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Research on the Career Personality of College Students Based on Machine Learning Model

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Abstract. *With the expansion and popularization of higher education, the number of college students is increasing year by year. How to make college students accurately identify their own personality traits and improve their comprehensive quality is an important content in college career planning education. Aiming at the technical challenge that existing occupational personality recognition methods are difficult to effectively fuse the deep semantics of text with psychological personality traits, this paper investigates a machine learning model-based occupational personality recognition method for college students. Firstly, the Latent Dirichlet Allocation (LDA) model is introduced to construct a personality analysis model based on the Big Five personality, which establishes the connection between text words and personality traits. On this basis, BERT is used to obtain psychological words with personality traits as input to BiGRU to better capture textual semantic features. Next, the Hard Attention Mechanism (HAM) is introduced to give different weights to each word, so that important words receive more attention, and the character features and textual semantic features are fused through the Soft Attention Mechanism (SAM). Finally, deeper feature extraction and dimensionality reduction is performed using fully connected networks as a way to recognize personality. The experimental outcome implies that the designed model has a recognition accuracy of 91.7%, which is superior to other models in terms of personality recognition accuracy.*
Keywords: Personality recognition; LDA model; Big five personality; BERT model; GRU

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1. **Introduction.** Developing students with a sound professional personality should be devoted to the moulding and development of a good professional character, in addition to the enhancement of personality dynamics. Occupational character is the requirement of a certain occupation on the character of the practitioner. By choosing an occupation that suits one's own character, and by making use of one's strengths, avoiding one's weaknesses and making up for one's shortcomings according to the needs of the society

and the characteristics of the occupation at any time and any place, the good character traits can be preserved and developed, and the bad character traits can be corrected and remodelled [1, 2]. With the increasingly severe employment pressure, how to let college students know themselves more accurately during their studies, improve their professional character and combine it with their professional traits will become an important hand in the professional education of college students in the future [3]. Currently, college students post their needs and evaluations for jobs on online recruitment platforms, and in-depth mining of the semantics of the text and accurate identification of personality traits can help colleges and universities better understand students' job preferences, make quick decisions, and improve satisfaction [4, 5].

1.1. **Related work.** Hirschmüller et al. [6] used a lens model to find out the relationship between students' personality and their email name naming habits and concluded that email names have the highest correlation with the openness dimension of the experience of an individual's personality. Alhendi [7] analyzed and investigated the characteristics of students with different personality dispositions in terms of their emotional expression based on an online recruitment platform. Dos Santos et al. [8] trained a personality classification model on a short text dataset and used its output as meta-features to predict the personality traits of Facebook students. Sharma and Kaur [9] predicted the personality traits of Facebook students by recording the student's dialogues with text and extracting features from it using LIWC [10] using a regression algorithm with an accuracy of only 73%. Maharani and Effendy [11] conducted a Big Five personality questionnaire on highly effective students, applied web crawlers to collect job demand data, and applied a regression algorithm to construct a personality prediction model that achieved an accuracy of 79.5%. Compared with the traditional manual recording methods, Machine Learning (ML) is the core of artificial intelligence, which is able to find a class of algorithms that can find potential rules from a large amount of seemingly irregular data by self-learning and simulating human thinking patterns. ML has a wide range of applications in classification, recognition, prediction and many other fields. Fernandes et al. [12] used Gradient Boosted Decision Tree (GBDT) for personality recognition using features such as student texts and behaviors in the Zhilian recruitment platform, but the high complexity of GBDT resulted in low recognition efficiency. Xu et al. [13] extracted student avatar features and used Pearson's correlation coefficient to measure the correlation between personality and different features of the avatar. Talaat et al. [14] applied Support Vector Machine (SVM) based on the collection of students' social data to train and build a personality classification model. Recently, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and

other ML techniques are applied to the field of character prediction, and the methods are innovative and have achieved relatively good results. Usselmann et al. [15] use Word2Vec to construct a character prediction model based on network text, but the efficiency is not high. Suman et al. [16] combined students' personal portraits with web text and used Convolutional Neural Networks for personality prediction. Mohades Deilami et al. [17] designed for extracting document level feature vectors from text and used CNNs for vocational personality recognition of students based on Big Five personality. Ren et al. [18] used Bert to train word embedding matrices and used CNN for personality prediction. Zhao et al. [19] compared the performance of CNN and RNN in a personality classification task and found that RNN outperforms CNN for extracting local features. Alotaibi et al. [20] utilized the advantages of convolutional neural networks and LSTM for character recognition with 86.2% recognition accuracy. Due to the simple structure, high computational efficiency, fast training speed and small number of parameters of GRU compared to RNN, LSTM, Kumar et al. [21] embedded words based on Word2Vec and combined BiGRU to form word vectors containing semantic information of the text, and finally used these word vectors for character recognition. The final character recognition is done by these word vectors.

1.2. **Contribution.** In the above-mentioned personality recognition methods, most of the researches ignored the students' personality features when extracting the text semantic features, which led to unsatisfactory recognition efficiency. Thus, to cope with this issue, this article designs a method for recognizing college students' professional personality based on ML model, which contributes to the field of personality recognition as follows. (1) The LDA model was used to generate the themes of the text such as job requirements, and the generated theme words were combined with the Big Five personality theory to effectively establish the connection between the theme words and the personality traits, and at the same time, the scores of the five personality dimensions of the text were obtained, and a personality trait vector of length five was obtained through the normalization process. (2) BERT is used to extract the deep semantic information embedded in the text, and psychological words with personality traits are obtained through lexical and syntactic analyses, which are used as inputs to BiGRU to better capture the dynamic semantic interactions between the deep semantics of the text and the personality traits. (3) Most of the current feature fusion is achieved using simple splicing, but such methods limit the further improvement of the overall model accuracy, therefore, the Soft Attention Mechanism (SAM) approach is used to effectively fuse personality features and semantic features to identify the final occupational personality. (4) The experimental outcome implies that the accuracy, precision, recall, and F1 of the suggested model are 91.7%, 93.2%, 90.5%, and 91.8%, respectively, which are all significantly improved compared to the comparison model, verifying the efficiency of the designed method.

2. Theoretical analysis.

2.1. **Big five personality model.** The big five personality model is the most researched and talked about structural model of personality in the field of psychology, which provides a framework for defining personality, unifies individual differences in personality, and classifies personality as Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism [22, 23]. The Big Five model is widely accepted because different psychological tests and analyses do not change the validity of the big five model. (1) Openness is the degree to which an individual is open to experiencing and experiencing various things. A person with a high degree of openness pursues art, is full of imagination, and is eager to try new things without bothering to follow the rules. (2) Conscientiousness refers to whether a person's behavior and thoughts are well organized and whether he or she has a sense of responsibility and duty. This trait determines whether people can have a long-lasting persistence to the set goals and whether they can maintain order in the process of long-lasting persistence. (3) Extraversion measures the degree to which people are interested in the outside world. Positive descriptors include energetic, bold, cheerful and gregarious. Negative descriptors include laid-back, shy, introverted, and independent. (4) Agreeableness defines how positive a person is in maintaining social relationships. People who are more easy-going show a greater degree of altruism, seeing helping others as a form of self-satisfaction rather than a sacrifice of self. (5) Neuroticism is the degree of sensitivity to people's emotions and their ability to adjust them. Individuals who are more emotional show stronger emotions and are more irritable and anxious.

2.2. **Gated recurrent unit.** GRU is an RNN obtained by improving on the LSTM model with the unique feature of using an update gate instead of the original input and forgetting gates [24]. Whether GRU decides to save a certain information or discard a certain information is obtained through learning in the process of training, so it can effectively obtain the corresponding relationship based on long-distance dependence, and the model structure of GRU is indicated in Figure 1. Each GRU network neuron contains 1 memory unit and 2 gate units, as shown in the following equations.

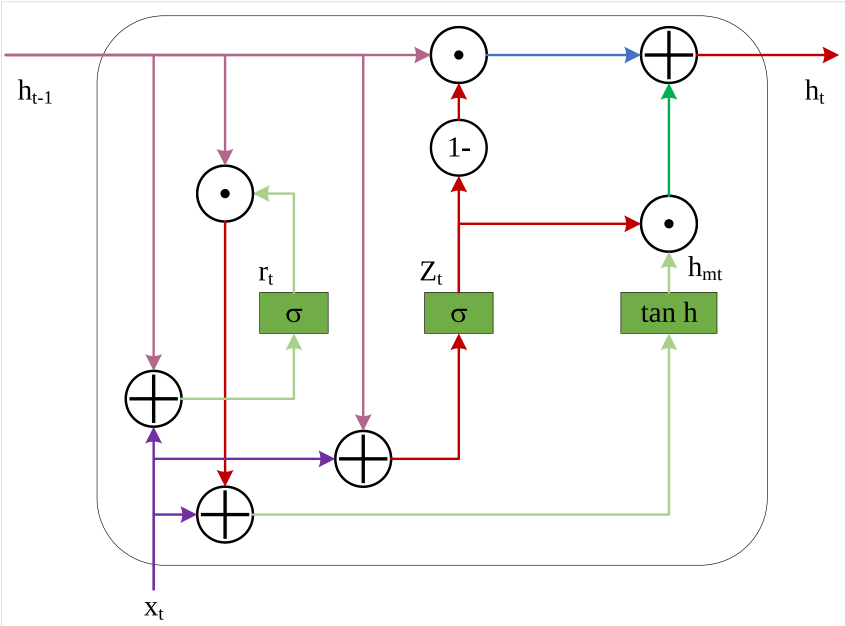

Figure 1. Structure of the GRU model

$$s_t = \delta(V_s x_t + W_s g_{t-1}) \tag{1}$$

$$z_t = \delta(V_z x_t + W_z g_{t-1}) \tag{2}$$

$$\tilde{g}_t = \tanh(V x_t + W (s_t * g_{t-1})) \tag{3}$$

$$g_t = (1 - Z_t)\, g_{t-1} + z_t\, \tilde{g}_t \tag{4}$$

where z is the update gate, s is the reset gate, V and W are the weight matrices of GRU, $\tilde{g}_t$ is the candidate memory unit at time t, g_t represents the state of the obscured level at time t, x_t represents the input at time t, g_{t-1} represents the obscured state at time $t-1$, δ and tanh are the activation functions.

3. **Analysis of occupational personality traits based on big fve personality model and LDA model.** Personality will have a certain impact on the way students express their emotions verbally, and it goes without saying that people with similar personalities tend to express their emotions verbally in the same way. Therefore, by analyzing the job requirements, electronic resumes, personality test questionnaires and other texts of college students in online recruitment platforms, this paper can effectively assist the personality analysis task to improve the accuracy of the personality recognition task. LDA model, known as Latent Dirichlet Allocation Model, is a kind of text generation model, which can automatically identify the latent topic information in large-scale text [25]. This paper uses the LDA model to extract themes from the text information posted by students on the online recruitment platform, and then through the principle of the big five personality, constructing the relationship between different theme word categories

and each personality dimension in the big fve personality, which is used as an important feature for analyzing the vocational personality of college students, and the specific steps are as follows $\vec{v}.\vec{\rho}$ $\vec{v}\vec{\rho}$

(1) For all topics $l \in [1, L]$, the "topic-word" mixture distribution Φ, i.e., $\phi_l \sim \mathrm{Dir}(\alpha)$, is obtained from the Dirichlet distribution obeying the parameter α. The distribution is the same as the Dirichlet distribution;

(2) For all texts $m \in [1, M]$, the length of the current document m is firstly generated by the Poisson distribution function, i.e., $N_m \sim \mathrm{Poiss}(\zeta)$. Then the "document-subject" mixed distribution is obtained by the Dirichlet distribution obeying the parameter β, i.e., $\vec{\vartheta}_m \sim \mathrm{Dir}(\beta)$. The length of the current document m is then obtained by the Poisson distribution function.

(3) For each word $n \in [1, N_m]$ in the current document m, generate the topic z to which the word belongs according to the mixture distribution of $\vec{\vartheta}$, i.e., $z_{m,n} \sim \mathrm{Mult}(\vec{\vartheta}_m)$, and randomly select the feature word $w_{m,n}$, i.e., $\vec{\omega}_{m,n} \sim \mathrm{Mult}(\;)$, according to the previously generated topic distribution Φ. From this, we can obtain the probability of generating the n-th word t in the m-th text as follows.

$$p(w_{m,n} = t \mid \vec{\vartheta}_m, \Phi) = \sum_{l=1}^{L} p(w_{m,n} = t \mid \phi_l)\, p(z_{m,n} = l \mid \vec{\vartheta}_m) \tag{5}$$

The distribution of the whole text is implied in Equation (6).

$$p(W \mid \vec{\alpha},\ \vec{\beta}) = \prod_{m=1}^{M} p(w_m \mid \vec{\alpha},\ \vec{\beta}) \tag{6}$$

The solution model is very important in LDA, and the solution model is to derive the hidden variables from the observed data. The observed data are the words in each document, while the topic distribution β corresponding to each document, the word distribution α corresponding to each topic, and the topic $z_{m,n}$ belonging to each word $w_{m,n}$ in the text are all unknown hidden variables. In this paper, the Gibbs sampling approach [26] is used to sample the topic of each feature word, determine the topic to which each feature word belongs, and finally calculate the approximation value of the parameter through frequency statistics. In this way, the parameter estimates can be approximated by the mixed probability distribution of the feature words, and the joint distribution is indicated below.

$$p(\vec{z}, \vec{w} \mid \vec{\alpha}, \vec{\beta}) = \prod_{z=1}^{K} \frac{\Delta(n_z + \vec{\beta})}{\Delta(\vec{\beta})} \cdot \prod_{m=1}^{M} \frac{\Delta(n_m + \vec{\alpha})}{\Delta(\vec{\alpha})} \tag{7}$$

All the processed documents are used as input text for the LDA model, and the parameters are set to extract potential themes from the text. The probability of each theme is calculated for each student for later training of classification process, as indicated below.

$$p(t, s) = \sum_{w \in t} p(t \mid w) \times p(w \mid s) \tag{8}$$

where t denotes the generated topic, w denotes the word item in topic t, and u denotes the corresponding student.

Using the associations between these potential subject words and the text, the corresponding values of each word to each personality dimension of the big five personality, BFM, and thus the corresponding values of the text to the five personality dimensions of the big five personality, can be obtained. Since a word may have multiple functions, the combined average of the values of the five big five personality dimensions corresponding to these subject words is used as the final relationship value. The personality factor values for the j-th dimension in word w are shown below.

$$\mathrm{BFM}(w_j) = \sum_{i=1}^{m} R_{ij} \tag{9}$$

where w_j represents the j-th personality dimension of a word w. m represents that a word w has m different thematic categories. R_{ij} represents the relationship value between the i-th functional category and the j-th personality dimension of a word.

Through the above equation, the size of the correlation value can be obtained between all the subject words and the five personality dimensions, and then the correlation value of all the words in a text can be added together to get the personality scores of the five personality dimensions corresponding to the whole text, and then we can get the final vector f_c reflecting the personality traits of the text through the normalization process of these five scores.

$$f_c = \frac{(X - X_{\text{mean}})}{X_{\text{std}}} \tag{10}$$

where X denotes the personality score, X_{mean} denotes the mean of the personality scores of the five personality dimensions, and X_{std} personality dimensions.

4. **Recognition of college students' occupational personality based on machine learning model.**

4.1. **BERT-based semantic encoding of text.** Focusing on the issue of low recognition efficiency of existing occupational personality recognition methods, this paper, on the basis of the above analysis of occupational personality traits, adopts BERT [27] to encode the textual information as the input of BiGRU to better capture the contextual semantic information, introduces the Hard Attention Mechanism (HAM) so that the relatively important words can get more attention, and through the SAM fuses the character features and semantic features extracted by LDA. Finally, deeper feature extraction and dimensionality reduction using fully connected networks are used for character recognition. The overall model of the designed personality recognition method is implied in Figure 3.

Most of the traditional models use Word2Vec to obtain word representations, which is a static encoding and cannot solve the problem of multiple meanings of words. BERT, as a pre- trained language model, adopts dynamic word representations, and can encode the contextual semantic information very well. Thus, to better explore the professional personality, this paper adopts BERT to encode the text information. First of all, the original text data are preprocessed to remove line breaks, tabs and other meaningless symbols, and the special markers [CLS] and [SEP] are used as the beginning and the end of sentence $S = \{x_1, x_2, \ldots, x_n\}$ to get the sentence. Secondly, existing research has shown that psychological knowledge and linguistic lexical features can help improve personality recognition performance [28]. This article adopts lexical annotation and psychological a priori knowledge to extract the set $B = \{B_1, B_2, \ldots, B_i\}$ of verbs and adjectives containing more character traits in the text, splice the words in B, and add special markers to form sentence P. Finally, BERT is used to vectorize sentences S and P respectively, and compute the contextual representations of each word, and get the corresponding word vector matrices denoted H_S and H_P.

$$C = \big[[\text{CLS}], x_1, x_2, \ldots, x_n, [\text{SEP}]\big]_{S\ (\text{cls},1,\ldots,n,\text{sep})} \tag{11}$$

$$P = \big[[\text{CLS}], b_1, b_2, \ldots, b_n, [\text{SEP}]\big]_{P\ (\text{cls},1,\ldots,n,\text{sep})} \tag{12}$$

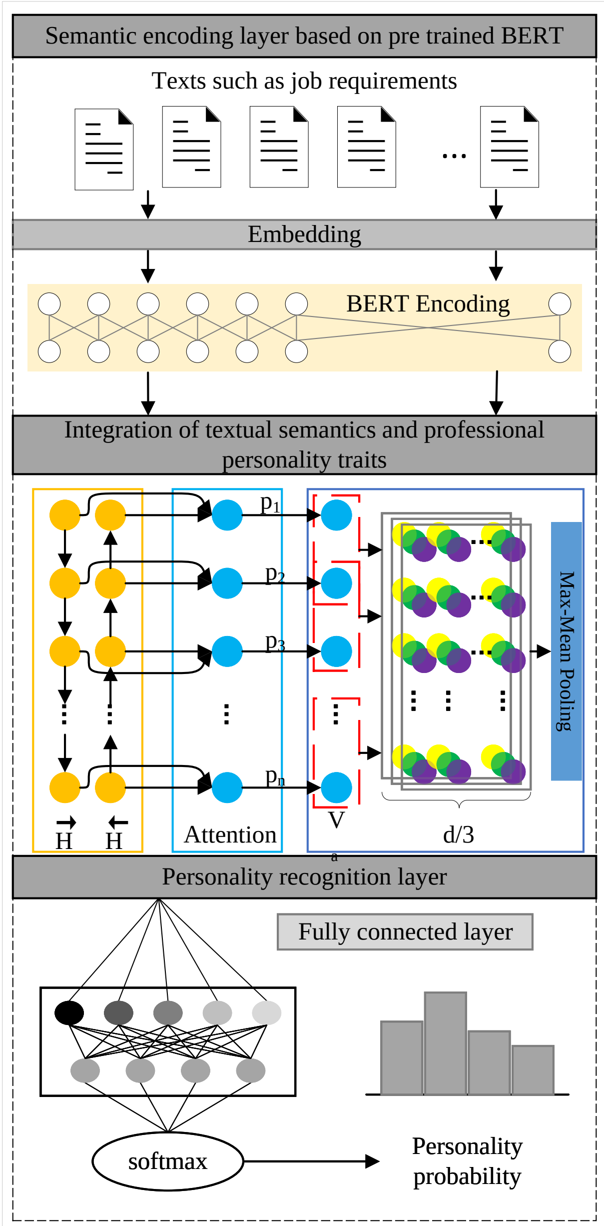

Figure 2. The ML-based career personality recognition model for college students

4.2. **Integration of textual semantics and professional personality traits.** Based on the text semantic feature vectors generated above and the character feature vectors generated in Section 3, for the goal of better mining the deep-level semantic interactions, this paper utilizes bidirectional GRU (BiGRU) to better extract the contextual semantic information and alleviate the gradient problem. HAM is introduced to give different weights to each word, and the vectors containing character features extracted by LDA are fused into the feature vectors of the text through SAM. Using the output of the above BERT encoding as the input to BiGRU, the obscured states g_t and $\overleftarrow{g}_t$ of the forward and backward outputs are computed as shown below.

$$g_t = \mathrm{GRU}(g_{t-1}, S_t) \tag{15}$$

$$\overleftarrow{g}_t = \mathrm{GRU}(\overleftarrow{g}_{t-1}, S_t) \tag{16}$$

$$g_t = V_t \overrightarrow{g}_t + W_t\, g_{t-1} + b_t \tag{17}$$

where the input at time t is denoted by S_t; b_t represents the bias vector; V_t and W_t are the weight matrices.

Then the weight of the target attention $W_t = \delta(g_t)$ is calculated by the HAM mechanism, and the weights of the HAM mechanism are processed by the probabilistic operation, and the probability vector is denoted by p_t, as shown below.

$$p_t = \frac{\exp(W_t)}{\sum_{i=1}^{m} \exp(W_t)} \tag{18}$$

Assign the corresponding W_t to g_t of the obscured level state with weights p_t, as follows.

$$\gamma_t = \sum_{i=1}^{m} p_t \cdot g_t \tag{19}$$

The final feature matrix f_d is finally obtained through the pooling level.

$$f_d = \left[\, \max\{\gamma_t\};\ \mathrm{mean}\{\gamma_t\} \right] \tag{20}$$

where $\max\{\cdot\}$ and $\mathrm{mean}\{\cdot\}$ denote maximum and average pooling, respectively. The input to the HAM is the output of the text sequence information extracted using BiGRU, and the output matrix covers the text serialization information well while putting more attention on the character trait vocabulary so that the semantic information can be better expressed. The above ML-based model mines semantic features through BERT and BiGRU, and to comprehensively use personality feature f_c and semantic feature f_d to predict the final personality category, it is necessary to effectively fuse the two, but the traditional feature fusion often adopts a simple splicing method, and cannot well fuse the semantic or scale inconsistent features. Therefore, this article considers a feature fusion approach relied on SAM.

Firstly, f_c and f_d are spliced by the following equation.

$$f^* = [f_c : f_d] \tag{21}$$

Then the weights V_a (consisting of real numbers between 0 and 1) are obtained over the forward propagation level and the Sigmoid level with the following equation.

$$V_a = \mathrm{Sigmoid}\big(W_2 \cdot \mathrm{ReLU}(W_1 V + b_1) + b_2\big) \tag{22}$$

The final fusion vector $F = f^* \cdot V$ is obtained by multiplying the weights V_a by the fusion vector splicing vector.

4.3. **Occupational character recognition for university students.** For occupational personality prediction, the final fusion vector F is fed into the fully connected network responsible for personality recognition and outputs the personality recognition vector F' which is subsequently pooled over F' to obtain the personality probability vector F_Y.

$$F' = (V^* F + b) \tag{23}$$

$$F_Y = \mathrm{softmax}(F') \tag{24}$$

where V^* denotes the occupational personality trait learning matrix, b denotes the bias value, and softmax denotes the activation function To further improve the recognition accuracy, in this paper, the model is optimized by the cross-entropy loss function [29], defined as shown in Equation (25).

$$\mathrm{Loss} = -\frac{1}{N} \sum_{n=1}^{N} \left[Y_n \cdot \log \hat{Y}_n + (1 - Y_n)\, \log(1 - \hat{Y}_n) \right] \tag{25}$$

where N is the dataset size, Y_n is the actual value and $\hat{Y}_n$ is the predicted value.

5. Experiments and analysis of results.

5.1. Comparative Experiments.

The experiment uses ubuntu 18.04 operating system, A100 GPU, 80G memory, pytorch deep learning framework, and Python 3.8 programming language. This article takes the data of 9172 college students in the class of 2023 from a university in China as the experimental object to evaluate the suggested method of recognizing college students' occupational personality based on ML model. The dataset contains students' basic information, psychological assessment information, etc., and the crawler technology is used to collect the text data of 53,691 texts generated from students' browsing of the online recruitment website. The details of data distribution for each text subgroup based on students' occupational personality are shown in Table 1.

Table 1. Distribution of datasets

Personality type	Number of text items
Agreeableness	9325
Conscientiousness	14296
Extroversion	11209
Neuroticism	8219
Openness	10642

The accuracy of the offered method BT-GRU on the recognition of various types of occupational personality is shown in Figure 3, the accuracy of personality recognition of Agreeableness, Conscientiousness, and Extroversion is above 90%, but the accuracy of recognition of Neuroticism and Openness is lower than 90%, which is because Neuroticism and Openness are both related to the emotional stability and are easily influenced by the outside world, and it is difficult to distinguish between their features, so the recognition accuracy is not as good as the other three personalities. However, the overall recognition accuracy is above 90%, which verifies the effectiveness of BT-GRU.

For the goal of better measuring the performance of the methods, accuracy (ACC), precision (PREC), recall (REC) and F1 are used as evaluation metrics to compare the experiments of SVM [14], BF-CNN [17], BR-CNN [18], CNN-LSTM [20], VE-GRU [21] and the designed method BT-GRU, and the experimental outcome are implied in Table 2.

Table 2. Comparison of performance of different occupational personality prediction methods

Method	ACC (%)	PREC (%)	REC (%)	F1 (%)
DVM	75.8	77.3	74.5	75.9
BF-CNN	81.6	83.8	80.4	82.1
BR-CNN	83.9	84.1	83.5	83.8
CNN-LSTM	86.2	83.5	85.9	84.7
VE-GRU	87.9	88.3	86.1	87.2
BT-GRU	91.7	93.2	90.5	91.8

As can be seen from Table 2, BT-GRU has the best performance in all the metrics, with an ACC of 91.7%, which is improved by 15.9%, 10.1%, 7.8%, 5.5% and 3.8% compared to DVM, BF-CNN, BR-CNN, CNN-LSTM, and VE-GRU, respectively. The F1 is the tonal

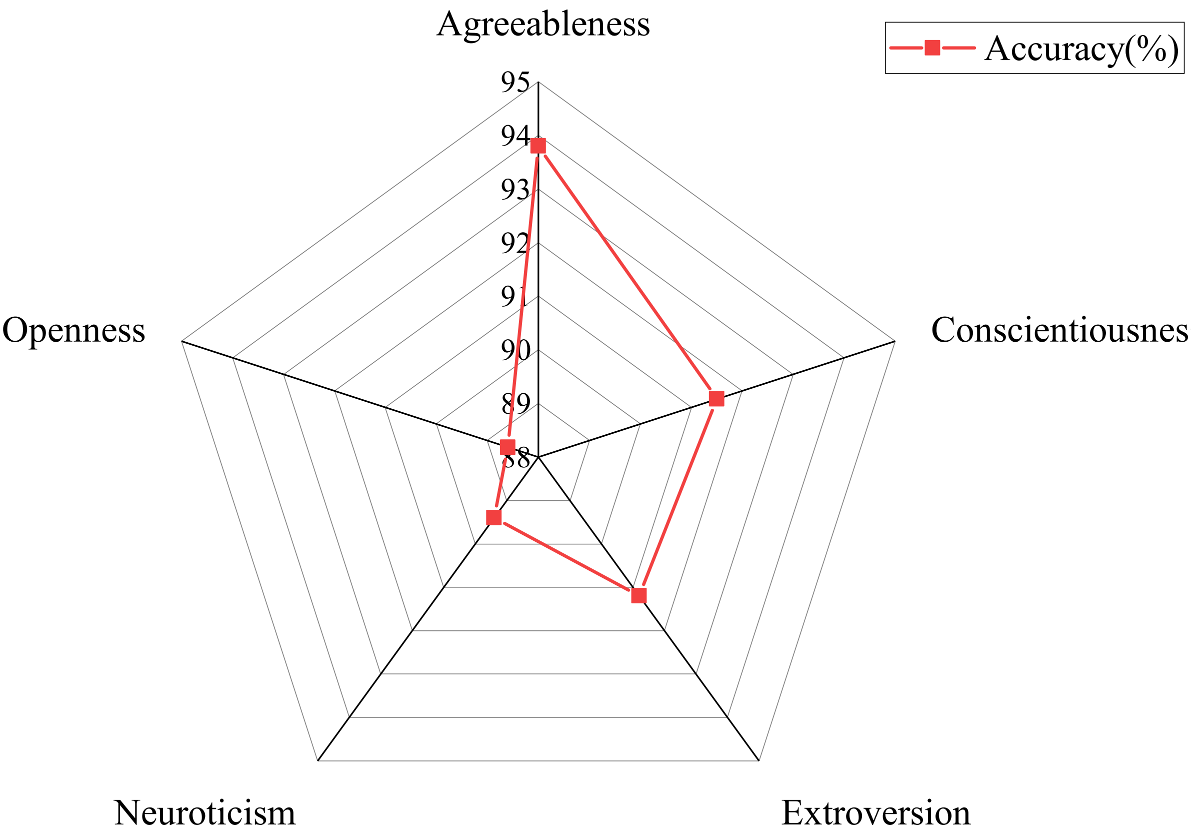

Figure 3. Recognition accuracy for different personality types

average of the PREC and REC, which best reflects the accuracy of recognition. The F1 of DVM, BF-CNN, BR-CNN, CNN-LSTM, VE-GRU, and BT-GRU are 75.9%, 82.1%, 83.8%, 84.7%, 87.2%, and 91.8%, respectively, and the F1 of BT-GRU is the highest, which indicates that BERT-GRU has the strongest ability of character recognition. DVM is based on SVM for character recognition of students, but SVM has higher computational complexity compared to neural networks, and is more sensitive to the choice of parameters and kernel function, so the recognition efficiency is not high. BF-CNN and BR- CNN are both based on CNN for character prediction and recognition, but they are insufficient to extract textual information about students in the online recruitment platform. CNN-LSTM is a hybrid model based on CNN and LSTM for students' personality recognition, which does not analyse the personality features and semantic features in the text, and the recognition efficiency is worse than VE-GRU. VE-GRU uses Word2Vec to encode textual information and BIGRU for semantic feature extraction and character classification, although it achieves good recognition results, Word2Vec has obvious shortcomings in dealing with polysemous words, training data requirements, interpretability, etc., so the recognition performance is weaker than that of BERT-GRU. In summary, BERT-GRU's all recognition performance is higher than other methods, and the recognition efficiency is more satisfactory.

5.2. **Ablation experiment.** To better verify the impact of each component of BERT text semantic encoding, text semantic feature extraction, LDA character feature analysis, and feature fusion on the recognition performance in BERT-GRU, ablation experiments are conducted, and four comparative models are designed for the analysis, and the metrics are still used as ACC, PREC, REC, and F1, and the outcome is implied in Figure 4. (1) Remove the BERT encoding component and replace it with the most basic Word2Vec embedding encoding, noted as "-BE". (2) Remove the textual semantic feature extraction component and extract only character features using LDA, denoted as "-TE". (3) Remove LDA character feature analysis and use only textual semantic feature extraction, noted as "-LDA". (4) Remove the SAM-based feature fusion component and use only simple splicing for feature fusion, denoted as "-SAM".

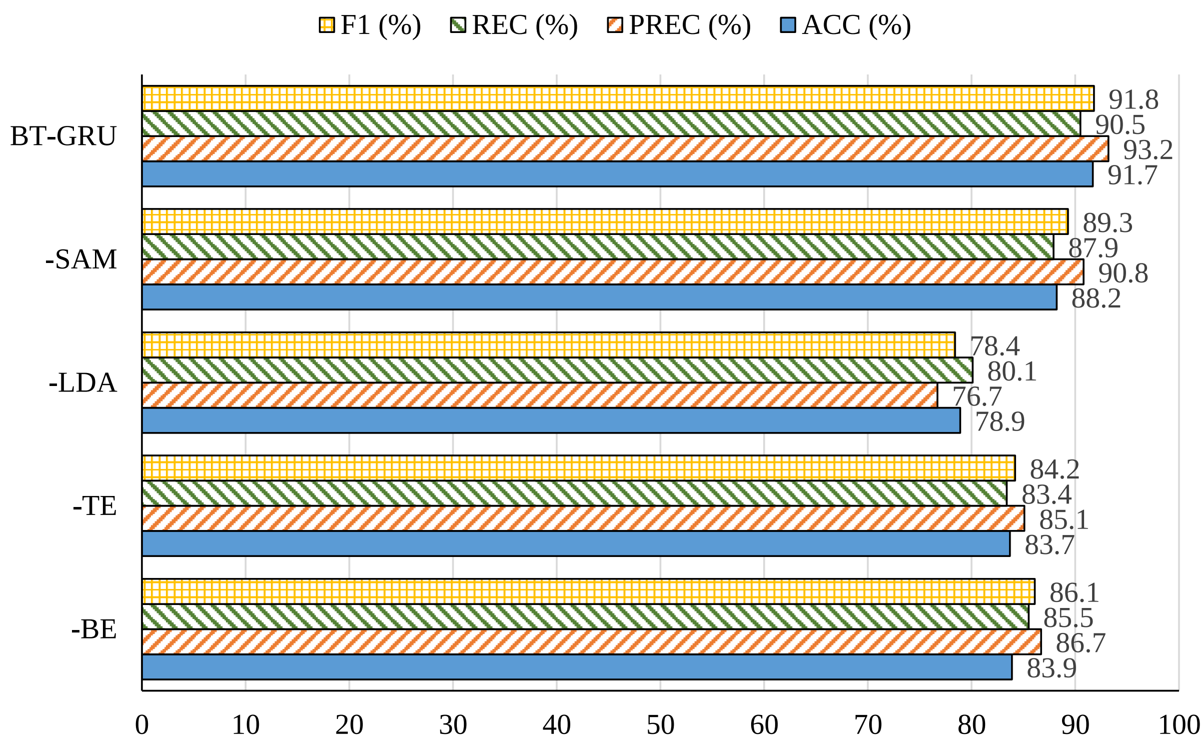

Figure 4. Comparison of ablation results for each component of BERT-GRU

As can be seen in Figure 4, the indicators of "-LDA" are the lowest, with ACC, PREC, REC and F1 being 78.9%, 76.7%, 80.1% and 78.4% respectively, indicating that the LDA personality trait analysis is very important for students' vocational personality recognition, and that analyzing the text through LDA and the big five personality model of the personality traits can improve the recognition efficiency. "-TE" has the next lowest recognition efficiency with 83.7%, 85.1%, 83.4%, and 84.2% for ACC, PREC, REC, and F1, respectively, suggesting that feature extraction of textual semantics is equally important for improving character recognition performance. The recognition performance of "-SAM" is higher than that of "-LDA", "-TE" and "-BE". This indicates that the inclusion of SAM has a better recognition effect than normal splicing fusion. In conclusion, BERT-GRU with all components fused achieves the best performance.

6. **Conclusion.** Intending to the issue that existing personality recognition methods ignore students' personality characteristics when extracting text semantic features, which leads to inefficient recognition, a ML model-based professional personality recognition method for college students is suggested, which has the following innovations. (1) Introducing the LDA model to theme mine the electronic resumes and other texts of college students in the online recruitment platform, and combining the mined theme words with the theory of big five personality psychology, so as to get the feature vectors reflecting the students' occupational personality. (2) Using BERT to encode text semantics to obtain psychological words with personality traits and use them as input to BiGRU to extract the potential text semantic features obtained. (3) Introducing HAM to give different weights

to each word, fusing the mined character feature vectors into the semantic feature vectors of the text through SAM, and outputting the character recognition results through the fully connected network.

(4) The experimental outcome implies that the recognition accuracy of the proposed method is improved by 3.8%-15.9% compared to machine learning models such as SVM, CNN, LSTM, etc., which exhibits superior recognition performance. This paper is mainly based on the big five personality for character trait analysis, and in the next step of the work, it will be further supplemented with more complete personality data and a more detailed test of the suggested method.

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