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RESEARCH ARTICLE

A Deep Learning Model for Psychological Support in Student Entrepreneurship

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ABSTRACT The rise in entrepreneurial endeavours has brought attention to college students' mental health issues, and developing an accurate assessment tool for them has become a key area of study. The paper proposes the fully embedded bi-order network (FE-BiON) model, a deep learning-based mental health evaluation tool that may be used to evaluate the mental health of college students launching their own businesses. The model innovatively combines fully embedded feature engineering and high-low order parallel network structure, thus improving the recognition ability and evaluation accuracy of psychological characteristics. In order to verify the validity of the model, this paper uses three datasets: The national health and nutrition inspection survey in the United States, the national health and nutrition inspection survey in South Korea, and the behavioral risk factor monitoring system for testing and comparative experiments. The findings demonstrate that in three public datasets, the accuracy and F1 value of the FE-BiON model reach as high as 0.91 and 0.88, respectively, outperforming other comparator models and demonstrating greater prediction performance. The results of ablation experiment further prove that the synergistic effect of high-low order networks and the fully embedded feature processing method have played a significant role in capturing the complex relationship between features and improving the prediction performance of the model. The suggested FE-BiON model performs better in mental health prediction, as evidenced by its accuracy of over 90% in all mental health levels on the assessment of college students' mental health. The research results provide scientific basis for the development of entrepreneurship education in colleges and universities, theoretical support for the formulation of mental health intervention measures, and practical guidance for improving the success rate of college students' entrepreneurship, which has important educational and policy influence.

INDEX TERMS Deep learning, mental health, college students' entrepreneurship, FE-BiON model, high-low order parallel network.

I. INTRODUCTION

A. RESEARCH BACKGROUND AND MOTIVATIONS

In today's fast-developing society, college students, as the future pillars of the country, bear important economic and social responsibilities. With the upsurge of entrepreneurship, more and more college students devote themselves to entrepreneurial activities, and the pressure and challenges they face also increase. According to research, mental health issues including anxiety, depression, and interpersonal conflicts are common among college students. These issues not only negatively impact the students' mental health but also have an adverse effect on the success rate of entrepreneurship [1], [2], [3]. It is critical to focus on college students' mental health because, as per the China Youth Entrepreneurship Development Report, up to 70% of entrepreneurial college students reported having encountered varying degrees of psychological pressure while launching a business [4], [5], [6]. Therefore, how to identify and intervene these psychological problems in time has become an important

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research topic to promote the success of college students' entrepreneurship.

In addition, the traditional mental health assessment methods usually rely on experts' subjective judgment, lacking systematicness and objectivity [7], [8]. Research on the use of artificial intelligence (AI) and deep learning technologies in mental health evaluation has progressively gained traction as these technologies have advanced. Relevant research demonstrates that the machine learning-based approach can successfully raise the identification rate of mental health issues and subsequently promote mental health interventions [9], [10]. College students are facing more and more psychological difficulties, particularly in the business setting. Consequently, it is especially crucial to create a deep learning-based mental health assessment model that can offer college students more methodical and scientific psychological help.

B. RESEARCH OBJECTIVES

This paper aims to put forward a mental health assessment model based on deep learning to test the mental health status of college students who are starting a business. Specifically, the research objectives include designing and implementing a fully embedded bi-order network (FE-BiON) model based on fully embedded feature embedding method and high-low order parallel network. Through feature extraction and classification of data, the mental health status of college students can be accurately identified, thus providing data-based decision support for universities. At the same time, the performance of the model on different datasets is verified, and the effectiveness and feasibility of the FE-BiON model are evaluated.

Compared with traditional mental health assessment methods, FE-BiON model overcomes the subjectivity and limitations of traditional methods by innovatively combining fully embedded feature engineering and high-low parallel network structure, and can more accurately capture the complex relationship between college students' psychological characteristics and entrepreneurial success. This model can effectively identify the mental health status of college students through feature extraction and classification, and provide data-driven decision support for colleges and universities. Compared with traditional machine learning methods, FE-BiON model not only improves the accuracy of mental health problems identification, but also improves the ability to capture complex relationships between features through the combination of high and low-level network structures. This makes the model have higher prediction accuracy and explanatory ability in solving the mental health problems of college students' entrepreneurship, and then promotes the optimization and development of college students' entrepreneurship education system. In addition, the application of FE-BiON model is not limited to the field of college students' entrepreneurship. Its unique deep learning framework and fully embedded feature processing method can also be extended to other fields, such as mental health survey, employee mental health assessment, etc., with wide applicability. By improving the scientificity and systematicness of mental health assessment, this paper provides new technical means and theoretical support for mental health intervention in related fields, which has important application value and social impact.

II. LITERATURE REVIEW

Academic circles are deeply concerned about the connection between the mental health of college students and their performance as entrepreneurs. Scholars have explored the relationship between mental health and entrepreneurship among college students from many perspectives in recent years. Wang emphasized the importance of college students' psychological qualities to their entrepreneurial success. He noted that mental health education in conjunction with innovation and entrepreneurship education in colleges and universities was an inevitable trend of educational reform in the new era [11]. Through the innovation of educational concepts that keep pace with the times, people can promote the organic combination of these two kinds of education and cultivate more high-quality innovative and entrepreneurial talents for national development. Margaça et al. based on the theory of planned behavior, analyzed the causal model of entrepreneurial intention through gender, and discussed how individual resilience and psychological well-being mediate these relationships. It was found that psychological resilience significantly mediated the relationship between perceived behavior control, attitude and entrepreneurial intention among female, but not among male [12]. Based on social exchange theory, Siyal et al. discovered that inclusive leadership had a favorable impact on employees' creative and innovative work behaviors and that this link was mediated through intrinsic motivation based on data gathered from 320 employees in a Chinese R&D business [13].

In the field of mental health assessment, traditional assessment methods are faced with problems of efficiency and accuracy, and the introduction of machine learning and deep learning technology provides new ideas for mental health assessment. Iyortsuun et al. retrieved 33 papers about the diagnosis of various psychological disorders through systematic evaluation and meta-analysis, and analyzed their applications in machine learning and deep learning technology, aiming at providing guidance for the future research direction of the diagnosis of mental health status and the prediction of treatment results [14]. Using a thorough literature review, Elyoseph et al. evaluated the performance of different Large Language Models (LLMs) in predicting the prognosis and long-term outcome of depression, and found that most LLMs were highly consistent with the views of mental health professionals, especially in the treatment expectation [15]. Their study showed that AI had the potential to supplement the judgment of professionals, but it needed to be strictly verified and combined with manual judgment to better promote the development of mental health care.

Tornero-Costa et al. systematically evaluated the application of AI in the field of mental health, and found that the application of AI in different mental health categories was uneven, and there were some problems such as insufficient data preprocessing, lack of external verification in model development, and low transparency in reporting. These defects and challenges showed that the application of AI in the field of mental health needed to overcome many obstacles to ensure that it could play an effective role in mental health management [16].

Although the existing research provides important insights into the relationship between mental health and entrepreneurship, most of the research mainly focuses on a single mental health factor or entrepreneurial dimension, lacking a comprehensive evaluation of the multi-dimensional characteristics of mental health. Traditional machine learning methods, such as random forest and logistic regression, improve the recognition accuracy of mental health problems to a certain extent. But because they mainly rely on manual feature extraction, it is difficult to capture the complex relationship between features, and the processing ability of high-dimensional data is limited. It cannot effectively deal with the diverse and complex mental health features in college students' entrepreneurial environment. In addition, traditional methods often rely on experts' subjective judgment and lack systematicness and objectivity. The proposed FE-BiON model overcomes the limitations of these traditional methods by innovatively combining fully embedded feature engineering and high-low order parallel network structure. FE-BiON model can effectively capture the complex relationship between multi-dimensional mental health characteristics, and improve the prediction accuracy and robustness of the model. By combining deep learning with mental health assessment, FE-BiON model provides a new solution for comprehensive assessment of college students' entrepreneurial mental health, and also provides an important reference for mental health assessment in other fields.

III. RESEARCH MODEL

A. A FEATURE EMBEDDING METHOD BASED ON FULLY EMBEDDING

In the process of improving the success rate of college students' entrepreneurship, the data-driven model is very important to identify the key factors that affect the success of entrepreneurship. Entrepreneurial data usually contains a variety of structural characteristics, such as students' educational background, entrepreneurial experience, mental health status and so on. These data include both discrete classification characteristics (such as education and gender) and continuous numerical characteristics (such as age, income and mental health score) [17], [18], [19]. To effectively capture these complex and diverse features, this paper proposes a feature embedding method based on Fully Embedding (FE). This method can refine different types of features, improve the model's ability to understand and model the data related to college students' entrepreneurship, and thus provide an effective basis for entrepreneurial psychological support and decision-making [20], [21]. When dealing with mental health characteristics, the model transforms psychological states such as anxiety and interpersonal adaptation into low-dimensional vectors by feature embedding method, which helps the model to better understand the relationship between these complex mental health characteristics and entrepreneurial success. For example, suppose that anxiety score is a numerical feature, and after nonlinear transformation, it forms an enhanced feature vector with the original feature. It is transformed into a high-dimensional space representation through the embedding process to better capture the potential relationship between psychological state and entrepreneurial performance.

For discrete data such as gender and education, the FE module embeds the classification features into a low-dimensional continuous vector space [22]. Specifically, assuming that the input classification feature is x_c, the embedding process can be completed by an embedding matrix $E_c \in \mathbb{R}^{n\times d}$, where n is the number of classification features and d is the embedding dimension. The embedding vector equation is expressed as:

$$e_c = E_c \cdot x_c \tag{1}$$

e_c is an embedded classification feature vector, which has better representation ability. Figure 1 shows the FE process of classification features.

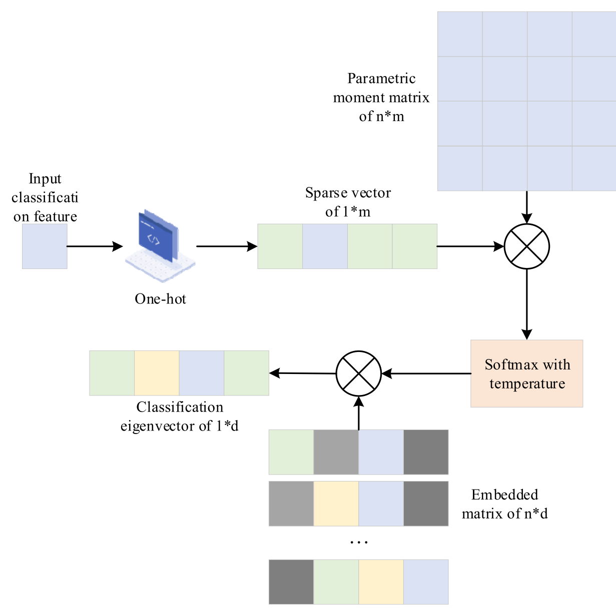

FIGURE 1. Classification characteristics of FE module engineering processing and embedding process.

For numerical features, such as age, income, etc., FE module supplements and restores the original information of numerical features through automatic feature engineering strategy [23], [24], and the process is shown in Figure 2.

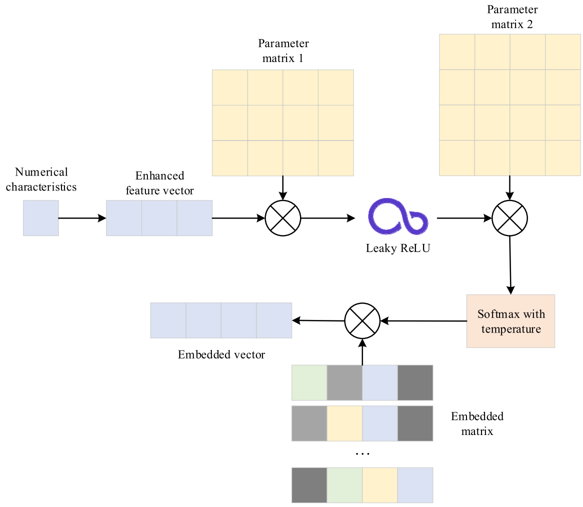

FIGURE 2. FE process of numerical features.

Firstly, the numerical feature x_n is transformed nonlinearly by a series of functions, such as logarithmic transformation and square root transformation, to simulate its potential distribution characteristics. Next, these transformed features and the original features are spliced into an enhanced feature vector $z_n \in \mathbb{R}^k$, where k is the dimension of the enhanced feature.

$$z_n = [x_n, \log(x_n), \sqrt{x}_n, \cdots] \tag{2}$$

To further optimize the feature representation, the enhanced numerical feature vector z_n is mapped to a higher dimensional vector space through a linear transformation, and a nonlinear activation function, such as Leaky ReLU, is introduced. Its mathematical expression is:

$$v_n = LeakyReLU(W_n \cdot z_n + b_n) \tag{3}$$

$W_n \in \mathbb{R}^{k \times d}$ is the learned weight matrix. b_n is the bias term. v_n is the numerical characteristic representation after nonlinear transformation.

Finally, the embedding vectors of classification features and numerical features are combined by Softmax function with temperature parameters respectively, and the optimal embedding vector combination is obtained:

$$p_i = \frac{\exp(h_i/T)}{\sum_j \exp(h_j/T)} \tag{4}$$

h_j is the bucket score of the embedded vector, and T is the temperature parameter. By adjusting T, the distribution of bucket weights can be controlled, thus optimizing the model's ability to capture features. When T approaches 0, the embedding vector approaches One-hot coding. When T approaches infinity, the embedding vector approaches to uniform distribution.

To sum up, the FE feature embedding method improves the modeling ability of neural network for structured data through different processing strategies for classification features and numerical features, so that the embedding vector can more fully express the characteristics of the original data, and then improves the performance of the model.

B. HIGH-LOW ORDER PARALLEL NETWORK ARCHITECTURE

In the process of improving the success rate of college students' entrepreneurship, the complexity of entrepreneurial data requires that the model not only has strong predictive ability, but also has good interpretability. Aiming at this demand, a feature interaction modeling method based on high-low order parallel network is proposed. The network structure consists of two parallel branches, namely, high-order network and low-order network. High-order network is mainly responsible for extracting complex nonlinear feature interactions to improve the prediction accuracy of the model. Low-order network is responsible for capturing more linear feature relationships and enhancing the interpretability of the model [25], [26].

In the concrete implementation, the low-order network is mainly used to capture the linear information between input features [27]. The network consists of two layers of neural networks. In the first layer, features are fused inside the features, and each input feature is converted into a new feature representation. The second layer combines these fused features linearly to generate an output probability value. After each layer of neural network, Sigmoid activation function is added to enhance the nonlinear ability. To ensure the interpretability of the model, the low-order network can quantify the impact of each input feature on entrepreneurial success through the calculation of feature contribution, as shown in equation (5). This contribution calculation provides a theoretical basis for the subsequent feature importance analysis:

$$Contrib(w_i) = \frac{|w_i| - \min(|w_1|, |w_2|, \cdots, |w_N|)}{\max(|w_1|, |w_2|, \cdots, |w_N|) - \min(|w_1|, |w_2|, \cdots, |w_N|)} \tag{5}$$

w_i is the weight of the i-th feature. N is the total number of features.

In contrast, high-order networks extract high-order nonlinear interactions between features through deeply stacked neural network layers [28]. The network consists of five layers of neural networks, four of which are hidden layers, and each layer is followed by a Batch Normalization layer, a random inactivation layer (Dropout) and a ReLU activation layer, which are used to prevent over-fitting and improve the generalization ability of the model. The output layer generates a one-dimensional vector and outputs the final prediction result in the form of probability after Sigmoid function. The design of high-order network can effectively capture the complex interaction between features, thus further improving the prediction accuracy of college students' entrepreneurial success rate.

To make full use of the respective advantages of high and low-order networks, this paper fuses the outputs of high and low-order networks by weighted summation to obtain the final prediction result, as shown in equation (6):

$$P(y) = w_H f_H(e) + w_L f_L(e) \tag{6}$$

$f_H(e)$ and $f_L(e)$ represent the outputs of high-order network and low-order network respectively. w_H and w_L are the weight parameters of the network, and e is the embedding feature. Through this parallel structure, the model not only considers the accuracy of prediction, but also improves the explanatory power of college students' entrepreneurial data, which is helpful to better understand the psychological factors and other key characteristics that affect the success of entrepreneurship.

C. CONSTRUCTION OF MENTAL HEALTH STATUS IDENTIFICATION MODEL

The FE-BiON model is constructed by synthesizing the feature embedding method based on FE and high-low order parallel network. The model can handle the complicated feature interactions and variety of feature types in the college student entrepreneurial data while also attempting to increase prediction accuracy and interpretability. Its overall structure is shown in Figure 3.

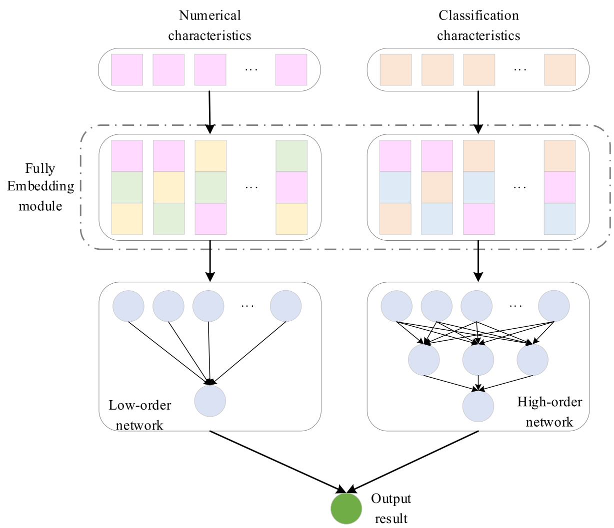

FIGURE 3. Overall structure diagram of FE-BiON model

Figure 3 shows that the FE-BiON model consists of three main modules: feature embedding module, low-order network module and high-order network module. The feature embedding module processes the classification and numerical features in the input data by FE method. For classification features, embedding matrix is used to map discrete classification features to continuous vector space, thus preserving the potential relationship and similarity between features. For numerical features, the original distribution information is preserved by nonlinear transformation and enhancement strategy, and the features are expanded and embedded on this basis. The low-order network module focuses on capturing the linear relationship between input features, linearly combining the enhanced features through the shallow neural network structure, and outputting the weight of each feature. The output of this module not only makes the model easier to understand, but it also keeps significant linear information, which is crucial for modeling data connected to entrepreneurship. The high-order network module uses the deep neural network structure to mine the nonlinear interaction between features. By stacking multi-layer neural networks and combining batch normalization, random inactivation and nonlinear activation function, the module can extract higher-order and more abstract feature interactions, thus improving the recognition ability of the model for complex entrepreneurial data. Different from low-order networks, high-order networks focus on exploring potential complex patterns, which is very important for predicting the hidden factors in the success rate of entrepreneurship. Through the synergy of these three modules, the model can handle different types of data and capture multi-level feature relationships, thus improving the prediction performance of entrepreneurial success rate.

In FE-BiON model, the choice of embedding dimension has an important influence on the performance of the model. The embedding dimension is determined to be 128 by cross-validation, which can ensure the performance of the model and avoid over-fitting. The selection of network layers is based on the analysis of existing literature. Usually, in deep learning, 3-5 layers of neural networks have been able to effectively extract high-order features from data. Therefore, a five-layer network is selected to ensure sufficient feature learning ability. ReLU is widely used in deep neural network in the selection of activation function, because it can effectively alleviate the problem of gradient disappearance and has high computational efficiency. Adam optimizer is chosen as the optimization method in the training process because it can automatically adjust the learning rate and is superior in dealing with sparse gradients. Compared with traditional machine learning methods (such as random forest and logistic regression), FE-BiON model has obvious advantages in dealing with high dimensions, complex relationships and multi-level features. Traditional methods usually rely on artificial feature engineering, and they are poor at capturing complex nonlinear relationships between features. The FE-BiON model can automatically extract the high-order interaction between features through deep learning technology, thus improving the prediction accuracy and interpretability. Compared with other mental health assessment models based on deep learning, the innovation of FE-BiON model lies in its high-low order parallel network architecture, which can consider both prediction performance and model interpretation, making it more suitable for complex and multidimensional data scenarios.

IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

A. DATASETS COLLECTION

The dataset used in this paper includes the National Health and Nutrition Examination Survey (NHANES), Korea National Health and Nutrition Examination Survey (KNANES), and Behavioral Risk Factor Surveillance System (BRFSS) [29], [30], [31].

Among them, NHANES dataset selects health and demographic data from 2005 to 2016, and combines with the score of Patient Health Questionnaire-9 (PHQ-9) to identify depression. PHQ-9 scale gets a score by evaluating the severity of common symptoms of depression, and then divides depression into two categories (with or without depression). This dataset not only provides basic data for the modeling of college students' mental health characteristics, but also helps people to explore the relationship between mental health and entrepreneurial success by including many related variables, such as health status and socio-economic characteristics. In model training and evaluation, this paper pays special attention to the linear characteristic relationships between these variables, and extracts these relationships through the high-low parallel network architecture of FE-BiON model to realize more accurate mental health status identification. Through these characteristics, people can deeply analyze the influence of different health factors on college students' mental state, thus providing data support for their mental health intervention in the process of starting a business.

KNHANES dataset covers the data of health, medical examination and nutrition survey in 2014, 2016 and 2018. Similar to NHANES, KNANES also collected data for many years. In order to ensure the consistency of data and the generalization ability of the model, this paper only keeps the common variables in the data of these years. The characteristic of KNHANES dataset is that it covers a wide range of people, especially Asian students, which provides people with a unique perspective on modeling entrepreneurial psychological state. Through the analysis of this dataset, the model can capture the mental health characteristics in a specific cultural background, and further optimize the applicability and accuracy of the model in different groups of people.

The BRFSS dataset focuses on data in 2019. Although BRFSS does not use PHQ-9 scale, it uses a broader screening variable for depression, which not only identifies severe depression, but also includes mental health states such as mild depression and dysthymia, and classifies these states into two categories (depression and non-depression). BRFSS dataset provides another dimension of depression recognition in this study, which can supplement the mental health status that may not be fully reflected in NHANES and KNANES data, and support the diversity and generalization ability of the model. In addition, BRFSS data also contains a variety of socio-economic, behavioral habits and other variables, and the linear relationship of these variables is further extracted by the feature embedding method of FE-BiON model, which provides strong support for accurately identifying the mental health status of college students in the process of starting a business.

The diversity and richness of the above three datasets enable the FE-BiON model to effectively train and test in different groups and mental health states, and improve the model's ability to understand and predict complex mental health data by extracting the linear feature relationships in the datasets. The combination of these datasets not only improves the accuracy of the model, but also provides more comprehensive support for college students' entrepreneurial mental health intervention.

B. EXPERIMENTAL ENVIRONMENT

The experiment runs on Windows 10 operating system, equipped with AMD R7-5800H CPU, clocked at 3.2GHz, with RTX 3060 as the graphics card, 16GB of memory and 512GB SSD as the hard disk. Logistic Regression (LR), Random Forest (RF), extreme gradient boosting (XGboost), Deep Neural Network (DNN) and Deep Factorization Machine (DeepFM) are used as comparison models. Accuracy (Acc), Precision (Pre), Recall (Rec), F1 value and Area Under the Curve (AUC) are used as evaluation indexes. Accuracy is an index to measure the correct prediction ratio of the model, which calculates the correct prediction ratio of the model among all predictions. The precision rate indicates the proportion of all the samples predicted by the model as positive. High precision means that the proportion of false prediction is low in the samples with positive model prediction. The recall rate indicates the proportion of all samples that are actually positive, which are correctly predicted by the model. High recall rate means that the model can identify more positive samples. F1 value is the harmonic average of precision and recall, which can comprehensively consider the precision and comprehensiveness of the model in positive prediction. The higher the F1 value, the better the performance of the model in positive prediction. AUC represents the area under the receiver's operating characteristic curve, which is an index to evaluate the ability of binary classification model to distinguish positive and negative samples. The closer the AUC value is to 1, the stronger the distinguishing ability of the model is. The calculation equations of Acc, Pre, Rec and F1 values are as follows:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$Pre = \frac{TP}{TP + FP} \tag{8}$$

$$Rec = \frac{TP}{TP + FN} \tag{9}$$

$$F1 = 2 \times \frac{Pre \times Rec}{Pre + Rec} \tag{10}$$

Among them, TP is true positive, TN is true negative, FP is false positive and FN is false negative.

C. PARAMETERS SETTING

The experimental parameter settings are shown in Table 1.

TABLE 1. Experimental parameter setting.

Dataset	PARAMETER NAME	Numerical value
NHANES	Numerical feature sub-bucket number and embedding dimension	8
	Number of numerical feature buckets and embedding dimension	4
	Number of hidden layers of high order network	4
	Number of hidden layer nodes	400
KNHANES	Number of numerical feature buckets and embedding dimension	12
	Number of numerical feature buckets and embedding dimension	6
	Number of hidden layers of high-order network	4
	Number of hidden layer nodes	800
BRFSS	Number of numerical feature buckets and embedding dimension	12
	Number of numerical feature buckets and embedding dimension	6
	Number of hidden layers of high-order network	4
	Number of hidden layer nodes	650
-	Dropout	0.5
-	Optimizer	Adam
-	Initial learning rate	0.0001

D. PERFORMANCE EVALUATION

1) COMPARISON WITH DIFFERENT MODELS

The comparison of the Acc and F1 values of the six models is shown in Figure 4.

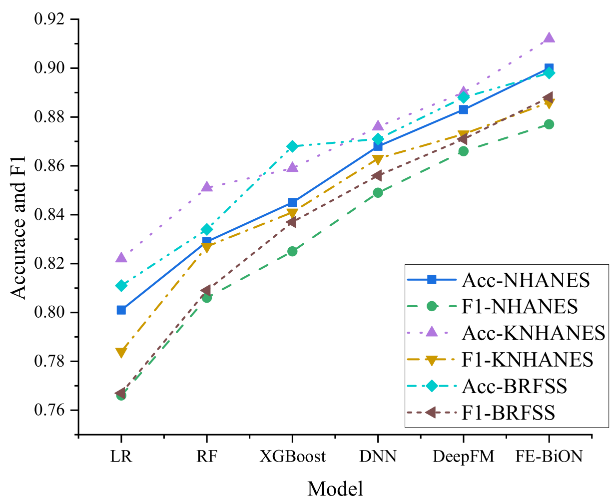

FIGURE 4. Performance comparison of different models.

In Figure 4, the Acc and F1 value of the proposed FE-BiON model on three datasets are better than those of other comparative models, showing stronger prediction performance. On NHANES, KNANES and BRFSS datasets, the Acc of FE-BiON is 0.90, 0.912 and 0.898 respectively, and the F1 values are 0.877, 0.886 and 0.888 respectively. This shows that the model can effectively capture the nonlinear interaction between features when dealing with multi-dimensional and complex feature data, and improve the accuracy and stability of prediction. In contrast, the performance of the traditional LR model on three datasets is relatively general, especially on the F1 value, which only reaches 0.76-0.79, indicating its shortcomings in dealing with complex data. Both RF and XGBoost have improved in Acc and F1 value, but there is still a gap compared with the deep learning model. Although DNN and DeepFM models perform better on three datasets, they are still not as good as FE-BiON, especially on the F1 value.

The AUC results of different models are displayed in Figure 5.

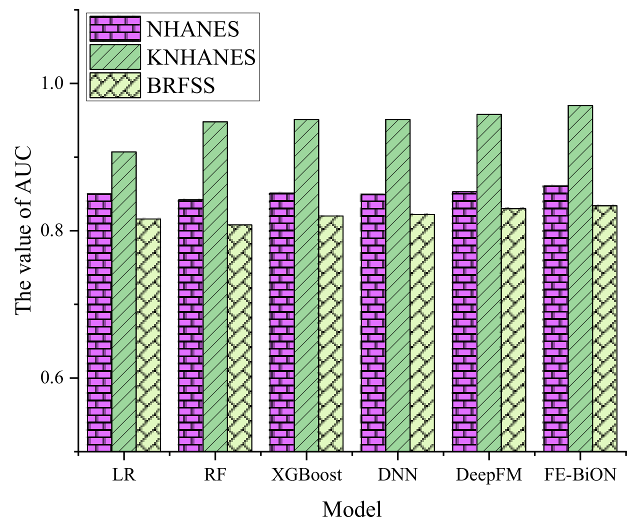

FIGURE 5. AUC comparison of different models.

In Figure 5, the AUC values of the proposed FE-BiON model are all higher than those of other comparative models, which are 0.861, 0.97 and 0.834, respectively, on three datasets of NHANES, KNHANES and BRFSS. Compared with the DeepFM model, FE-BiON has improved the AUC significantly, and the three datasets have improved by 0.94%, 1.25% and 0.48% respectively. This result shows that FE-BiON has obvious advantages in capturing complex feature relationships and handling different feature types.

2) ABLATION EXPERIMENT

To further verify the effectiveness of FE module and high-low order network model in FE-BiON model, ablation experiments are carried out. It can be divided into FE-BiON, BiON without FE module, fully embedded high-order network (FE-HON) model without low-order network module, and fully embedded low-order network (FE-LON) model without high-order network module. The test results of Acc and F1 value on three datasets are shown in Figure 6.

In Figure 6, compared with BiON model without FE module, the Acc of FE-BiON on NHANES, KNHANES and BRFSS datasets is increased by 2.51%, 2.24% and 1.13% respectively, and the F1 value is also slightly improved. This shows that FE module plays an important role in improving the model performance. In addition, compared with FE-HON

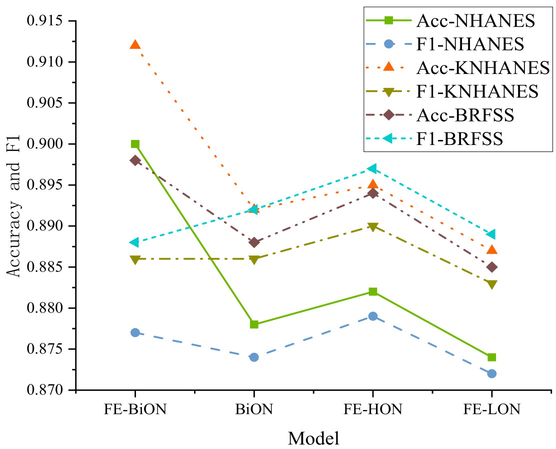

FIGURE 6. Performance test results of ablation experimental module.

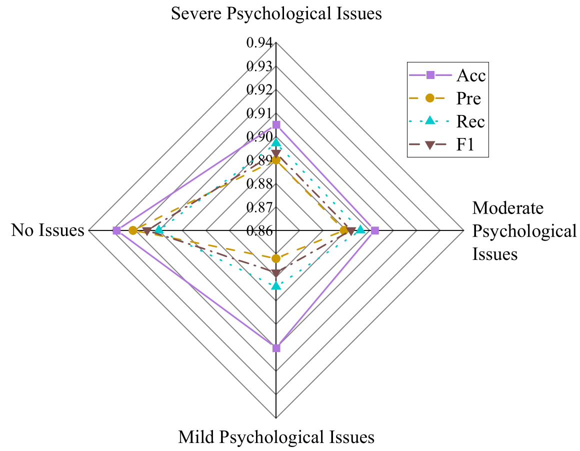

FIGURE 7. Grading results of mental health test for entrepreneurial college students.

and FE-LON models, FE-BiON has the best Acc and F1 value on each dataset. This result shows that the synergistic effect of high-low order networks and the fully embedded feature processing method have played a significant role in capturing the complex relationship between features and improving the prediction performance of the model.

3) APPLICATION OF COLLEGE STUDENTS' ENTREPRENEURSHIP

The proposed FE-BiON model is applied to the grading test of college students' mental health status. The data comes from the University Entrepreneurship Support Center, including 203 college students who participated in entrepreneurial activities. These students experienced different degrees of psychological problems in the process of entrepreneurship. The data contains the basic information of students (such as gender, place of origin, whether they are only children, education, college) and the results of their psychological survey during their entrepreneurship, and evaluates many psychological dimensions closely related to entrepreneurship, such as entrepreneurial pressure, anxiety, depression, and interpersonal adaptation. In addition, each case also contains the diagnosis results of psychologists. According to the diagnosis results, the mental health status is divided into four grades: first-class psychological problems, second-class psychological problems, third-class psychological problems and no problems. In order to train the model, 203 cases are divided into training set, verification set and test set according to the ratio of 8:1:1. Because there are few samples, SMOTE method is used to amplify the positive samples in the training set, verification set and test set by 10 times, and the same number of samples without psychological problems are selected as negative samples. After training, the FE-BiON model performs well on the test set, and the results are shown in Figure 7.

In Figure 7, the proposed FE-BiON model shows excellent performance in the grading test of college students' mental health status. In the sample of 203 college students who participated in entrepreneurship, the Accuracy of the model exceeded 90% at all levels of mental health. Among them, the best performance is aimed at the problem-free college students, with an Acc rate of 0.928, a Pre rate of 0.921, a Rec rate of 0.910 and a F1 value of 0.915. The application shows that FE-BiON model can effectively identify the mental health problems of entrepreneurial college students in the process of starting a business, which provides an important guarantee for college students' entrepreneurial psychological support and helps to improve their entrepreneurial success rate.

E. DISCUSSION

In a word, the proposed FE-BiON model performs well in the mental health status grading test, which shows that the FE-BiON model has strong feature capture ability when dealing with complex mental health data. Compared with other studies, FE-BiON shows superior performance in identifying mental health levels. Chung and Teo empirically evaluated the performance of many popular machine learning algorithms in classifying and predicting mental health problems, and found that gradient lifting provided the highest classification accuracy (88.80%) in the task of mental health binary prediction [32]. Tutun et al. developed a decision support system using advanced analysis and AI, which can automatically diagnose psychological disorders by only 28 questions, with an Acc rate of 89% [33]. Marriwala and Chaudhary proposed a hybrid model based on deep learning algorithm, which was used to detect depression by analyzing patients' text and audio answers. The audio convolutional neural network has the highest Acc (98%) in detecting depression [34]. As a result, the effective implementation of the FE-BiON model offers a new deep learning framework for the field of mental health in addition to a theoretical foundation and useful guide for the development of mental health support systems in colleges and universities.

In addition, the application of AI in the field of mental health has also attracted widespread attention. Abdelwahed discussed the role of ChatGPT in the decision-making process of Egyptian entrepreneurs and the identification of mental health disorders. Through quantitative analysis, it was found that users' cognition and trust in ChatGPT had a positive impact on the decision-making process and the identification of psychological barriers, but the decision-making process had a negative effect on the identification of psychological barriers [35]. This discovery reminded people of the potential of AI in entrepreneurial decision support system, and also warned people that they should be cautious about the possible deviations caused by the decision-making process when applying AI in mental health assessment. Elyoseph et al. discussed the application of generative AI in the field of mental health, analyzed the historical background from limited information to openness, and pointed out that generative AI represented a new stage of information democratization, which can improve the accessibility and personalized response of mental health services. At the same time, it was also mentioned that this technology also brought risks and challenges, which need to be dealt with cautiously [36]. This view emphasized that in future AI applications, ethical norms must be strictly observed to protect users' privacy and data security. Castañeda-Garza et al. discussed the application and potential of AI in the field of mental health, focusing on how AI could provide mental health support by combining cognitive behavioral therapy with machine learning, voice pattern recognition and computer vision. Examples were given to illustrate the application of AI in three different fields, and related ethical issues, such as privacy, security and accessibility, were discussed, and it was emphasized that these issues should be fully considered when developing AI in the field of mental health [37]. With the progress of deep learning technology, the bias of AI has gradually attracted widespread attention in academic and practical fields. The training data of AI model is often influenced by social and cultural prejudice, which may lead to misjudgment of some groups, and then affect the fairness and accuracy of mental health assessment. Therefore, future research should pay more attention to the collection of diversified data and the design of fairness algorithm to ensure that the application of AI in mental health assessment can provide fair and accurate support for all people.

In this paper, the FE-BiON model successfully identifies the mental health status of college students in the process of starting a business, which is closely related to the existing psychological theories, especially the "stress-coping theory". According to the stress and coping model, individuals will decide whether they can cope with the stress by evaluating the severity of the stress source and the availability of their coping resources. The pressure in the process of starting a business often comes from many aspects, such as economic pressure, time pressure, social pressure and fear of failure. These stressors will affect the mental health of entrepreneurs, especially the emergence of negative emotions such as depression and anxiety. FE-BiON model can capture the relationship between these different levels of stress factors and college students' mental health through multi-level feature extraction and complex data processing. For example, economic pressure and lack of social support often led to anxiety and depression symptoms of entrepreneurs in the early stage of starting a business, which is consistent with the lack of coping resources and emotional adjustment ability mentioned in the existing theories. FE-BiON model can identify these potential risk factors by analyzing multi-dimensional data such as health, social and economy, and predict the mental health status of college students in the process of starting a business. In addition, the PHQ-9 scale is also closely related to the "cognitive behavior theory" in psychology. The scale helps to identify the severity of depression by evaluating individual emotional and behavioral changes. In the process of starting a business, how individuals interpret and respond to failures or stressful events is one of the key factors that determine their mental health. By dealing with these emotional and cognitive characteristics, FE-BiON model can more accurately identify the mental health problems of college students in entrepreneurship, and provide personalized intervention suggestions according to different coping strategies. Therefore, FE-BiON model not only improves the accuracy of mental health assessment, but also conforms to the theory of stress and coping in psychology, and can provide more accurate psychological support for entrepreneurs.

V. CONCLUSION

Based on fully embedded feature embedding method and high-low order parallel network architecture, this paper constructs FE-BiON model to identify the mental health status of college students who are starting a business, and verifies its performance through experiments, and draws the following conclusions:

A. RESEARCH CONTRIBUTION

(1) On the datasets of NHANES, KNANES and BRFSS, the Acc of FE-BiON is 0.90, 0.91 and 0.91 respectively, and the F1 value is 0.87, 0.88 and 0.88 respectively, all of which are better than other comparative models, showing stronger prediction performance.

(2) Compared with BiON model, FE-HON model and FE-LON model, the Acc and F1 value of FE-BiON on NHANES, KNHANES and BRFSS datasets are improved. This shows that the synergistic effect of high -low order networks and the fully embedded feature processing method have played a significant role in capturing the complex relationship between features and improving the prediction performance of the model.

(3) The Acc of the FE-BiON model is over 90% at all mental health levels in the grading test of college students' mental health status. This result shows that FE-BiON model can effectively identify the mental health problems of entrepreneurial college students in the process of starting a business, which provides an important guarantee for college students' entrepreneurial psychological support and helps to improve their entrepreneurial success rate.

In this paper, FE-BiON model effectively improves the evaluation accuracy of college students' mental health status in the process of starting a business through deep learning technology, and provides new tools and ideas for mental health support. Based on this achievement, universities and policy makers can consider applying this model to the practical psychological support system for college students' entrepreneurship. Firstly, universities can use this deep learning model to regularly evaluate the mental health of entrepreneurial students to find potential psychological problems early and provide customized psychological counseling and support. By identifying the mental health problems of entrepreneurial students in time, schools can implement targeted psychological intervention measures, such as providing emotional adjustment training, stress management courses or regular psychological counseling services. These interventions can help students effectively cope with the common psychological stress, anxiety and depression in the process of starting a business, thus improving their decision-making ability, innovation ability and entrepreneurial will, and ultimately improving the success rate of starting a business.

Secondly, policy makers can learn from the framework of this model and promote the embedding of mental health assessment mechanism in the nationwide college students' entrepreneurship education system. By extending this technology to more colleges and universities, policy makers can provide more comprehensive and scientific psychological support for entrepreneurial students and ensure that they can get timely psychological health intervention in the process of starting a business. Specifically, the policy can advocate the establishment of mental health files, and provide students with tailor-made mental health intervention plans based on the results of mental health assessment to help students get timely psychological counseling and support when facing the pressure in starting a business, thus reducing the risk of entrepreneurial failure caused by psychological problems.

In addition, the high accuracy and reliability of this model make it potential to be applied to personalized entrepreneurship counseling platform. In these platforms, FE-BiON model can provide real-time feedback and prediction based on students' mental health status, and help entrepreneurs to understand students' psychological changes and take appropriate intervention measures. Through the data-driven way, the platform can provide accurate mental health prediction for entrepreneurial students, and intervene in time when students are depressed or facing psychological challenges. This real-time monitoring and intervention mechanism can effectively help students adjust their mentality, ease the negative emotions in the process of starting a business, and then improve their problem-solving ability and confidence in the sustainability of starting a business.

To sum up, FE-BiON model not only provides new ideas for academic circles, but also provides effective technical tools for universities and policy makers to support their mental health in practical entrepreneurship education. By combining mental health prediction with targeted intervention measures, this paper can effectively improve the mental health level of college students in the process of starting a business, help them better cope with the challenges of starting a business, and then enhance the overall success rate of starting a business and promote the vigorous development of college students' innovation and entrepreneurship.

B. FUTURE WORKS AND RESEARCH LIMITATIONS

Although the FE-BiON model has performed well in the evaluation of college students' mental health, there are still some shortcomings, and future research can improve and expand these problems. Firstly, the dataset is small, with only 203 cases from the University Entrepreneurship Support Center. Although these data cover different levels of mental health problems, the limitation of sample size may affect the generalization ability of the model, especially when it is applied to different groups or wider scenarios, it may not be able to fully capture the mental health status of students with different backgrounds. In order to overcome this limitation, future research should expand the scale of data sets and collect more samples from different regions, cultures and social backgrounds to enhance the robustness and generalization ability of the model. In addition, increasing diversified data sources, including students' data from different education systems, age groups, gender and cultural backgrounds, will help to improve the applicability and accuracy of the model in different groups.

Secondly, the existing datasets mainly come from students in a specific region or background, which makes the verification scope of the model relatively limited. Future research can be extended to groups of different cultures, social backgrounds and regions to further explore the influence of cultural differences, social support and background factors on college students' mental health assessment. Mental health is not only influenced by individual emotional state, but also influenced by social support network, cultural background and other multidimensional factors. Therefore, integrating these factors will help to improve the cross-cultural adaptability and wide application of the model.

In addition, although the FE-BiON model shows high accuracy in dealing with common mental health problems, there is still room for optimization in the face of more complex mental health problems. In the process of starting a business, students may face complex emotional problems such as anxiety, depression and stress. The manifestations and influencing factors of these problems are very complex, and it may be difficult for a single model to fully capture these diverse psychological characteristics. Therefore, future research can consider introducing more psychological characteristic data, such as social interaction mode, mood fluctuation, lifestyle, etc., combined with more complex deep learning algorithms, such as multimodal learning and self-supervised learning to better capture and analyze the deep-seated correlation and dynamic changes of mental health problems.

In addition, with the continuous development of deep learning technology, the application of AI in the field of mental health is facing a trade-off between accuracy, interpretability and computational efficiency. FE-BiON model improves the accuracy through complex network architecture, but it may bring challenges in terms of computational overhead and model interpretability. In practical application, especially in the mental health support system that needs real-time feedback, how to balance the accuracy, computational efficiency and interpretability of the model is still an important issue in future research. Therefore, the future work can focus on how to optimize the reasoning speed of the model and improve its transparency to enhance users' trust in the model.

To sum up, the following aspects should be explored in future research: (1) Expand the scale and diversity of datasets, especially in culture, social background and region to enhance the universality and cross-cultural adaptability of the model; (2) Introduce more abundant mental health characteristic data, and combine with advanced algorithms such as multimodal learning and self-supervised learning to improve the model's ability to identify complex mental health problems; (3) Solve the trade-off between the interpretability and computational efficiency of AI model in application, optimize the real-time response ability of the model, and provide technical support for the practical application of mental health support system. Through these improvements, the FE-BiON model is expected to provide a more accurate and comprehensive solution for the evaluation and intervention of college students' entrepreneurial mental health, and promote the wider application of deep learning technology in the field of mental health.

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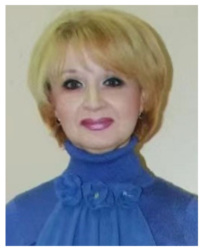

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