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Application of Social Network Text Sentiment Analysis in Monitoring Students' Mental State

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ABSTRACT Social-network text provides real-time and natural signals for monitoring students' emotional fluctuations, but its informal, implicit, and context-dependent expressions make reliable psychological-state assessment difficult. This study develops a deep-learning-based sentiment analysis framework for student mental-state monitoring by integrating contextual semantic representation and temporal emotion modeling. Social-network texts are filtered, cleaned, semantically normalized, and vectorized after processing emoticons, abbreviations, and nonstandard expressions. A BERT pre-trained model is used to extract contextual semantic features, and a BiLSTM network captures sequential emotional dependencies and semantic reversal patterns. An emotion-intensity attention mechanism further enhances text segments associated with stress, anxiety, and depressive tendencies. Based on the sentiment distribution within continuous time windows, a psychological-state scoring model and a risk-discrimination function combining emotion intensity and temporal variation are constructed. Experimental results on 12,500 annotated texts from 850 users show an average F1 score of 0.89 for multi-class emotion recognition, with depressive emotion recognition reaching 0.91. High-risk student identification achieves an accuracy of 0.94. The method provides a text-signal processing and temporal risk-assessment framework for intelligent monitoring and early warning systems.

INDEX TERMS sentiment analysis,bert-bilstm,text signal processing,temporal modeling,risk assessment

I. INTRODUCTION

STUDENT's textual expressions on social media have become increasingly significant indicators of their emotional states and psychological transitions and psychological transformation with the extensive use of social networking sites among students. The social network texts are superior to the traditional questionnaires and interviews in that they have high real-time performance, extensive coverage and natural expression, which offers a new data base in monitoring the psychological state of students [1]. Nonetheless, these texts tend to be unstructured, colloquial and implicit in their expression attributes and emotional information is often stored as a metaphor, irony or weak signals and this presents a great challenge to emotion detection. Current approaches are largely positive or negative polarity or simple multi-classification tasks, so it is challenging to represent the differences in emotions in fine-grained terms, including stress-anxiety-depression. In order to counter all the above, the present paper develops a text sentiment analysis of social networks as a tool to keep track of the mental states of students. An introduction of a BERT pre-trained model at the level of text representation can be used to extract contextual semantic characteristics, and a BiLSTM framework is integrated to extract the information of the emotional sequence, which allows identifying the implicit emotions successfully. On this basis, a sentiment distribution-based mental state scoring model is created, which transforms the result of multiple-category emotions into measurable mental state predictors. Moreover, a risk discrimination capability is developed based on the combination of intensities and temporal trends of emotions, which attains hierarchical recognition and dynamic early warning of psychological risk.

II. RELATED WORK

It is in this context that, as the concerns of mental health issues among students have risen, the academic community has performed a multi-dimensional study on educational intervention, risk detection, and tech nology assistance. Current literature tends to assume that the information technology landscape (particularly social media tools) offers novel directions and channels of mental health education and status surveillance. Chen has mentioned that social media is significant in mental health education in universities and colleges. Teachers are to enhance media literacy and refine communication techniques, develop a multi-channel publicity system which is dependent on the platform, foster online and offline integration and interaction and develop the mental health of students by using professional counseling teams and integrating resources both within the school and outside of it [2]. In this paper, the platform is highlighted in terms of its usefulness in the context of the educational practice, yet it is primarily concerned with the process of intervention and communication, and the automated recognition and data-driven assessment of the mental state of students. In terms of risk detection and intervention mechanisms, Li et al. reported the ongoing increase in the rate of psychological crisis reporting in colleges and universities. Integrating policy directions and ecosystem theory, they suggested that a multi-level system of psychological interventions with the focus on prevention ought to be created [3]. Despite the relatively systematic theoretical framework of this study, its deficiencies are its deficiency of operable technical implementation paths. Additionally, in a meta-analysis conducted by Yu and Huang, it was observed that the prevalence of mental issues among Chinese students was 18.9 percent in general, most of which were depression and sleep issues, and had apparent regional and temporal variations [4]. The psychological quality viewpoint on the topic by Wang et al. showed that the psychological quality is strongly negatively correlated with the level of depression and is mediated by measurement instruments and gender variables [5]. The studies above found the universality and complexity of psychological issues of students based on the macro data point of view, yet they predominantly use statistical analysis and scale measurement and cannot yet track dynamic and real-time psychological conditions.

As the technology of artificial intelligence is developed, other researchers have started to attempt to bring in data-driven approach to predicting mental state. Jia and Wei presented the SBTM-SABMHP model that combines multi-source behavioral and introduces an attention mechanism to attain time modeling and fore casting of the mental health status of students and does better than traditional models in most indicators [6]. Even though such an approach has come far in terms of accuracy in prediction, its data sources are primarily limited to the behavioral logs, and the extraction of emotional information present in social network texts remains inadequate.

III. METHODS

A. SOCIAL NETWORK TEXT PREPROCESSING METHODS

1) Student Text Data Filtering and Cleaning

For unstructured text data in student social media platforms, the first step is to construct a data filtering mechanism targeting the specific user group. Let the original text set be denoted as $D = \{d_1, d_2, \ldots, d_n\}$. Using a set of keywords $K = \{k_1, k_2, \ldots, k_m\}$ and user tag constraints (U), the text is initially filtered to obtain a target subset D'. The filtering process can be expressed as: when the text d_i satisfies the keyword matching function $f(d_i, K) = 1$ and the user attributes satisfy the constraints $g(d_i, U) = 1$, then $d_i \in D'$.

Based on this, noise cleaning is performed on the filtered text. Considering the prevalence of URL links, special symbols, and meaningless characters in social network texts, a noise filtering function is defined $\phi(d_i)$ to denoise the text and transform it into normal text $d_i^* = \phi(d_i)$. Simultaneously, to reduce interference from redundant information, a stop word set S is introduced to filter the text, retaining only the words that $W_i = \{w_1, w_2, \ldots, w_t\}$ meet the specified $w_j \notin S$ criteria. In the word segmentation stage, a method combining statistics and a dictionary is employed to divide the text sequence into a sequence of terms W_i. The goal is to maximize the probabilistic representation of the word sequence, i.e., to achieve optimal word segmentation path selection by solving for conditional probabilities $P(W_i|d_i^*)$. Through this process, the original unstructured text is transformed into a structured set of terms, providing a foundation for subsequent semantic modeling.

2) Text Semantic Standardization Processing

Because social network texts exhibit significant colloquial and non-standardized characteristics, further semantic standardization is required to improve the consistency and computability of text representation. First, abbreviations in the text are expanded. Let the set of abbreviations be $A = \{a_1, a_2, \ldots, a_p\}$ and its corresponding standard form set be $A' = \{a'_1, a'_2, \ldots, a'_p\}$. A normalization transformation is achieved through a mapping function $h(a_i) = a'_i$.

For emoticons and emotion markers, an emoticon mapping function is constructed $\psi(e_i)$ to convert them into corresponding emotion tags (such as “happy” or “sad”), thereby embedding non-textual emotion information into the semantic space. This process can be represented as expanding the original text sequence W_i into a semantically enhanced sequence W'_i that includes the emotion mapping results.

Furthermore, to eliminate semantic differences caused by word form changes, a word form restoration function is introduced $l(w_j)$ to uniformly map different word forms to the basic form. For example, unifying “learning” and “learned” into “learning” ensures semantic consistency.

After completing the above processing, to facilitate subsequent model input, the text is represented in vector form. Let the word embedding function be

$$E(w_j) \in \mathbb{R}^d \tag{1}$$

the text d_i can then be obtained by weighting the word vectors:

$$v_i = \frac{1}{|W'_i|} \sum_{w_j \in W'_i} E(w_j) \tag{2}$$

Here, v_i represents the overall semantic vector of the text, and $|W'_i|$ represents the number of terms. This representation method, while ensuring computational efficiency, can initially characterize the semantic features of the text.

B. METHODS FOR CONSTRUCTING EMOTION RECOGNITION MODELS

1) Text Representation Based on Pre-trained Models

The texts in sentiment analysis tasks of student social network text are frequently highly semantically implicit and indirectly expressed in a manner that is not easily amenable to a traditional bag-of-words or fixed wordvector approach, requiring a deep semantic information representation. Thus, the current paper presents a BERT pre-trained model, which is used to carry out contextual semantic modelling of the text.

Suppose the preprocessed student text sequence is denoted as $T_i = \{w_1, w_2, \ldots, w_n\}$. When inputting it into the BERT model, it is transformed into an input format with special tags $[\mathrm{CLS}], w_1, w_2, \ldots, w_n, [\mathrm{SEP}]$. The model encodes the sequence through a multi-layer Transformer structure to obtain a context-dependent representation of each word h_j.

Taking into account that the psychological state of students is usually identified by the general semantics, and not by a single word, the vector of the $[\mathrm{CLS}]$ position, denoted as h_{CLS}, is chosen as the global semantic representation of the text to describe the emotional tendency. In addition to incorporating intra-sentence contextual cues, this representation also represents implicit emotions (like saying something like under pressure but not saying tired).

Furthermore, to enhance sensitivity to psychological and emotional characteristics, an emotion weighting adjustment mechanism is introduced to reinforce potential emotion words in the text. Let the set of emotion words be denoted as $E = \{e_1, e_2, \ldots, e_k\}$, and when $w_j \in E$, a weight coefficient $\alpha > 1$ is applied to its corresponding representation h_j, thus obtaining the enhanced emotion representation:

$$h'_j = \begin{cases} \alpha \cdot h_j, & w_j \in E, \\ h_j, & \text{otherwise.} \end{cases} \tag{3}$$

Based on this, by weighted aggregation of all word vectors, a text representation that better reflects the characteristics of students' emotional expression is constructed:

$$H_i = \sum_{j=1}^{n} \beta_j h'_j \tag{4}$$

Here, β_j represents the weights calculated based on the contextual attention mechanism, reflecting the degree of contribution of different terms to the overall sentiment expression.

2) Design and Optimization of Sentiment Classification Model

Once having the semantic representation of the text H_i, a BiLSTM-based sentiment classification model is built to further investigate the emotional development aspects in the sequence. Bearing in mind that semantic reversals are frequent occurrences in student texts (like actually, I'm fine, just a little upset) the sequence is modeled with a bidirectional long short-term memory network.

Given an input sequence $h'_1, h'_2, \ldots, h'_n$, BiLSTM encodes the text in both forward and backward directions to obtain hidden states $\overrightarrow{s}_t$ and $\overleftarrow{s}_t$, which are then concatenated to form a context representation $s_t = [\overrightarrow{s}_t; \overleftarrow{s}_t]$. In order to improve the capacity of the model to identify the psychological emotions of students, a system of attention in terms of the intensity of emotions is proposed, weighted and fused with the output of the BiLSTM. The attention weights γ_t are determined by the emotion activation function and are calculated in connection with the density of negative emotions in the text, thereby enabling the model to devote more attention to the parts with substantial emotional fluctuations. The last text sentiment representation is as follows:

$$S_i = \sum_{t=1}^{n} \gamma_t s_t \tag{5}$$

Here, γ_t reflects the importance of the t-th word in the expression of psychological emotions, and it usually gets a higher value when it is a word with negative emotions or at the position of emotional transition.

3) Methods for Identifying Psychological States and Assessing Risk

The mapping mechanism of emotions to psychological states

Let the set of texts $D_u = \{d_1, d_2, \ldots, d_m\}$ for student u within a time window Δt be denoted. The sentiment label for each text can be obtained using a sentiment classification model $y_i \in C$, where $C = \{\mathrm{positive}, \mathrm{stress}, \mathrm{anxiety}, \mathrm{depression}\}$. Further, the distribution ratio of each sentiment type within this time window is statistically analyzed:

$$p_c = \frac{1}{m} \sum_{i=1}^{m} I(y_i = c) \tag{6}$$

Here, p_c represents the proportion of emotion category c, and $I(\cdot)$ is an indicator function.

Based on the characteristic in student psychology research that "multiple emotions cumulatively determine psychological state," a psychological state scoring function is introduced, assigning different weights to different emotions to reflect their degree of influence on mental health. For example, "depression" and "anxiety" contribute significantly more to psychological risk than general "stress." Based on this, a comprehensive psychological state score is defined as follows:

$$M_u = w_1 p_{\mathrm{stress}} + w_2 p_{\mathrm{anxiety}} + w_3 p_{\mathrm{depression}} - w_4 p_{\mathrm{positive}} \tag{7}$$

Here, w_1, w_2, w_3, w_4 are the empirical weighting coefficients and satisfies $w_3 > w_2 > w_1 > 0$ the condition that is used to reflect the differences in the severity of different negative emotions.

Based on this, students' psychological states are divided into intervals according to the scoring results, for example:

$M_u < \theta_1$	Stable psychological state
$\theta_1 \leq M_u < \theta_2$	There is a risk of stress.
$M_u \geq \theta_2$	There is a high psychological risk.

This mapping mechanism enables the transformation from "single text sentiment recognition" to "stage-based psychological state assessment," thereby improving the overall quality and interpretability of the results.

4) Psychological Risk Assessment Strategies

Building upon psychological state identification, a risk assessment strategy based on "emotional intensity + time trend" is introduced to further capture abnormal psychological changes in students. Unlike static analysis methods, this strategy focuses more on the fluctuation characteristics during the emotional change process.

First, we define $\Delta t_1, \Delta t_2, \ldots, \Delta t_k$ a sequence of student psychological state ratings over a continuous time window $M_u^{(1)}, M_u^{(2)}, \ldots, M_u^{(k)}$. We then characterize the degree of fluctuation in psychological state by calculating the rate of change between adjacent time windows.

$$\Delta M_u^{(t)} = M_u^{(t)} - M_u^{(t-1)} \tag{8}$$

When $\Delta M_u^{(t)} > 0$, negative emotions continue to increase, indicating an accumulating trend, which may foreshadow an increase in psychological risk.

Furthermore, to comprehensively reflect the risk level, a risk discrimination function is introduced, which integrates the "current state intensity" with the "change trend":

$$R_u = \lambda M_u^{(t)} + (1 - \lambda)\Delta M_u^{(t)} \tag{9}$$

Here, R_u represents the student's current psychological risk value, with $\lambda \in [0, 1]$ serving as a trade-off coefficient. A λ higher indicates greater focus on the current intensity of emotions; a λ lower emphasizes the trend of change.

Based on risk values R_u, a tiered early warning mechanism is constructed:

$R_u < \eta_1$	Normal state
$\eta_1 \leq R_u < \eta_2$	Mild risk (recommended for monitoring)
$\eta_2 \leq R_u < \eta_3$	Moderate risk (intervention recommended)
$R_u \geq \eta_3$	High risk (requires timely intervention)

Moreover, to prevent misclassifications with some emotional variation, a time limit minimum is imposed, that is, an early warning is raised only when the risk status satisfies the threshold condition in a series of time windows.

C. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

1) Data Sources and Preprocessing

The primary source of experimental information is the social networking sites used by students such as Weibo, campus forums and comment boxes of learning and communication websites. The original set of texts totaling 12,500 entries from 850 unique users was built by screening with keywords between September 2025 and March 2026. For annotation, three researchers with psychological backgrounds independently labeled

the data, achieving an inter-annotator agreement (Cohen's Kappa) of 0.84. Regarding ethics, all data were anonymized at the source, and the study was approved by the institutional review board. No private identifying information was stored, and the research strictly adhered to the platforms' terms of service. Lastly, $D = \{d_1, d_2, \ldots, d_n\}$, a text set was created and manually marked based on the sentiment category to create a multicategory sentiment dataset (positive, stress, anxiety, depression). It is acknowledged that these emotional states can be comorbid in clinical psychology; however, this study focuses on the primary dominant emotion for classification. Future work will explore multi-label frameworks to capture co-occurring emotions. To ensure the clinical relevance of the labels, the annotation guidelines were developed in consultation with licensed psychological counselors, and a subset of the data was cross-validated against standard self-report scales (such as PHQ-9 and GAD-7) to ensure semantic labels correspond to meaningful psychological distress. Preprocessing of the original text is done systematically following the method in Section 3.1 and it includes:

(1) stripping out URLs, special characters and invalid characters;

(2) word segmentation and stop word filtering;

(3) semantic mapping and restoring of emoticons through abbreviation;

(4) text standardization and representation in the form of vectors.

Once processed, normalized text sequences T_i and their labels y_i are obtained y_i ,and the training set and test set are proportionately split (e.g. 8:2) to give a framework on wh ich to train the model.

2) Experimental Setup and Environment

A BERT + BiLSTM fusion structure is used in the emotion recognition model. BERT and BiLSTM are applied in the context of generating semantic representations with context and sequence emotion features, respectively. The essential parameters settings include:

The hidden layer in BERT would be 768-dimensional;

BiLSTM will have 128 hidden cells;

The dropout rate will be 0.5 to avoid overfitting; batch size = 32;

The learning rate will be an adaptive adjustment policy (original value is 2×10^{-5}).

In the psychological state discrimination stage, the emotion weight parameter satisfies $w_{\text{depression}} > w_{\text{anxiety}} > w_{\text{stress}}$, and the specific value is determined through validation set optimization. The experiments were executed in a Python environment, with deep learning frameworks (including PyTorch or TensorFlow) to build and train a model. To enhance model training efficiency, GPU acceleration (including NVIDIA graphics cards) was used. At the same time data processing and feature extraction were performed with common natural language processing tools (word segmentation tools and pre-trained models libraries).

3) Performance Evaluation Methods

In sentiment classification tasks, accuracy, precision, recall, and F1 score are used as evaluation metrics. The F1 score, which considers both precision and recall, is calculated using the following formula:

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

To verify the effectiveness of the proposed fusion architecture, the BERT+BiLSTM model is compared against three baselines: a traditional SVM model with TF-IDF features, a standalone BiLSTM model, and a standalone BERT model.The overall performance of the model in multi-category emotion recognition tasks is evaluated using the above metrics.Experimental results indicate that the proposed fusion model outperforms the SVM- TFIDF baseline by 15% and the standalone BERT model by 4% in terms of average F1 score, justifying the integration of contextual semantics with sequential emotional features.

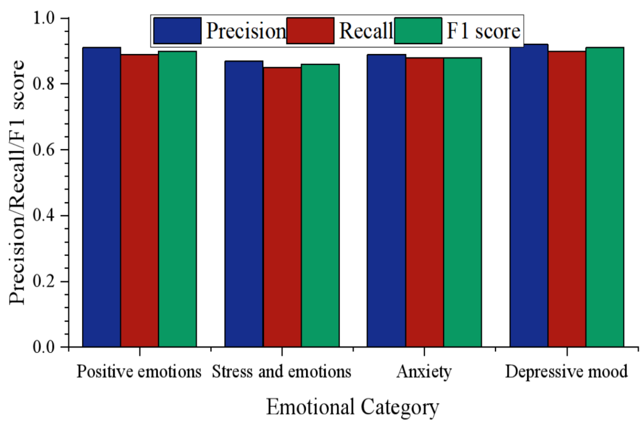

FIGURE 1. Performance evaluation results of the sentiment classification model

The model had the highest accuracy in identifying depressive emotions with a precision of 0.92, a recall of 0.90 and F1-score of 0.91. This shows that the model possesses high capability of capturing the common emotional expressions (e.g., use of negative words and negative semantics persistence) in depressive texts and can effectively reveal the high-risk psychological cues. To further analyze the classification performance across all categories, Table 2 presents the detailed precision, recall, and F1-score for each emotion. Conversely, the model was a bit weaker in identifying stress emotions (F1-score of 0.86), with a precision of 0.87 and a recall of 0.85. Analysis of the confusion matrix indicates that 12% of 'stress' instances were misclassified as 'anxiety', while 8% of 'normal' texts were falsely identified as 'stress' due to overlapping semantic features like 'busy' or 'tired'. This is primarily due to the fact that all the emotions of stress are implicit and unclear in their expression, and they are often expressed in neutral or slightly negative sentences (like a little tired, or a lot to do), which the model finds it hard to differentiate between stress and the normal states or other emotional categories. The performance of the model in identifying positive emotions has been relatively constant (F1- score of 0.90) which means that the model is good at identifying positive emotional features (Figure 1) . The dataset comprises a total of 1,000 unique students with 5,685 individual text samples.

TABLE 1. Statistics on the results of student psychological risk assessment

Risk level	Sample size	Percentage (%)	Recognition accuracy
Normal state	520	52	0.93
Mild risk	210	twenty one	0.88
Moderate risk	160	16	0.9
High risk	110	11	0.94

The 'Ground Truth' risk labels for these samples were determined by professional psychological experts who reviewed the students' anonymized behavioral history and text patterns, rather than being generated by the model itself.

Table 1 above demonstrates that the largest percentage (52.0) is in a normal state, which means that the majority of students are in a relatively stable psychological state. The prevalence of mild and moderate risks is 21.0% and 16.0% respectively, which means that a significant percentage of students continue to face different levels of psychological stress or emotional swings. High-risk samples are 11.0 percent, which is a rather small percentage, yet, a population that needs to be considered and given specific attention and treat ment. This distribution is in line with the fundamental features of real psychological conditions of students:

general stability with a high probability of serious risks.In terms of identification performance, the high-risk category has the highest sensitivity (0.94), defined here as the true positive rate for identifying critical cases. Furthermore, the model achieved a specificity of 0.91 for the normal state category, resulting in a low false positive rate (0.09). This indicates that the system effectively minimizes the risk of over-diagnosis—flagging healthy students as high-risk—which is essential for practical campus deployment.

IV. CONCLUSION

The paper will discuss the necessity of monitoring the mental health of students through building a mechanism of identification and risk calculation using sentiment analysis of texts in a social network. It models student text emotions on a deep semantic scale through a combination of BERT and BiLSTM models and develops a sentiment distribution-based mental health scoring and risk evaluation system, which constitutes a combined analytical model of emotion identification-state assessment-risk warning. As demonstrated in experimental studies, the approach has a high accuracy and stability in multi-category sentiment recognition and psycho logical risk prediction tasks, and it is efficient in detecting important psychological indicators, including anxiety and depression, and offers a viable technical solution to monitoring and intervening in the mental health of students during their education. Nonetheless, there are still some limitations in this paper, including the fact that the source of data is predominantly based on publicly available texts of social media platforms, and there is a lack of information integration and validation of results with real-intervention feedback. Future studies might also integrate multi-source behavioral information and cross-modal attributes to create a more sophisticated and individualized dynamic monitoring and smart intervention framework of the mental health conditions of students.

AUTHOR CONTRIBUTIONS

Xiang Ji designed, collected and analyzed the data, and drafted the manuscript. Xiang Ji conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xiang Ji participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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