved to be an excellent approach for text categorization problems. Large-scale data processing demands cannot be met by the efficiency of GC decomposition because of its time and space needs. Lemma 1 demonstrates that the OCA may be formulated in the optimization framework as well.

Lemma 1. *The following optimization issue is equivalent to solving OCA,*

$$U^* = \arg\max_{U \in M_{va}} N_{\text{DRE}}(U) = \arg\max_{U \in M_{va}} yc\{U^Y K_i U\}. \tag{10}$$

It is clear from equations (6), (9), and (10) that the PCA, MMC, and OCA are all working toward the same goal, which is to maximize the trace of the various matrices. Because of this, we can refer to these linear feature extraction techniques as trace-oriented approaches.

3.5. Prediction of Participants' Writing Fluency Level.

The methods that AGAN-DSVM uses will be covered in this section of the article. First, the justification behind and the specifics of using AGAN as a strategy to create more data on the performance of training students are discussed. After that comes DSVM, which is the part of the algorithm that handles the prediction model for the student's performance.

3.5.1. Generation of Training Data by GAN.

Unsupervised and semi-supervised learning are two of the most common applications for GAN. The generator (GR) network creates synthetic data samples that seem like actual data, whereas the discriminator (DR) network uses both real and fake data samples to determine what is real and what is not to make accurate classifications. A Nash equilibrium is reached when both networks are working together. To communicate with the generating network, it must use a discriminator that can distinguish between actual and fraudulent data samples. Data generated by the GR are checked against the ground truth by the discriminator, which generates an error signal. The error signal is utilized to enhance the generator's ability to produce more high-quality fake data.

A generator or discriminator often employs a multi-layered network composed of layers that are either fully linked or convolutional. The generator and discriminator do not have to be perfectly invertible for this to work. The adaptive GAN proposed in this paper incorporates the best aspects of prior CGANs. It can be expressed as follows:

$$
\begin{aligned}
P_{\text{source}} &= A\left[\log L(K = \text{real}|Z_{\text{real}})\right] \\
&\quad + A\left[\log L(K = \text{fake}|Z_{\text{fake}})\right], \\
P_{\text{class}} &= A\left[\log L(R = e|Z_{\text{real}})\right] \\
&\quad + A\left[\log L(K = e|Z_{\text{fake}})\right], \\
B(e, Q(j,e)) &= A_{z \sim Q(j,e)}\left[A_{e \sim L(e/z)}[\log G(e|z)]\right] + M(e).
\end{aligned}
\tag{11}
$$

This formulation's goal is to optimize $P_{\text{source}} + P_{\text{class}} - \lambda B(e, Q(j,e))$ for the discriminator and optimize $P_{\text{class}} - P_{\text{source}} - \lambda B(e, Q(j,e))$ for the generator. Both of these optimizations are intended to be carried out in the context of the $Q(j, e)$ function. Keep in mind that λ is the hyperparameter and that $B(e, Q(j, e))$ is the representation of the information that lies between $Q(j, e)$ and e. The architecture of the currently operational CGAN is shown in Figure 3(a). The term NS refers to the noise source, CR denotes the category or class, GR stands for generator, Y stands for actual data, Y' offers synthetic data, and A stands for added network.

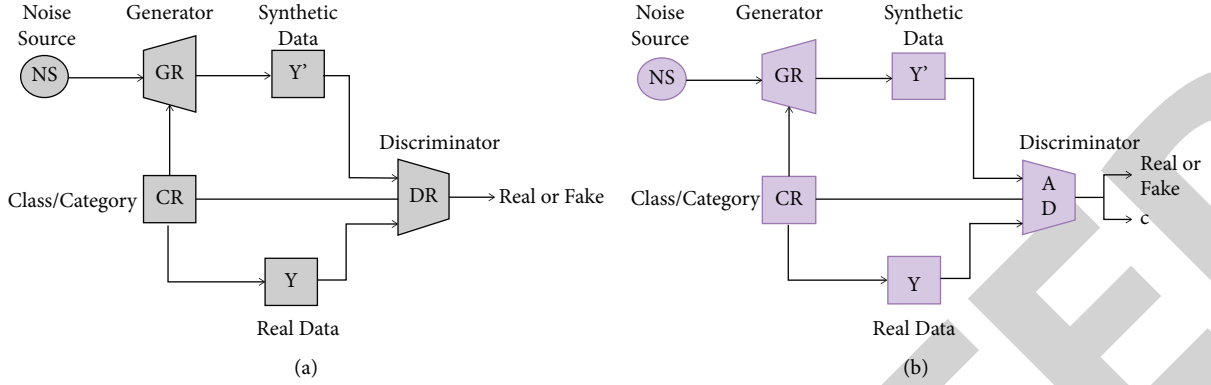According to the likelihood score, D can tell whether the incoming data coming from a GR dataset or a real

Figure 3: Architectural diagram of (a) existing CGAN and (b) proposed AGAN.

dataset. The GR and D networks are both conditional. By enhancing the data's diversity, it is possible to avoid bias in the generated data. The proposed AGAN is shown in Figure 3. AGAN has made three changes to the existing CGAN:

(i) Added a class variable or conditional statement to D.

(ii) Added a D-based extended network.

(iii) Each sample of data was tagged with a unique name.

3.5.2. Prediction of Students' Performance. Deep SVM layers are used to build a model that predicts students' writing performance. Like a deep neural network model, the framework is composed of numerous hidden layers of SVM. SVM, on the other hand, has a more flexible architecture because of its kernel function estimate and can handle large-scale inputs. It is more effective with smaller datasets. Because of its robust regularization ability, the suggested SVM can avoid overfitting. Figure 4 depicts the architecture of deep SVM in its entirety. Depending on the training data, the number of hidden layers may vary. The number of hidden layers was reduced in this work by using the grid search strategy, which also minimizes the computational cost. The model's performance may suffer as a result of an increase in the number of layers.

Existing research in the SVM model often uses kernels such as radial basis, linear, sigmoid, and polynomial. Several studies have also employed custom kernels because of the low performance of these kernels for many applications. Mercer's theorem is used to create a customized kernel in this study. It is more accurate to use radial-based kernel functions, as illustrated in equations (12)–(15), which show linear, sigmoid, and polynomial kernels, respectively.

$$S_1(z_1, z_2) = (z_1, z_2), \tag{12}$$

$$S_2(z_1, z_2) = \exp\left(\frac{\|z_1 - z_2\|^2}{2\sigma}\right), \tag{13}$$

$$S_3(z_1, z_2) = (z_1, z_2 + R)^L, \tag{14}$$

```
sL = SVC(kernel = 'linear')
//SL denotes "svcLinear"
sP = SVC(kernel = 'poly', degree = 8)
//sP denotes "svc Poly"
sG = SVC(kernel = 'rbf')
//sG denotes "svcGaussian"
sS = SVC(kernel = 'sigmoid')
//sS denotes "svcSigmoid"
model = Sequential()
model.add(sL)
model.add(sP)
model.add(sG)
model.add(sS)
model.fit_generator(X_train, Y_train)
```

Algorithm 1: Deep SVM.

$$S_4(z_1, z_2) = \tanh(z_1, z_2 + R), \tag{15}$$

where $k(x1, x2)$ is the kernel function, c is a real number, and p is a positive value. A heuristic approach has been used to learn numerous kernels. The M-heuristic is shown in equation (16) by examining the mean square error.

$$\mu_b = \sum_{b=b}^{4} \frac{(H_b - H_n)}{\sum_{n=b}^{4} \sum_{b=b}^{4} (H_b - H_n)}. \tag{16}$$

It is important to note that the structure of the numerous kernels used in SVMs might differ from one layer to the next. There are two main reasons why the technique that was just described is preferable to those that were presented in the earlier research. In the first place, the complexity of AGAN is comparable to that of the existing GAN because it is built on the same techniques. Second, other DL models are not as complicated. To put the suggested method into action, Algorithm 1 provides an implementation of the proposed approach.

4. Results and Discussion

In the following part, the findings of an evaluation of the student's writing fluency using a machine learning algorithm
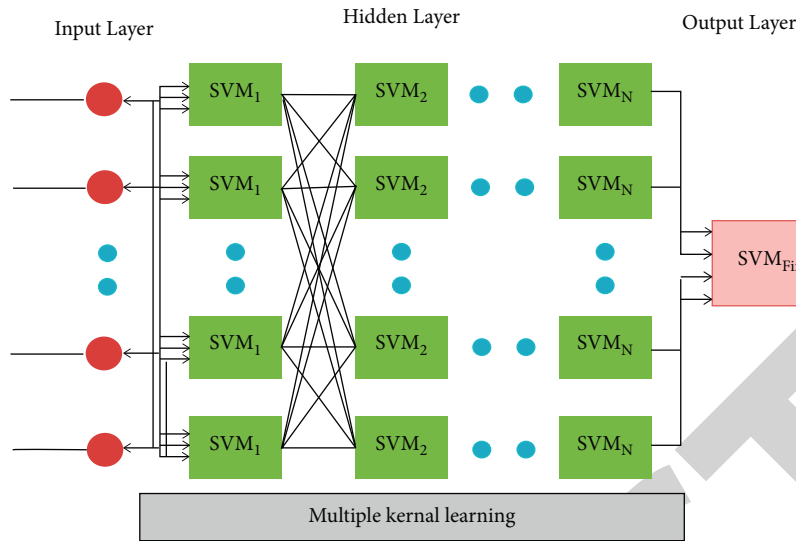
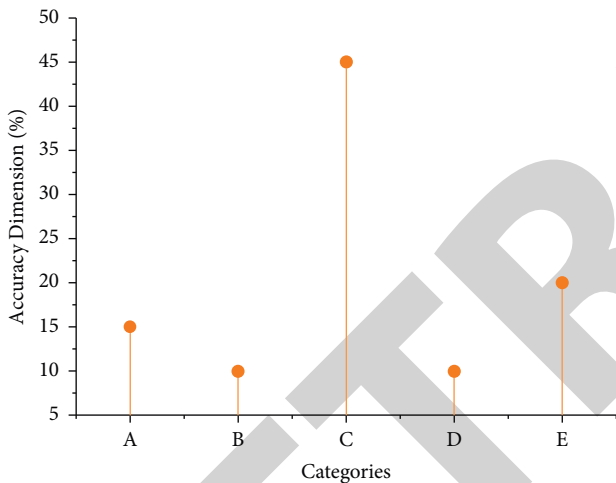FIGURE 4: Architecture of proposed deep SVM.
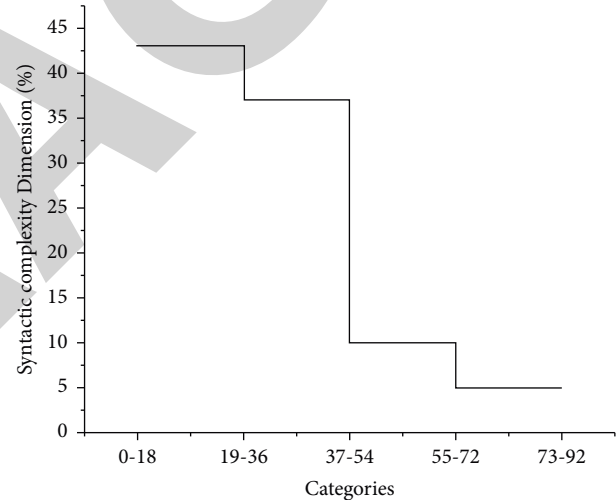

FIGURE 5: Fluent writing's accuracy dimension.

FIGURE 6: Syntactic complexity dimension.

are presented. The "scikit-learn library" and the "Natural Language Process Tool Kit (NLTK)" are used to implement the ML models. Our proposed method is compared with existing methods to prove the proposed method's efficiency. Figure 5 depicts the accuracy dimension of fluent writing for the students that participated in the study. A indicates that the pupil did not produce a writing sequence that could be analyzed; B indicates that the reader understands obvious deficiencies in "words," "spelling," "punctuation," or "grammar"; C indicates that the reader sees obvious deficiencies in the organization of words, and *E* suggests that the reader does not see any grammar errors. The majority of the students' works were graded as belonging to the C category, as shown in the figure. The percentage of pupils whose texts were placed in category A was 15%, category B was 10%, category C was 45%, category *D* was 10%, and category *E* was 20%.

Figure 6 shows the fluent writing points earned by students in the syntactic complexity category. Figures from

this study show that 5% of students wrote an essay with a score of 0–18. Similarly, 5% of students had a text grade between 73 and 92. The majority of secondary school students wrote an essay with a point value ranging from 19 to 36.

Figure 7 depicts students' fluent writing scores regarding the organization of ideas dimension. "A" suggests a weak link between ideas and the topic, "B" indicates a clear main idea, "C" indicates a strong relationship between ideas and the topic, and "D" indicates that ideas have not strayed too far from the topic, according to this figure. Over three-fifths of student texts (35%) fall into the B category.

To check the progress that the pupils had made in their writing ability, additional factors, such as sentence structure, which was denoted as "A," sentence component, which was denoted as "B," collocation, which was denoted as "C," misuse of tense, which was denoted as "D," misuse of different parts of speech, which was denoted as "E," and misuse
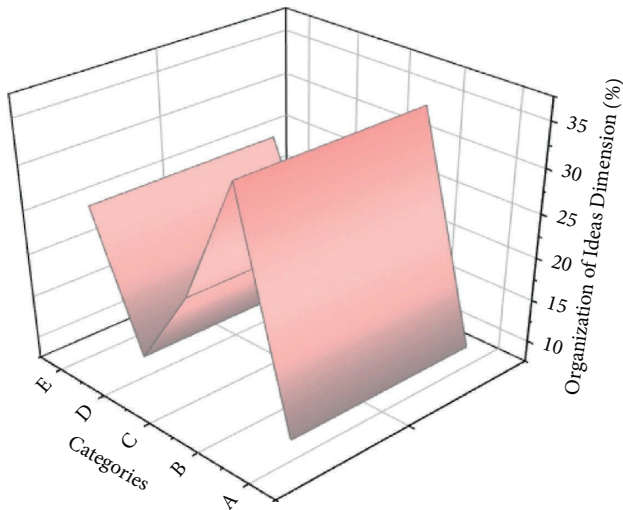
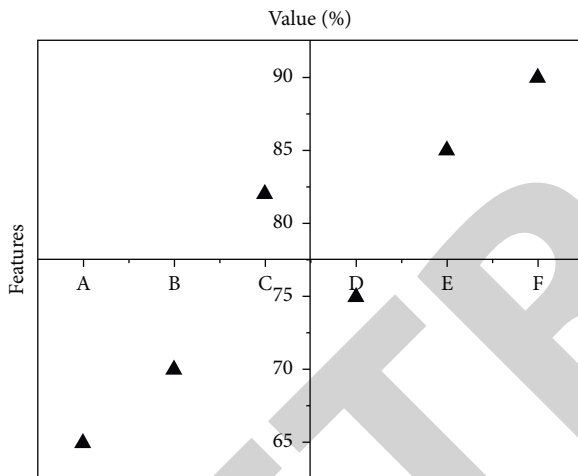Figure 7: Organization of idea dimension.

Figure 8: Distributions of the mistakes in text.

of spelling, which was denoted as "F," were analyzed. The features of the errors in the text are illustrated in Figure 8. The figure shows that the majority of the students' work falls within the "F" category.

Language complexity is defined as "the fraction of relatively unusual or advanced terms in the text that is being read by learners." It can tell you how good your writing is and how formal it is. Figure 9 compares the lexical complexity prediction of the proposed method with existing methods. Proposed methods outperform existing methods.

The ratio of clauses to the total number of T units (C/T) was used to determine the sentence complexity. "An independent clause and all its dependent clauses" is the definition of a T unit. C/T was chosen because it has been proved to predict both syntactic and wring proficiency. Figure 10 illustrates how the proposed method's sentence complexity prediction compares to other methods. Proposed methods outperform existing methods.

The $F1$ score is evaluated by finding the harmonic mean of the recall and precision scores. The $F1$ score of the
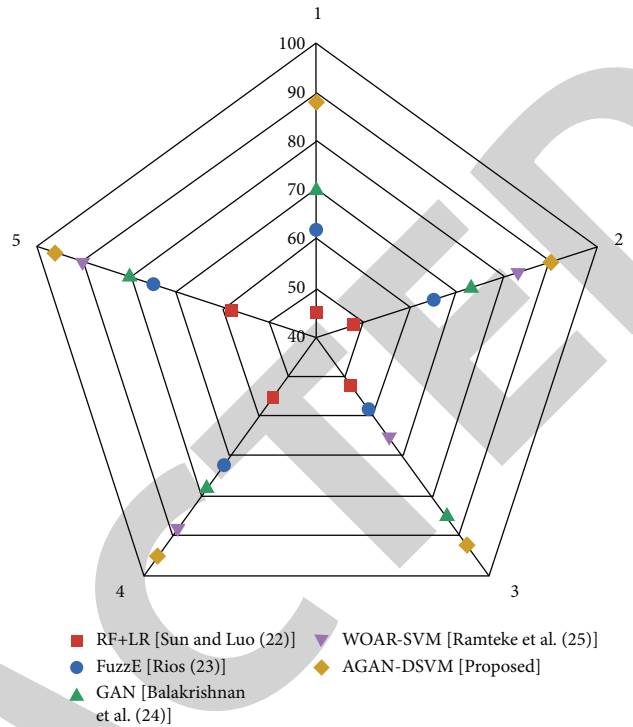

Figure 9: Lexical complexity.

suggested approach is compared to the $F1$ score of the existing methods in Figure 11. It is abundantly evident that the suggested method is superior to the methods that are already in use. It is determined by applying the formula to the calculation.

$$F1 - score = \frac{2 \times precision \times recall}{precision + reccall}. \tag{17}$$

The relative level of difficulty of each portion of the essay is displayed in Figure 12, which may be found here. The letter "A" in the figure denotes the background information, the letter "B" indicates the primary contents, the letter "C" indicates the topic sentences, the letter "D" indicates the supporting thoughts, and the letter "E" indicates the concluding sentences, and the letter "F" indicates the main conclusion. The majority of pupils had the most trouble with items in the categories "B" and "F," as shown in the figure.

Accuracy is a classifier's predictions that match the true value of a label during the evaluation phase. It may also be expressed as a percentage of right assessments relative to the total number of exams. Figure 13 shows the comparison of accuracy for existing and proposed methodologies. When compared to the existing method, the proposed method has greater accuracy. RF + LR has a 55%, FuzzE has a 63%, GAN has a 74%, WOAR-SVM has a 85%, and the proposed AGAN-DSVM has 94% accuracy.

In this context, syntactic complexity refers to "the variety and sophistication of grammatical resources demonstrated in linguistic creation." This means that syntactic complexity encompasses similar ideas like variety, diversity, and the level of linguistic fanciness. Figure 14 shows the comparison
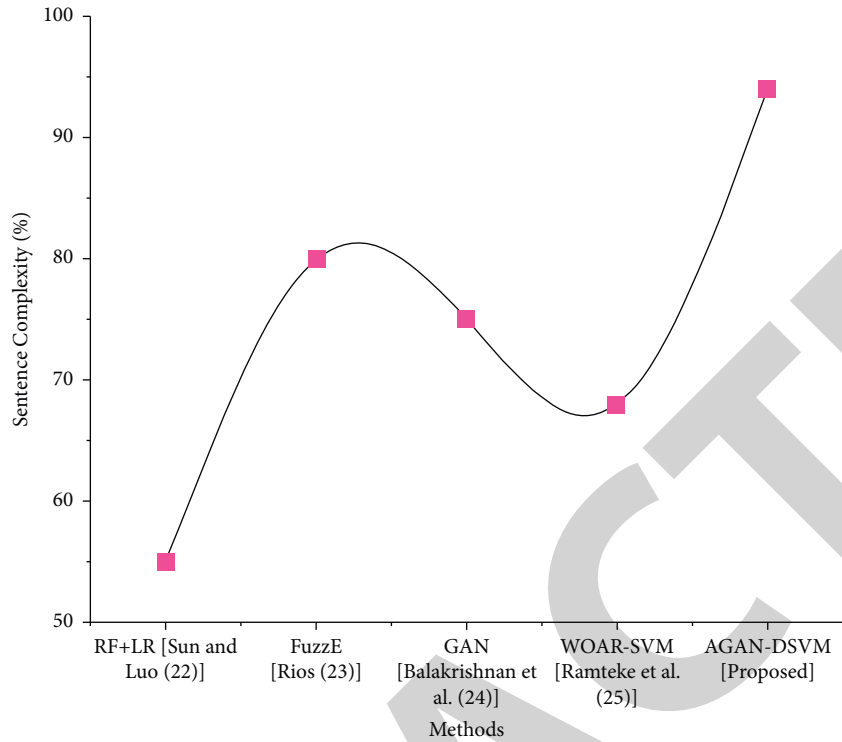
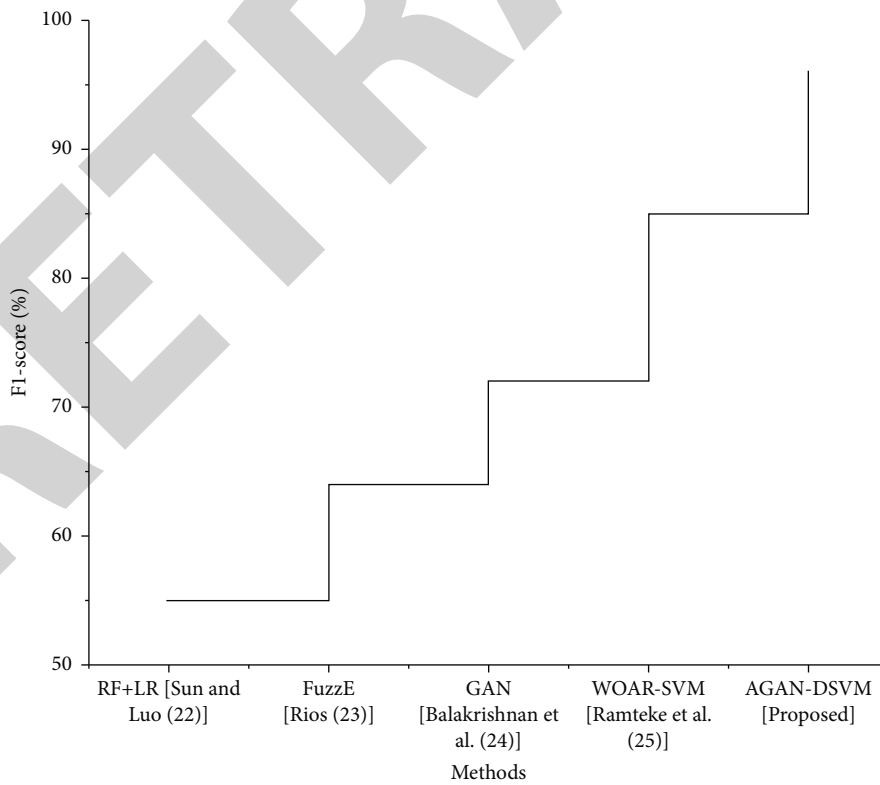Figure 10: Sentence complexity.
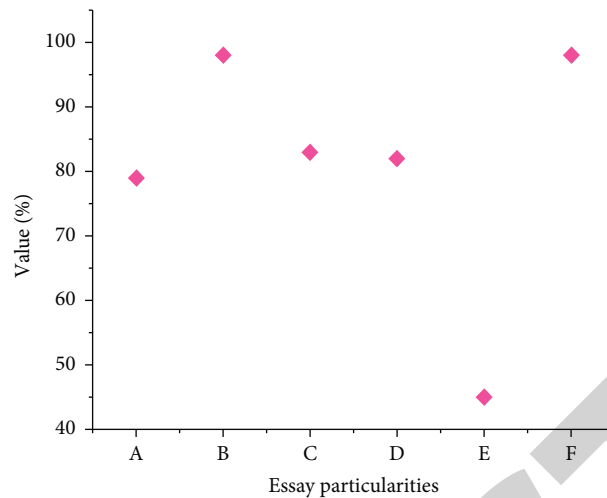

Figure 11: Comparison of F1-score.
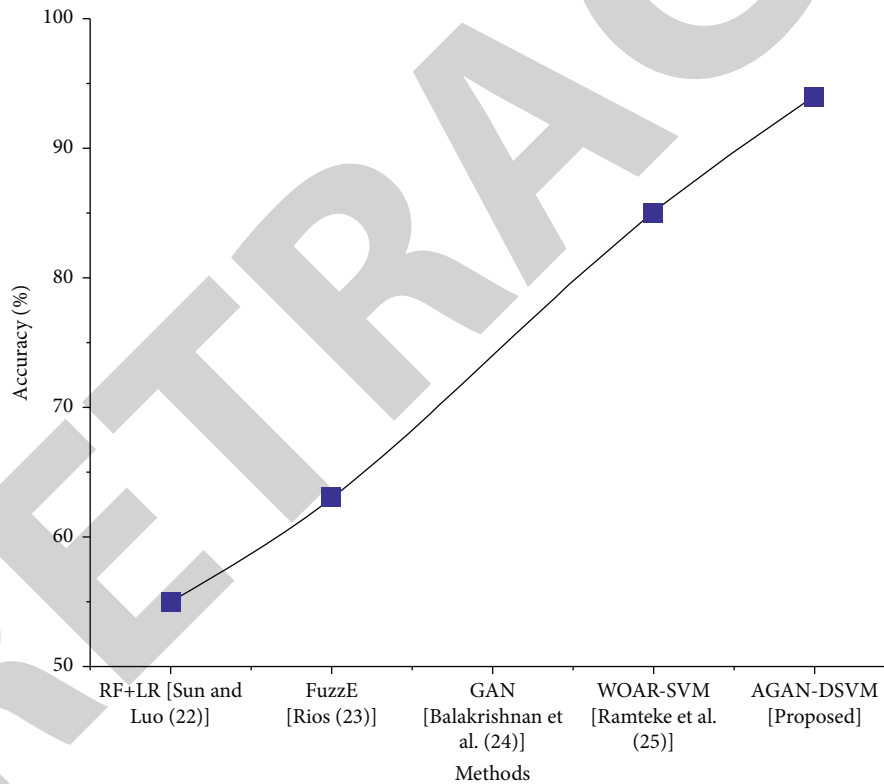
Figure 12: Essay particularities.

Figure 13: Comparison of accuracy for existing and proposed methods.

of syntactic complexity for existing and proposed methodologies. When compared to the existing method, the proposed method has lower syntactic complexity. RF + LR has a 91%, FuzzE has a 82%, GAN has a 74%, WOAR-SVM has a 66%, and the proposed AGAN-DSVM has 53% syntactic complexity.

Comparative analysis of the proposed technique with existing models is depicted in Figures 9–11. "Random forest + logistic regression (RF + LR)," "FuzzE," "generative

adversarial network (GAN)," and "weighted one-against-rest support vector machine (WOAR-SVM)"are the existing methods employed in this research. Figures prove that the proposed strategy outperforms the existing methods, because of the shortcomings of the existing approach. The following is a list of the current approaches' shortcomings. Predictions made using RF + LR, FuzzE, and GAN are ineffectual for real-time predictions, while WOAR-SVM does not work well with very large datasets.
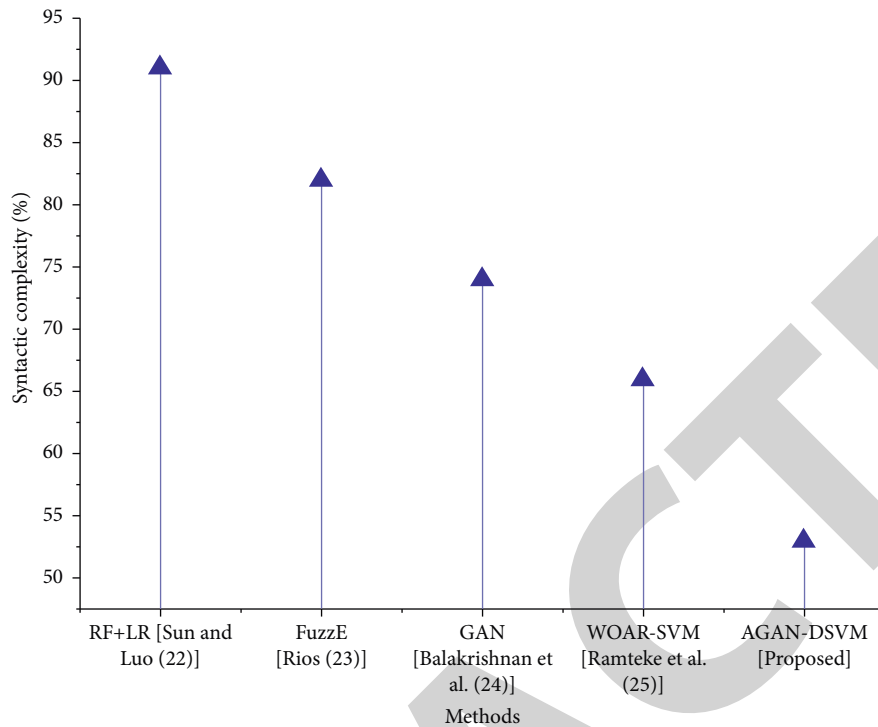
FIGURE 14: Comparison of syntactic complexity for existing and proposed methods.

5. Conclusion

To assess students' writing fluency, this study used a machine learning technique. A novel AGAN-DSVM technique can predict writing fluency. Examining the features is possible through the use of a trace-oriented technique. Numerous studies have found that students' inability to use punctuation correctly, their failure to follow spelling standards, their failure to construct structurally appropriate sentences, and their inability to choose the right words are the most common causes of errors in their writing. According to the findings of our study, the spelling mistakes made by students account for 90% of all faults found in their written work. Our suggested strategy can attain 90 and 95% accuracy for predicting lexical difficulty and sentence complexity, respectively. When taken together, these results show that writing composition is an essential field of inquiry for future research to focus on in Chinese students. Given the importance of writing to one's academic and professional success, researchers should continue their work in this field by expanding their focus to include a variety of additional abilities that might boost one's ability to write effectively.

Data Availability

The data used to support the findings of this study can be obtained from the author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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