Integrating BiLSTM-based Sentiment Analysis and GCN for Academic Performance Prediction under Academic Stress

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In order to build a more comprehensive and refined emotional perception mechanism, future intelligent education systems urgently need to integrate multidimensional emotional modeling capabilities. In response to this demand, this article constructs a bidirectional long short-term memory network (BiLSTM) emotion classification model, which is based on text data posted by students on social media platforms and integrates self attention mechanisms. The study selected online course learning data and social media data from 3146 college students at a certain university. The accuracy comparison between the model proposed in this article and the model used in the task of identifying students' mental health status. The experimental results show that the model proposed in this paper is significantly better than the comparative models in terms of accuracy indicators. The BiLSTM structure based on self attention mechanism has been introduced, which can more effectively capture fine-grained emotional features in social media texts. The combination of BiLSTM and self attention mechanism effectively captures emotional and psychological state features in student texts, with an accuracy performance of over 90%. GCN enhances situational awareness prediction ability by modeling student social relationship maps, integrating group behavior and individual learning data. The synergistic effect of the two enables the model to maintain high accuracy while also having good recall ability, thereby achieving more robust and balanced academic performance prediction.

Povzetek: Raziskava pokaže, da lahko računalniški model iz študentskih spletnih objav precej zanesljivo prepozna njihova čustva in počutje, kar lahko pomaga pri boljšem razumevanju in podpori študentom.

1 Introduction

With the rapid development of artificial intelligence (AI) and big data technology, intelligent online education is becoming increasingly popular, and educational data mining and learning analysis have become research hotspots in the field of educational technology [1]. Utilizing the massive student behavior data accumulated in online teaching platforms to predict learning outcomes and implement precise teaching interventions has become an important path to improving education quality and achieving personalized learning [2]. However, while focusing on academic performance, students' mental health issues are becoming increasingly prominent. In recent years, college students have experienced frequent psychological problems such as anxiety and depression due to excessive academic pressure, which not only cause serious harm to their personal growth, but also have profound negative impacts on their families, schools, and even society [3]. This reality urgently requires education researchers to go beyond traditional academic evaluation paradigms and incorporate mental health into the overall framework of learning effectiveness analysis. Traditional student performance analysis often relies on the statistics and trend judgments of historical exam scores, ignoring the interactive effects of complex factors such as psychology, emotions, and social environment in the learning process [4].

In fact, learning is not an isolated cognitive activity, but a dynamic process deeply regulated by non cognitive factors such as emotional states, psychological stress, and motivation levels. Therefore, relying solely on experience or intuition to develop teaching strategies is no longer sufficient to meet the scientific needs of modern education [5]. Educational decision-making urgently needs to be based on multi-source and multi-dimensional learning data, and explore hidden patterns through data-driven methods to improve the accuracy and effectiveness of interventions. In recent years, the academic community has conducted extensive exploration on the relationship between mental health and academic performance [6]. Intelligent Cognitive Assistant (ICA) technology is used in various fields to simulate human behavior expressed through synchronous communication, especially written dialogue. Due to their ability to use tailored natural language, they provide a powerful container to support attitude and behavior change. Behavioral change support systems are becoming a key tool in digital mental health services, and ICAs have shown excellent performance in effective support, especially for stress, anxiety, and depression (SAD). ICAs guide people's thinking processes and actions by analyzing their emotional and cognitive phenomena [7]. Some scholars have proposed a prediction model that combines Random Forest (RF) and Gated Recurrent Unit (AGRU) with attention mechanism. By filtering key features through RF and dynamically modeling temporal behavior using AGRU, the accuracy of performance prediction has been significantly improved. Some experts focus on the emotional dimension and have constructed a VAD (Happiness, Arousal, Dominance) emotion computing network based on orthogonal convolution, which achieves accurate measurement of learners' multidimensional continuous emotional states and applies it to academic risk warning [8]. Some systems use a cognitive architecture composed of a series of computational models to simulate psychological theory, utilizing cognitive modeling and machine learning models trained on new datasets and ontologies. The system was evaluated through a computational experiment of predicting mental health phenomena through text and an empirical intervention study of 42 participants to alleviate mental health problems. The system outperforms state-of-the-art systems in terms of the number of detection categories and detection accuracy by 91.41%. The confirmation of the hypothesis suggests that incorporating psychological simulation theory into the conversation subject can significantly improve its efficacy in computational psychotherapy, providing promising progress for mental health intervention and support compared to current state-of-the-art systems [9]. The RF model identified that "perfectionism tendency" is a key psychological factor causing psychological internal friction among college students, and further constructed a neural network prediction model to provide a basis for psychological intervention. It designed a dual channel recurrent neural network (RNN) model that integrates attention mechanism and conducted comparative experiments with CNN and DNN to verify the superiority of multi-channel structure in online learning performance prediction [10]. Some scholars have explicitly proposed incorporating emotional features into the performance prediction framework, preliminarily verifying the enhancing effect of emotional information on predicting performance [11]. Based on the above research, this paper proposes a DL score prediction model that integrates emotional features. By jointly modeling the two-dimensional information of mental health and learning behavior, this model can not only more accurately predict academic performance, but also reveal the quantitative correlation mechanism between the two, providing scientific and operational data support for universities to carry out academic warning and psychological support [12].

2 Related work

Existing research has achieved the integration and application of multi-source learning behavior data. Douding.com 'research points out that the current model can integrate multidimensional information such as students' personal information, educational background, campus one card consumption records, library borrowing data, etc [13]., and capture dynamic changes in learning habits through time series analysis technology. In terms of model selection, Convolutional Neural Networks (CNNs) are widely used to process unstructured data such as homework texts and exam answers, extracting semantic features through word vector transformation (such as Word2Vec, BERT pre trained models) [14]; Recurrent neural networks (RNNs) and their variants LSTM and GRU perform outstandingly in processing time-series learning data, such as daily learning duration and weekly test scores, and can effectively capture long-term dependencies [15]. The introduction of hyperparameter optimization and ensemble learning strategies further improves model performance, while the application of techniques such as Bayesian optimization and Stacking ensemble significantly reduces the risk of overfitting. In the exploration of specific psychological dimensions, the role of emotional regulation ability has received particular attention [16]. Research has found that negative emotions such as anxiety and depression can affect academic performance by reducing attention span and disrupting the execution of learning strategies, while positive emotions can enhance cognitive flexibility and problem-solving abilities. Standardized scales such as the Simplified Resilience Scale and the Self Rating Depression Scale (SDS) are commonly used in psychological measurement methods [17]. Data is obtained through questionnaire surveys and correlation analysis is conducted. Some studies have attempted to introduce physiological indicators such as heart rate variability and cortisol levels, but due to the accessibility of detection equipment, large-scale applications have not yet been achieved [18].

The popularity of social media has provided a new path for non-invasive monitoring of mental health status, and the potential application of emotion analysis technology in the field of education is gradually emerging. The research on originality documents points out that social media emotions have multidimensional characteristics, covering emotional, attitude, cognitive, and other levels, and form dynamic evolution through resonance communication mechanisms. This feature enables it to reflect an individual's psychological state in real time, providing a natural data source for monitoring academic stress [19]. Deep learning has promoted the accuracy improvement of social media sentiment analysis. Traditional machine learning methods such as Naive Bayes and SVM have limited performance in fine-grained emotion recognition due to their difficulty in handling contextual complexity and semantic ambiguity. Based on the Transformer architecture, pre trained models such as BERT and RoBERTa effectively capture long-distance semantic associations through attention mechanisms, achieving breakthroughs in multi-dimensional emotion classification such as anger, anxiety, and joy [20]. Multimodal fusion has become a new trend, and some studies attempt to combine multiple types of data such as text, emoticons, and speech intonation to further improve the accuracy of emotion recognition. In the application of educational scenarios, existing research is still in its infancy: on the one hand, data processing faces multiple challenges, such as high noise, inconsistent labels, and lack of standardized solutions for student privacy protection issues in social media data [21]; The neglect of relevant features, limitations on the analysis of existing data points, and ambiguity in student records are just a few of the issues. Some scholars have proposed a new Student Academic Performance Prediction (SAPP) system to address these issues and improve prediction accuracy. It has a better architecture that combines a 4-layer stacked Long Short Term Memory (LSTM) network, Random Forest (RF), and Gradient Boosting (GB) techniques to predict students' pass or fail outcomes. In addition, the proposed SAPP system was compared with existing prediction systems that use publicly accessible student OULAD datasets and add self planned sentiment datasets. The proposed SAPP system achieved a prediction accuracy of approximately 96%, which is relatively higher than existing systems. [22]. Boulkroune et al. solved the projection lag synchronization problem based on output feedback control for chaotic drive response systems with input dead zones and sector nonlinearity. This type of driving response system adopts the form of Brunovsky, but the state is unavailable and the dynamics are unknown. In order to effectively handle dead zones and sector nonlinearity, the proposed controller is designed in a variable structure framework [23]. Boulkroune et al. investigated the practical fixed time master-slave synchronization problem of different fractional order chaotic systems. Two novel adaptive fuzzy sliding mode controllers using non singular fixed time sliding surfaces were proposed to achieve practical fixed time synchronization [24]. Rigatos et al. proposed a nonlinear optimal control method for the dynamic model of a gas centrifugal compressor driven by an induction motor (IM). The dynamic model of the integrated compressor induction motor system was initially represented in a nonlinear and multivariate state space form, and approximately linearized around the temporary operating points recalculated at each time step of the control method [25].

Table 1: Summary and comparison table of existing models

Source of literature	Methods used	Dataset type	Accuracy/Performance	Advantage	Limitation
[13] Douding.com	Time series analysis techniques and multi-source data integration methods	Multi dimensional structured data such as campus one card consumption records and library borrowing data	Can effectively capture the dynamic changes in learning habits	Effectively integrate multi-source heterogeneous data and dynamically track changes in learning habits	No explicit mention of performance in academic prediction or specific tasks, and no involvement in unstructured data processing
[14] Research on Unstructured Data Processing	Convolutional neural network, word vector transformation technique	Unstructured text data such as homework texts and exam answers	Can effectively extract semantic features from text, but specific accuracy values are not specified	Excellent performance in semantic feature extraction of unstructured text data	Not involving time series data processing, applicable to a single data type
[15] Research on Time Series Data Processing	Recurrent neural networks and their variants LSTM and GRU; Hyperparameter optimization and ensemble learning	Time series data such as daily learning duration and weekly test scores	Effectively capturing long-term dependencies and improving model performance	Proficient in handling time series data, improving performance and reducing overfitting through optimization strategies	Insufficient ability to process unstructured data
[17] Psychological measurement related	Standardized scale measurement, questionnaire	Questionnaire survey data	Quantitative assessment of psychological states can be achieved,	Directly quantifiable psychological dimension	Data collection relies on subjective filling, which is

Source of literature	Methods used	Dataset type	Accuracy/Performance	Advantage	Limitation
research	survey method, correlation analysis		clarifying the correlation between negative/positive emotions and academic performance	indicators, relatively easy to operate	inefficient
[19,20] Research on Social Media Sentiment Analysis	Traditional machine learning Transformer architecture pre training model	Multi modal data such as social media text, emoticons, voice tone, etc	Multimodal fusion can further improve accuracy, but the specific accuracy value is not clear	Pre trained models can effectively capture long-range semantic associations	There are issues with high noise and inconsistent labels in the data
[23] Boulkroune et al.'s research	Output Feedback Control Method under Variable Structure Framework	Data of chaotic driven response system with fan-shaped nonlinearity	Implementation of projection lag synchronization based on output feedback control for chaotic driven response systems, with no specific accuracy values specified	Can effectively handle dead zone and sector nonlinearity problems in the system	Only applicable to specific types of chaotic driven response systems, with limited generalization
[24] Boulkroune et al.'s study	Two new types of adaptive fuzzy sliding mode controllers	Master slave synchronization related data of different fractional order chaotic systems	Practical fixed time master-slave synchronization for different fractional order chaotic systems, with no specific accuracy values specified	Fast synchronization speed, using adaptive fuzzy method to improve control effect	Only for the synchronization problem of fractional order chaotic systems, with a single application scenario
[25] Rigatos et al	Nonlinear Optimal Control Method	Dynamic model data of gas centrifugal compressor driven by induction motor	The effective control of the induction motor system for the compressor has not been specified with specific accuracy values.	Adapt to the nonlinear characteristics of the system and improve control accuracy through real-time linearization	Temporary operation points need to be recalculated at each time step

3 Methodology

3.1 Construction of DL score prediction model integrating emotional features

Emotion, as an important non cognitive factor affecting the learning process, can usually be divided into positive emotions and negative emotions. Numerous studies have shown that emotional states significantly affect learners' information processing strategies, attention allocation, and memory retention abilities. However, current sentiment analysis in the education field often uses discrete emotion labels for simple quantification, ignoring the complex representation of emotions in continuous dimensions such as valence, arousal, and dominance. This study used supervised learning to obtain mental health labels, which were annotated using a combination of validation scales and manual calibration. Using the Self Rating Depression Scale (SDS) and Generalized Anxiety Disorder Scale (GAD-7) as core tools, standardized psychological assessments were conducted on 3146 participants to obtain preliminary labels. At the same time, a labeling team consisting of two psychology professionals and one educational technology professional manually corrected the preliminary labels based on the social media text context of the subjects. Ensure label validity through intra group consistency testing (Kappa value ⩾ 0.85), provide reliable supervision signals for model training, and guarantee research reproducibility. To build a more comprehensive and fine-grained emotional perception mechanism, future intelligent education systems urgently need to integrate multidimensional emotional modeling capabilities. In response to this demand, this article constructs a bidirectional long short-term memory network (BiLSTM) sentiment classification model that integrates self attention mechanism based on text data posted by students on social media platforms. The model consists of four core modules: word embedding layer, semantic learning layer, weight adjustment layer, and sentiment classification layer (as shown in Figure 1). Firstly, the word embedding layer transforms the original text sequence into dense word vector representations, providing a semantic foundation for subsequent neural network processing.

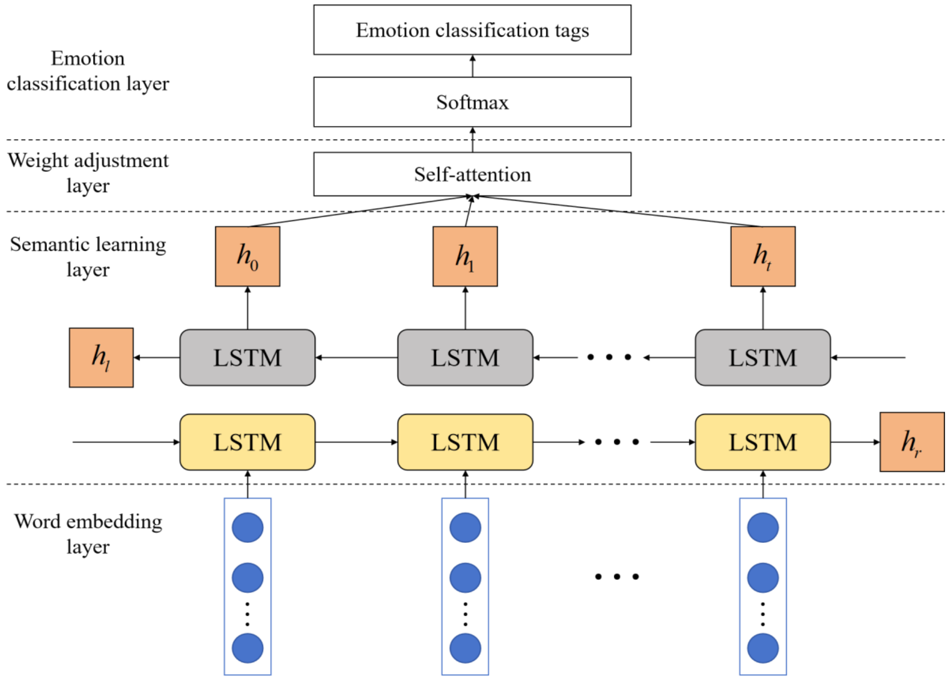

Figure 1: BiLSTM sentiment classification model incorporating self attention mechanism

Secondly, the semantic learning layer adopts the BiLSTM structure to capture the contextual dependencies of the text in both forward and backward directions, effectively encoding sentence level semantic features. Next, the weight adjustment layer introduces a self attention mechanism to dynamically evaluate the contribution of each semantic unit to the overall emotional tendency, generating weighted context aware feature vectors. Finally, the emotion classification layer outputs the probability distribution of the text belonging to various emotions through the Softmax function, achieving fine-grained emotion recognition and further mapping it into a quantitative indicator of mental health status. In addition to textual data, the interactive relationships formed by students in social networks also contain rich psychological and behavioral clues. However, this type of graphical data has characteristics such as varying node sizes, disordered connection structures, and complex topological relationships, making it difficult for traditional neural networks to effectively model. Graph neural networks (GNNs) have shown great potential in educational data mining due to their powerful structural awareness and interpretability. The semantic learning layer adopts the BiLSTM structure to capture the contextual dependencies of text in the front to back direction, effectively encoding sentence level semantic features. The core hyperparameter settings are as follows: pre trained GloVe-300d word vectors are used as initialization parameters for the embedding layer, with an embedding dimension of 300. The hidden layer dimension of BiLSTM is set to 256, and after bidirectional output, it is concatenated into a 512 dimensional feature vector. Set the batch size to 64 and use the Adam optimizer (learning rate 0.001, weight decay coefficient 1e-5) for parameter updates. The number of training iterations (epochs) is 20, and an early stopping strategy (patience=5) is adopted to prevent overfitting.

Based on this, this article further introduces Graph Convolutional Networks (GCN) to construct a performance prediction model that integrates emotional features. This model models students and their social relationships as a graph structure: nodes represent individual students, edges represent their social interactions, node attributes include the aforementioned emotional classification results and learning behavior characteristics, and edge attributes reflect interaction frequency and emotional tendencies. GCN aggregates information from neighboring nodes through stacking multi-layer graph convolution operations, achieving high-order representation learning for each student node. Its core lies in using the symmetric normalized Laplacian matrix for spectral domain convolution, effectively capturing local and global structural information. Figure 2 shows the structure of GCN. This article further introduces Graph Convolutional Networks (GCN) to construct a performance prediction model that integrates emotional features. This model models students and their social relationships as graphical structures. Nodes represent individual students, edges represent their social interactions, node attributes include the emotional classification results and learning behavior characteristics mentioned above, and edge attributes reflect interaction frequency and emotional tendencies. GCN adopts a 3-layer graph convolution structure, with the input layer dimension being the node attribute dimension, the hidden state dimensions of the 1st and 2nd layers set to 128, and the output layer dimension set to 1. The overfitting relief adopts the "Dropout+Early Stop" combination strategy, with a Dropout probability of 0.3 and an early stop strategy patience value of 5. The data splitting adopts a 7:2:1 ratio to divide the training set, validation set, and testing set, while keeping the distribution of students of different grades and majors in each set consistent with the overall data. The model constructed in this article not only retains the individual characteristics of emotions and behaviors, but also incorporates the group influence effect in social networks, thus more comprehensively characterizing the multidimensional factors that affect academic performance. Ultimately, the model achieves precise modeling and quantitative analysis of the interaction between students' mental health status and academic performance by jointly optimizing emotion recognition and performance prediction tasks.

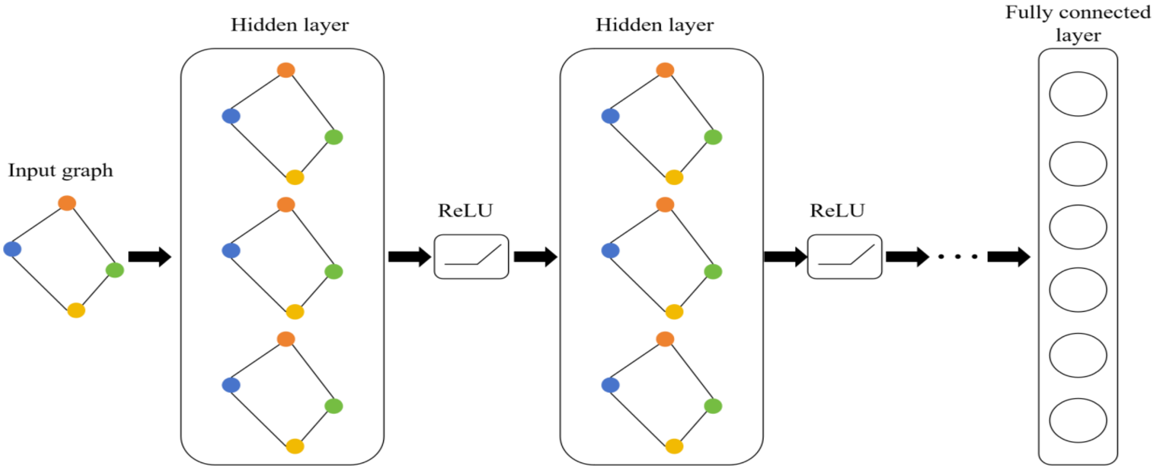

Figure 2: GCN structure

This article introduces Graph Convolutional Networks (GCN) to construct a performance prediction model that integrates emotional features. This model models students and their social relationships as graphical structures. Nodes represent individual students, edges represent their social interactions, node attributes include the emotional classification results and learning behavior characteristics mentioned above, and edge attributes reflect interaction frequency and emotional tendencies. GCN adopts a 3-layer graph convolution structure, with the input layer dimension being the node attribute dimension (128 emotional features+64 learning behavior features, totaling 192 dimensions), the hidden state dimensions of the 1st and 2nd layers being set to 128, and the output layer dimension being 1 (corresponding to the predicted academic performance). The overfitting relief adopts the "Dropout+Early Stop" combination strategy, with a Dropout probability of 0.3 and an early stop strategy patience value of 5. Basic GCN model, 2-layer structure, input layer 192 dimensions, hidden layer 128 dimensions, no emotional feature fusion.

3.2 Algorithm principle

In the captured social media image and text data, text data is often limited by its inherent characteristics, making it difficult to fully and completely reflect the true semantic and emotional characteristics of users. To enhance the model's ability to represent social media text, this article mainly focuses on short text data and conducts targeted data augmentation and preprocessing. The process of augmenting and preprocessing social media short texts can be formally described as follows: let $C=\{C_1,C_2,\cdots,C_n\}$ represent a corpus consisting of n social media texts, and each document C_i can be further represented as a weighted vector of terms. Under this framework, the weight of the j word in the i document is calculated using the following expression:

$$C_m(i,j)=tf\left(b_{(j,i)}\right)\times idf\left(b_{(j,i)}\right) \tag{1}$$

Among them, $tf\left(b_{(j,i)}\right)$ is the frequency of the word $b_{(j,i)}$ in the i document, reflecting the frequency of its occurrence in the current document; $idf\left(b_{(j,i)}\right)$ represents the inverse document frequency of the word $b_{(j,i)}$.

Due to the fact that word vectors and their semantic features cannot equally reflect learners' emotional characteristics, there are differences in the importance of emotional expression among different word vectors and their semantic features. Therefore, a self attention mechanism is introduced in the weight adjustment layer to adjust the attention weights of the semantic features output by the BiLSTM model, assigning higher weights to key semantic features. Meanwhile, utilizing self attention mechanism to re encode the hidden state output vector generated by BiLSTM to extract higher-level semantic features. The attention weight α_t of semantic features is calculated as follows:

$$\alpha_t = \frac{\exp(v_t A)}{\sum_t \exp(v_t A)} \tag{2}$$

$$v_t = \tanh(W_1 B_t + b_1) \tag{3}$$

Among them, $v_t A$ is a scoring function used to measure the importance of semantic features at the t th moment; B_t is the hidden state of BiLSTM at time t; A, W_1 is a learnable weight matrix, and b_1 is a bias vector. The value of semantic features in predicting grades varies significantly at different times. For example, when students mention text features such as "anxiety" and "low review efficiency" near final exams, they are more able to reflect the impact of academic pressure on grades than everyday casual conversations. The scoring function will assign a higher importance score to the feature by calculating its matching degree with the hidden state of BiLSTM. This dynamic weight allocation mechanism enables the model to focus on key semantic information and avoid irrelevant text features interfering with the prediction results.

After obtaining the attention weights of each semantic feature, it is weighted and summed with the corresponding semantic feature to obtain the output B_t' of the weight adjustment layer.

$$B_t' = \sum_t \alpha_t B_t \tag{4}$$

Text sentiment analysis is essentially a classification task. Therefore, the BiLSTM text sentiment classification model based on self attention mechanism sets an sentiment classification layer in the last layer, whose input is the semantic feature vector weighted by the self attention mechanism. This layer uses the Softmax function as the activation function to map the input to the probability distribution p of the text belonging to various emotional categories, and determines the final emotional category label l based on this. Meanwhile, the model defines corresponding loss functions to guide the training process:

$$p = soft\max(WB_t' + b) \tag{5}$$

$$l = \arg\max(p) \tag{6}$$

Among them, W, b represents the weight matrix and bias vector of the linear transformation. p is the probability distribution vector of text in different emotional categories. By applying the Softmax function to the weighted semantic feature B_t', its normalized probability in each emotional category is obtained. The category with the highest probability corresponds to the predicted emotional label l.

GCN can effectively handle large-scale graph structured data and continuously improve the model's expressive power by stacking multiple layers of graph convolution operations to aggregate neighbor node information layer by layer. The core calculation formula is as follows:

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)}\right) \tag{7}$$

Among them, $H^{(l)}$ is the node feature matrix of the l th layer; The adjacency matrix A describes the topological structure of the graph and reflects the interaction relationships between nodes. However, using only A will ignore the node's own information, so an adjacency matrix $\tilde{A} = A + I$ with self loops is introduced, where I is the identity matrix. $\tilde{D}$ is the degree matrix corresponding to $\tilde{A}$, $W^{(l)}$ is the learnable weight matrix of the l layer, and $\sigma(\cdot)$ is the nonlinear activation function.

During the learning process, the emotional state of learners can significantly affect their learning outcomes, and implicit learning states are difficult to directly observe. Therefore, the model converts the hidden learning state $c_k(i)$ of the k th time step into an observable actual learning state $y_k(i)$ through the output gate $o_k(i)$.

$$o_k(i) = \sigma(W_o[y_{k-1}(i); x_k(i)] + b_o) \tag{8}$$

$$y_k(i) = o_k(i) \otimes \tanh(c_k(i)) \tag{9}$$

Among them, W_o, b_o are the weight matrix and bias vector of the output gate, respectively.

This article adopts a semi supervised learning paradigm, where each set of data contains a real score for training. Given a graph G consisting of students and their social relationships, and a subset of students' actual grades $V_D = \{v_j \mid j \in D\}$ (where D is the annotated node subset), the goal is to predict the grades of unlabeled students. Specifically, the aim is to learn the function $f(j \mid \theta, G)$ to estimate student homework scores. The model parameter θ is optimized by combining the known score V and graph structure G, and the function used is implemented by GCN, as shown below:

$$f(j \mid \theta, G) = \sigma\left(w^{(0)} z_j + b^{(0)}\right) \tag{10}$$

Among them, $\sigma(\cdot)$ is the output function that maps node embeddings to predicted values through linear transformation, and $w^{(0)}, b^{(0)}$ are the weight matrix and bias parameters of the output layer, respectively. The core value of GCN lies in generating high-quality "node embedding" student comprehensive feature vectors. In academic prediction scenarios, the graph convolution process will optimize features in two steps. The first step is to weight and aggregate the initial characteristics of each student, such as their own historical homework grades, study duration, social media emotion vectors, and the initial characteristics of their social relationships with neighboring nodes and peers, in order to capture the academic impact brought about by social associations. The second step is to introduce nonlinear transformations through activation functions such as ReLU to simulate the interaction between students' own characteristics and peer characteristics. The negative impact on homework performance will increase nonlinearly when the "high anxiety of target students" and "low learning motivation of peers" are combined.

3.3. Design plan for ablation study

To quantify the core components of the model (BiLSTM, self attention GCN、 The independent contribution and interactive effects of sentiment analysis require the design of a systematic ablation study, combined with the improved evaluation index system in the previous section to conduct comparative experiments. The specific plan is as follows: clarify the role boundaries of each module in academic prediction tasks, and verify the necessity of "multi module integration" - that is, integrating the temporal feature capture of BiLSTM, the key feature reinforcement of self attention, the social relationship modeling of GCN, and the psychological state characterization of sentiment analysis, etc., to determine whether the model performance is significantly better than that of a single or partial module combination version, providing empirical support for the rationality of the model architecture. Based on the "complete model", a comparative experimental group is constructed by removing core modules one by one or in combination. All experimental groups use the same dataset, training parameters (such as learning rate and iteration times), and evaluation metrics to ensure fairness in comparison,

1. Experimental group 1: Only the basic time series model (without self attention, GCN, emotion analysis) retains the BiLSTM module, and the input data is the time series data of students' basic learning behavior (such as historical homework grades, learning duration sequences), which is used to verify the basic performance of time series modeling and serves as the most core baseline.

2. Experimental group 2: Time series+self attention (without GCN or emotion analysis). On the basis of experimental group 1, a self attention mechanism is added to evaluate the improvement effect of self attention on "screening key learning behavior characteristics", such as whether it can strengthen the weight of core features such as "high-frequency wrong question types" and "pre-exam review time".

3. Experimental group 3: Time series+self attention+GCN (emotion free analysis) version, which is the "learning behavior data only (emotion free)" version. Based on experimental group 2, the GCN module is integrated to add student social relationship features (such as peer interaction frequency and group collaboration records) to the input data, which is used to quantify the improvement of social relationship modeling on predictive performance.

4 Results and discussion

To validate the performance of the proposed grade prediction model, this study selected online course learning data and social media data from 3146 college students at a certain university, of which 70% were graduates and 30% were current students. When this study included data from 3146 college students, the inclusion criteria were undergraduate/graduate students registered or graduated from the university. And it also has complete online course learning data and traceable social media text data. The exclusion criteria include serious data loss (online learning core behavior data loss rate ⩾ 30% or social media text data volume less than 10 valid records), obvious abnormalities or traces of forgery in the data, and students explicitly refusing to participate in the study or not signing the data usage consent form. The experimental environment configuration is as follows: Intel Xeon E5-2678 v3 CPU, 64 GB of memory, NVIDIA RTX 3090 Ti GPU (24 GB of video memory), Windows 10 operating system, GPU driver version 537.13, CUDA 11.8， cuDNN 8.2.0.53， The programming platform uses PyTorch and PyCharm.

Figure 3 shows the accuracy comparison between the model proposed in this paper and the model in the task of identifying students' mental health status. The experimental results show that the model proposed in this paper is significantly better than the comparative model in terms of accuracy indicators. This improvement is mainly due to two aspects: firstly, the introduction of BiLSTM structure based on self attention mechanism, which can more effectively capture fine-grained emotional features in social media texts. The second is the integration of multidimensional emotional representations and contextual semantic information, which enhances the ability to distinguish complex psychological states. Therefore, the model proposed in this article demonstrates stronger performance and robustness in identifying students' mental health status. This provides a more reliable foundation for predicting academic performance and psychological intervention in the future.

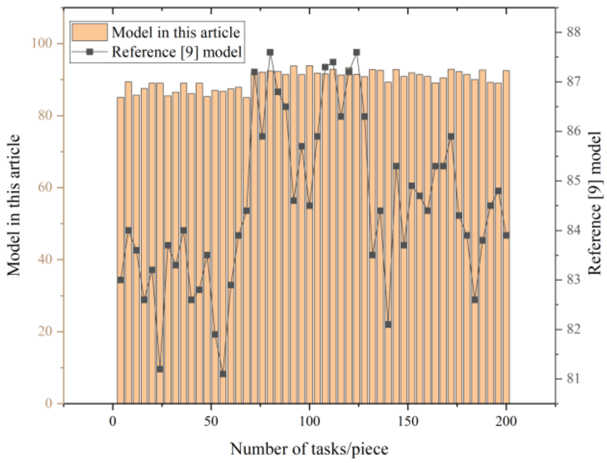

Figure 3: Comparison of accuracy in identifying mental health

Figure 4 shows the comparison of recall rates between the model proposed in this paper and the model in the task of identifying students' mental health status. The recall rate here reflects the proportion of students with actual psychological distress identified by the model, that is, the coverage ability of positive samples. The experimental results show that the recall rate of our model is significantly higher than the method, indicating that it is more sensitive in capturing individuals with real psychological risks. This advantage mainly stems from the model's integration of the BiLSTM sentiment analysis module based on self attention mechanism and multidimensional sentiment feature representation, which can more comprehensively explore the psychological signals hidden in social media texts and effectively reduce missed judgments. A high recall rate is particularly important for early psychological warning and intervention in universities, which helps to timely identify potential high-risk students and improve the coverage and effectiveness of mental health support.

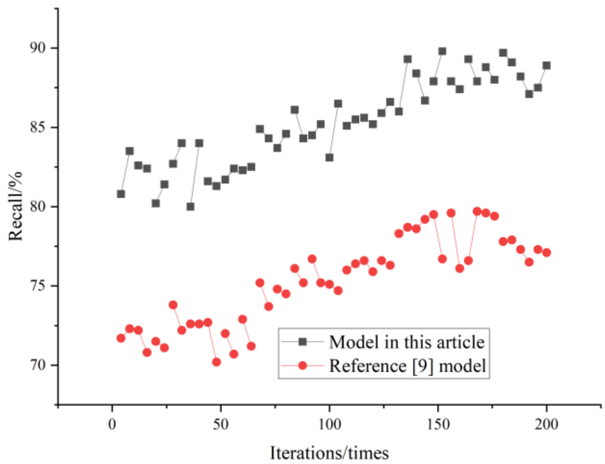

Figure 4: Comparison of recall rates

Figure 5 shows the accuracy comparison between the model proposed in this paper and the model in predicting student academic performance tasks. The experimental results show that our model significantly outperforms the comparison methods in terms of prediction accuracy. This advantage stems from the dual design of the model: on the one hand, BiLSTM combines self attention mechanism to effectively extract emotional features from students' social media texts, accurately depicting their mental health status. On the other hand, GCN fully utilizes the structure of student social relationship graphs, aggregates neighbor node information, and captures the potential impact of group interactions on academic performance. By jointly modeling the three dimensions of individual emotions, learning behavior, and social networks, the model has achieved more comprehensive and accurate prediction of academic performance, verified the close correlation between mental health and academic performance, and provided strong support for precise intervention in intelligent education.

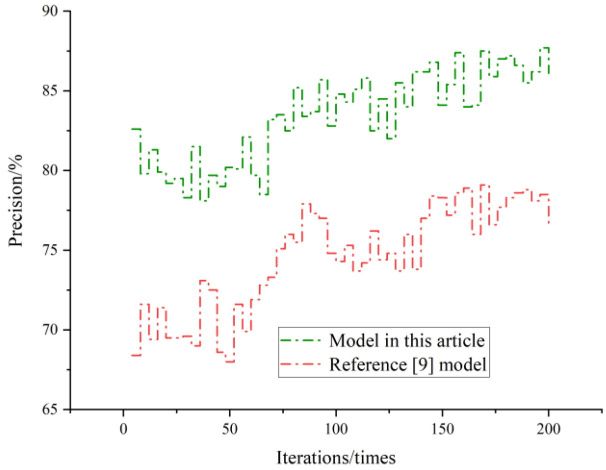

Figure 5: Comparison of prediction accuracy

From Figure 5, it can be seen that the accuracy change trend during the iteration process. The accuracy fluctuates between 80% and 83% in the initial stage (0-50 iterations). Subsequently, the accuracy rapidly increased from approximately 80% to around 85% during 50-100 iterations. In the initial stage (0-50 iterations), the accuracy fluctuates within the range of * * 68% to 73%, and the fluctuation amplitude is relatively large; During 50-100 iterations, the accuracy improved from approximately 70% to around 75%. After 100 iterations, the accuracy fluctuated within the range of 75%~78% * *, although there was an improvement, the overall accuracy was still much lower than that of our model, and the upper limit of accuracy after convergence was significantly lower. This model not only has higher accuracy, but also tends to stabilize faster during the iteration process, with better convergence efficiency and stability. Figure 6 shows the comparison of F1 values between the model proposed in this paper and the model in the task of predicting student academic performance. The F1 value, as a harmonic average of precision and recall, can more comprehensively measure the comprehensive performance of the model under imbalanced data. The experimental results show that our model significantly outperforms the method in terms of F1 value. In this model, BiLSTM combined with self attention mechanism effectively captures emotional and psychological state features in student text, while GCN enhances the context aware ability of prediction by modeling student social relationship graphs, integrating group behavior and individual learning data. The synergistic effect of the two enables the model to maintain high accuracy while also having good recall ability, thereby achieving more robust and balanced academic performance prediction.

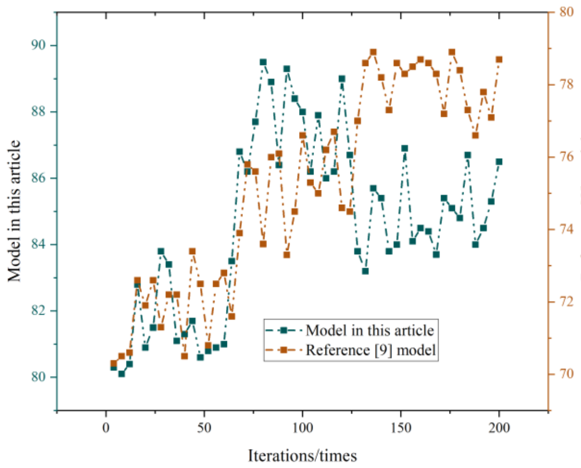

Figure 6: Comparison of F1 values

Figure 7 shows the comparison results between the model proposed in this paper and the model in terms of user satisfaction. User satisfaction is comprehensively evaluated through questionnaire surveys and system interactive feedback, covering dimensions such as prediction accuracy, timely intervention, and interpretability of results. The experiment shows that the model proposed in this paper is significantly better than the method in terms of user satisfaction. This advantage mainly stems from the model's ability to integrate emotional perception and social relationship modeling. On the one hand, the sentiment analysis module based on BiLSTM and self attention mechanism can more accurately reflect students' psychological state. On the other hand, GCN effectively integrates social network information, making the prediction results more personalized and context adaptive. In addition, the model output is more interpretable, which helps teachers and counselors understand the predictive basis, thereby enhancing their trust and willingness to use the system, ultimately leading to higher overall user satisfaction.

This article adopts the Likert scale method (such as a 5-point or 7-point scale, graded from "very dissatisfied" to "very satisfied"), allowing users to rate the experience dimension, and finally calculate the overall satisfaction score through weighted average or direct average.

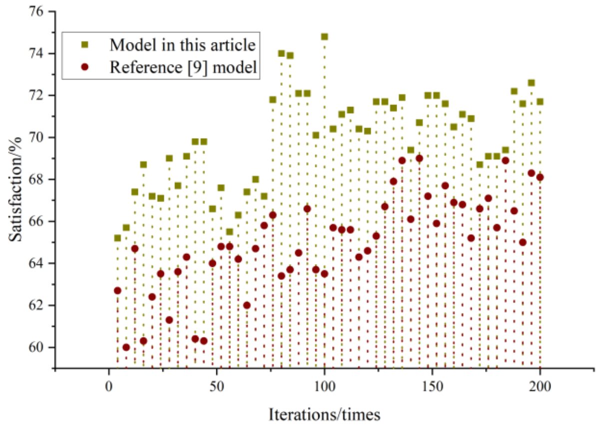

Figure 7: Satisfaction comparison

The scoring range in the figure (60%~76%) conforms to the quantitative characteristics of the scale, which summarizes the user's ratings for each dimension and presents them in percentage form. The number of participants in the figure ranges from 400 to 600 to ensure the representativeness and stability of the data. The project follows a logical hierarchical design of "behavior → attitude → intention" in combination with the research theme structure. Collecting large-scale sample data through quantitative scales, covering multidimensional experiential projects, and ensuring the reliability of the results through reliability and validity testing.

In terms of academic warning, the model breaks through the traditional limitation of relying on historical grades for lagging. By analyzing students' social media texts in real-time and extracting emotional probability distribution vectors, combined with learning behavior data to construct dynamic representations, the risk of academic performance decline can be identified in advance. For example, when the model detects that students have been posting texts containing anxiety and low mood for several consecutive days, and the library borrowing frequency and online learning duration have significantly decreased, it can automatically trigger a warning. Compared to traditional warning systems, this model significantly advances the warning time point and effectively reduces the probability of students failing or dropping out of courses. In psychological intervention scenarios, the model achieves precise and personalized services. Traditional psychological interventions often rely on students actively seeking help or manual screening, resulting in narrow coverage and delayed response. The model quantifies the mental health status and can grade and label students with potential psychological crises. Push emotional regulation guidelines and learning method suggestions to students with small emotional fluctuations but declining learning status; Promptly refer students with high anxiety and depression tendencies to a psychological counseling center.

This hierarchical intervention model not only improves the efficiency of psychological services, but also avoids resource waste, allowing limited psychological service resources to be tilted towards high demand students. To enhance the scalability and generality of the model, this paper adopts domain adaptation and transfer learning strategies. Train model infrastructure using annotated data from source domains for different countries, languages, or education systems. Through unsupervised domain adaptation or transfer learning, the model's dependence on specific environments can be reduced, achieving effective cross scenario generalization.

5 Discussion

The experimental results (Figures 5 and 6) show that the accuracy and F1 score of our model in academic performance prediction tasks are significantly better than existing comparative methods. And it has shown outstanding performance in user satisfaction evaluation (Figure 7), which needs to be interpreted in conjunction with the SOTA model features in relevant work. In terms of accuracy performance, the model proposed in this article significantly outperforms the two core SOTA models. Firstly, for models based on single text sentiment analysis, although these models can capture text semantic associations through attention mechanisms, they only focus on the personal emotional dimension and do not consider the synergistic effects of learning behavior and social networks. After extracting emotional features from social media texts through the BiLSTM self attention mechanism, this model further utilizes GCN to aggregate neighbor node information from student social relationship graphs. This achieves a deep integration of individual emotions and group interaction characteristics, expanding the prediction criteria from the "single emotional dimension" to the "emotion behavior social" three-dimensional dimension, resulting in a significant improvement in accuracy. Secondly, compared with ensemble models based on multi-source learning behavior data, although such models can integrate learning behavior data and capture long-term dependency relationships, they lack modeling of the key implicit factor of mental health. This study has verified that negative emotions such as anxiety and depression can affect academic performance by shortening attention span and other pathways. The introduction of emotional features fills this gap and makes predictions more in line with the actual driving mechanisms of students' academic development. The F1 value, as a core indicator for measuring comprehensive performance under imbalanced data, highlights the advantages of the model proposed in this paper. In the existing SOTA models, traditional machine learning methods have a low recall rate in fine-grained sentiment recognition due to their difficulty in handling the complexity of text context, resulting in limited F1 values. Although a single deep learning model can improve the accuracy of feature extraction in a single dimension, it tends to prioritize accuracy over recall, resulting in poor performance in edge sample prediction. The model in this article utilizes the collaborative design of BiLSTM and GCN, which not only retains the precise extraction ability of BiLSTM for sequential text sentiment features, but also covers student samples of different social relationship types through GCN's graph structure modeling, significantly improving recall rate and ultimately achieving a balance between accuracy and recall rate. The F1 value advantage is thus formed. The dual path fusion mode of "sequence feature graph structure feature" is adopted, which breaks through the limitation of "linear concatenation" in existing models. At the context modeling level, this article achieves dual coverage of "temporal context social context". The bidirectional propagation mechanism of BiLSTM can capture the temporal dynamic changes of emotional expression in social media texts, solving the shortcomings of traditional models that only focus on single sentence semantics and ignore the temporal dimension. To verify the interpretability of the model, this article supplements a specific technical verification plan: selecting typical samples with different combinations of academic performance and emotional characteristics, and visually demonstrating the reasoning logic of the model from emotional text and learning behavior data to grade prediction through case analysis. Introduce two interpretability analysis tools, SHAP and LIME, to quantitatively decompose the contribution of each text feature (such as negative emotion keywords, academic related semantic fragments) and learning behavior feature (such as learning duration, interaction frequency) to the prediction results, and clarify the influence weights of each feature. By combining the built-in attention weight visualization module of the model, the focus areas of the BiLSTM layer on key emotional text information and the fusion focus of the GCN layer on two-dimensional information are presented. The system clarifies the core influencing features and their mechanisms, making the model's prediction results more reliable and persuasive.

6 Conclusion and prospect

This article proposes a DL score prediction model that integrates emotional features, aiming to explore the intrinsic correlation between college students' mental health status and academic performance. The model first uses BiLSTM based on self attention mechanism to perform fine-grained sentiment analysis on the texts posted by students on social media, extracts the probability distribution vector of emotions, and quantifies their mental health status; Meanwhile, integrating multidimensional behavioral data from online learning platforms to construct dynamic learning state representations. On this basis, by integrating dual dimensional information of mental health and learning behavior through GCN, not only high-precision prediction of academic performance is achieved, but also the quantitative interaction mechanism between emotional state and academic performance is revealed. The experimental results show that compared with existing methods, the model proposed in this paper has achieved significant improvements in various indicators, providing strong data-driven support for universities to build intelligent academic warning and psychological intervention systems. However, this study still has certain limitations: for example, social media data may have sample bias, and sentiment analysis relies on textual expression, making it difficult to cover inactive users. Future work will explore multimodal data fusion and cross platform behavior modeling to further enhance the model's generalization ability and applicability.

7 Moral compliance section

Given that this study involves social media psychological data, ethical compliance is the core premise. The study will strictly anonymize all social media data, stripping identifiable personal information such as name, account, and geographic location, and only retaining behavioral and content feature data for analysis. In the data acquisition process, all data subjects will be clearly informed of the research purpose, scope of data use, and duration to ensure obtaining written informed consent. Meanwhile, this study has been submitted to the Institutional Review Board (IRB) in accordance with regulations and has been approved. The entire process follows ethical review requirements to safeguard the privacy and rights of data subjects.

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