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Construction and Optimization of Online Assessment Model of College Students' Mental Health Micro-Media Based on Factor Analysis and Deep Learning

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Abstract. *Mental health among college students is a growing concern, with increasing recognition of the need for effective diagnostic and support systems. This paper introduces a novel artificial intelligence framework, employing a Complex Value Convolutional Neural Network (CVCNN-MHFA), to analyze and classify mental health status from textual comments. The study leverages data from an online platform catering to student mental health in the Hangzhou province, with a focus on identifying stress indicators through natural language processing. A dataset comprising 23,325 comments was collected and preprocessed for model training and validation. The CVCNN-MHFA model was rigorously tested against other established deep learning architectures, demonstrating superior performance with an accuracy of 94.56%, precision of 96.07%, recall of 94.54%, and an F1 score of 95.30%. Statistical analysis, including expert comparison and radar chart visualization, provided insight into the model's predictive capabilities. The research establishes the potential of CVCNN-MHFA as a scalable tool for early detection and monitoring of student mental health, with implications for the development of responsive support systems within educational institutions.*
Keywords: Stress detection ; Factor Analysis ; Complex Value Convolutional Neural Network ;Online micro-media data.

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1. **Introduction.** Mental health disorders, epitomized by conditions such as depression, exact a profound toll on individuals and by extension, society. The grim reality of their impact is unambiguously mirrored in suicide statistics, a harrowing metric of mental health crises. With the prevalence of mental illness so stark, for example 20% of Canadian are expected to encounter these challenges in their lifetime [1], and alarmingly 20% of

mental health conditions in youth manifest before the age of 14 [2], the need for effective detection and treatment modalities is urgent. The global burden of mental and substance use disorders is not to be understated, with a staggering 23% of all years lost due to disability attributed to these conditions [2]. This is exacerbated by the stigma associated with mental illness, which acts as a formidable barrier to seeking treatment, leaving many to suffer in silence [3].

In the contemporary landscape of technological advancement, machine learning models have emerged as a promising solution for early detection and intervention in mental health disorders. These models have shown particular promise in mining social media data for patterns indicative of mental health issues [4]. Specifically, deep learning, a subset of machine learning characterized by Deep Neural Networks (DNNs), has the capacity to autonomously learn informative features from vast datasets without the need for labor-intensive manual feature engineering [5]. Our study focuses on the utilization of enhanced Convolutional Neural Networks (CNNs) for the detection of depression using data from online platform. This approach is grounded in the understanding that online platforms are a reflection of user sentiment and can thus serve as a barometer for mental health [6].

Innovatively, this research introduces optimized word embeddings to improve the representational learning of textual data, combined with a sophisticated CVCNN-MHFA (Complex Value Convolutional Neural Network for Mental Health Factor Analysis) . The word embeddings are fine-tuned to capture the nuances of language used in the context of stress and mental health, which is crucial for the accurate classification of such states in social media posts [7]. The significance of this study is underlined by the critical issue of academic stress, which has been identified as a substantial contributor to mental health deterioration among university students [8]. The academic environment, with its unique stressors, serves as an incubator for psychological distress, which can adversely affect students' academic performance, social relationships, and overall well-being [9].

Our analysis seeks to unravel the complex relationship between academic workload, stress, psychological distress, and social contact among students. By employing a combination of computational techniques and stress factor analysis, we aim to paint a comprehensive picture of the mental health landscape within the academic context. By bridging the gap between computational methods and mental health, this research contributes to a growing body of literature that seeks to understand and mitigate the challenges posed by mental health conditions. It is a step towards the creation of a more robust framework for the early detection and treatment of mental health disorders, leveraging the ubiquity and expressive power of social media [10].

Through this exploration, the study aspires to advance the understanding of mental health challenges that university students face. By leveraging the power of computational analysis and deep learning, we aim to identify the stress factors that are most predictive of psychological distress. In doing so, this research hopes to inform the development of targeted interventions that can ameliorate the mental health outcomes of this vulnerable population . The research presented herein is a testament to the interdisciplinary nature of modern scientific inquiry, combining the rigor of computational analysis with the sensitivity of mental health research to foster a greater understanding of the human condition.

2. **Related Work.**

2.1. **Student's Mental Health with Various Affections.**

Student mental health is a mosaic of varied influences that extend beyond academic rigor to include the emotional and social spheres of university life [11]. The construct of academic stress is a significant aspect, comprising not only the challenge of meeting high self-expectations and facing continuous assessments but also the emotional burden of fulfilling both parental and self-imposed ambitions [12].

The stressors that students encounter are multifaceted. Evaluation methods, extensive coursework, and financial concerns, such as tuition fees, contribute to their academic pressure. These elements are known to have long-lasting effects, which may pervade all aspects of a student's life, inducing chronic stress and anxiety. The social fabric of a student's life, including relationships with peers, family, and the academic community, is equally influential. These social contacts can act as a buffer against stress or, conversely, as additional sources of pressure [13]. The correlation between academic stress and severe mental health issues, including suicidal ideation, is alarming. Particularly vulnerable periods are exam seasons, where an increase in suicidal thoughts among students has been documented, signaling a crisis in mental health support within educational institutions [14]. Depression is prevalent and intricately linked to the pressures of academic life, with a high incidence of depressive disorders among students [15]. The academic workload, while a substantial factor, is just one part of the equation. It includes the pressures of balancing coursework with independent study and coping with the demands of various types of assessments. However, it's essential to also consider the impact of social interactions and support structures within the university setting. The quality of these interactions and the presence of a supportive social network are critical in moderating the stress levels experienced by students [16].

In addressing student mental health, it is crucial to not only evaluate academic workload but also to give due consideration to the broader context of a student's life, which includes social contacts, personal relationships, and the availability of mental health resources. Universities have a responsibility to cultivate an environment that supports both the academic achievement and psychological well-being of their students. This comprehensive approach is vital for fostering resilience against the myriad pressures faced by students during their formative university years [17].

2.2. **Deep Learning in Detecting Mental Health Conditions.** Deep learning, a subset of artificial intelligence marked by intricate neural networks, has revolutionized the detection and diagnosis of mental health conditions. By sifting through complex data, these models uncover patterns that might be missed by traditional methods, offering new potential for early detection and treatment. The strength of deep learning lies in its feature learning capabilities, which autonomously discern the most telling data representations, a boon for identifying the often-subtle signs of mental health issues. Text analysis via deep learning, for example, has led to the identification of linguistic markers of depression or anxiety in social media content, such as changes in emotional tone or posting patterns indicative of circadian rhythm disruptions [18].

In clinical settings, deep learning extends its reach, interpreting a vast array of data from electronic health records to intricate imaging scans, to detect nuanced speech patterns and facial expressions that suggest mental health conditions [19]. The advancements in natural language processing (NLP) powered by deep learning have been particularly notable. These algorithms can dissect complex human language to reveal underlying psychological states from patient interactions, while sentiment analysis algorithms process extensive patient feedback, identifying mental health trends and individuals at risk [20].

CNNs are pivotal for analyzing visual data, identifying mental health indicators from facial expressions, while RNNs and LSTMs track mood and behavior changes over time, essential for monitoring conditions like depression and bipolar disorder [21]. Autoencoders in anomaly detection signal deviations from typical behavioral patterns, potentially indicating the onset of conditions such as schizophrenia [22]. GANs address the issue of data scarcity by generating synthetic data that enhances the training sets for these deep learning models, thus maintaining user privacy [23]. Transfer learning fine-tunes pre-trained models to detect mental disorders from language use patterns, and attention mechanisms in models like Transformers ensure the focus is on the most pertinent data segments, facilitating better context understanding for condition detection [24]. These deep learning applications underscore the field's adaptability and robustness. By leveraging various data types and learning complex representations, deep learning models are critical in the early detection and ongoing monitoring of mental health conditions, marking a transformative era in mental healthcare. Yet, these models are not without their challenges. The need for extensive, diverse training datasets raises data privacy concerns, and the 'black box' nature of AI decision-making necessitates greater transparency for clinical integration [25].

Recent advancements in computational techniques have significantly influenced various sectors, including healthcare and urban planning. Wu et al. [26] introduced a groundbreaking authentication and key agreement protocol, specifically designed for remote surgeries, marking a crucial intersection between cybersecurity and healthcare. This protocol emphasizes the importance of secure data transmission in critical medical procedures. Concurrently, the realm of medical imaging has witnessed notable innovations. Ma et al. [27] presented a transfer learning model adept at reducing false positives in lymph node detection, demonstrating the potent synergy between sparse coding and deep learning in enhancing diagnostic precision

Furthermore, the application of quantum genetic algorithms for optimizing neural networks, as explored by Zhang et al. [28], showcases the transformative potential of computational models in urban infrastructure, with significant implications for healthcare logistics. Similarly, the field of visual data interpretation has advanced, exemplified by Wang et al.'s [29] development of a multilayer dense attention model for image captioning, demonstrating the breadth of deep learning applications. Additionally, the study by Wu et al. [30] on Kelly-based options trading strategies highlights the versatility of supervised learning algorithms, further broadening the scope of computational applications.

3. Methodology.

3.1. Factor Analysis on Student's Mental Health.

In our study, we conducted a factor analysis to assess the mental health of students, focusing on various dimensions of their well-being. Five key factors were selected, each aimed at capturing a different aspect of mental health. These factors are crucial in comprehensively understanding the students' psychological state and are as follows:

Emotional Stability (ES): This factor evaluates how students manage their emotions and maintain a stable mood, serving as an indicator of their emotional regulation capabilities and resilience. High scores suggest effective emotional regulation, while low scores may indicate mood swings, anxiety, or depression symptoms [31].

Social Connectedness (SC): Measuring the depth of students' social networks, this factor assesses their sense of belonging and social support. High scores denote strong social relationships, whereas low scores might point to feelings of loneliness or social isolation [32].

Academic Engagement (AE): This factor reflects the students' motivation and involvement in academic activities. High scores represent a positive attitude and motivation towards learning, while low scores could indicate a lack of interest or negative attitudes towards education [33].

Coping Strategies (CS): Assessing the students' ability to manage stress, this factor examines the effectiveness of their coping mechanisms. High scores indicate healthy coping methods, whereas low scores suggest reliance on maladaptive strategies or a lack of coping mechanisms [34].

Physical Well-being (PW): Acknowledging the link between physical and mental health, this factor evaluates aspects like sleep quality and energy levels. High scores are associated with good physical health, which supports mental well-being, while low scores might indicate physical health issues impacting mental health [35].

Each comment from the dataset was scored from -5 to +5 for each factor. The sum of these scores categorized the students' mental health state as "Stressed" (total score less than 0) or "Normal" (total score from 0 to +5), providing a detailed view of their mental health status. We clarify this approach by providing two instances of comments along with their respective scores across the proposed factors.

Comment 1: "I'm feeling a bit overwhelmed with my workload, but I'm trying to stay on top of things. My friends have been supportive, which helps a little."
Scores per Factor:
Emotional Stability: -2 (The expression of feeling overwhelmed suggests some emotional distress, though there is an effort to maintain control.)
Social Connectedness: 2 (Mention of supportive friends denotes positive social interactions and a solid support system.)
Academic Engagement: -1 (Overwhelm due to workload indicates a struggle in academic engagement.)
Coping Strategies: 1 (Attempts to manage work and receiving support from friends reflect positive coping mechanisms.)
Physical Well-being: -1 (Feeling overwhelmed might impact physical health, though no explicit details are provided.)
Total Score: -2 + 2 +(-1) + 1+ (- 1) = -1
Mental Health Category: The total score of -1 places the student in the "Stressed" category, highlighting stress but also the presence of supportive elements.

Comment 2: "I've been a bit worried about my upcoming tests, but I'm generally doing okay in my studies and staying active."
Scores per Factor:
Emotional Stability: -1 (Indicating mild stress due to worry about tests.)
Social Connectedness: 0 (The comment does not provide information about social connectedness.)
Academic Engagement: 1 (Stating they are doing okay in studies reflects a reasonable level of engagement.)
Coping Strategies: 1 (Balancing concerns with active lifestyle indicates effective coping.)
Physical Well-being: 1 (Activity implies good physical health, which can positively influence mental well-being.)
Total Score: -1 + 0 + 1 + 1 + 1 = 2
Mental Health Category: With a total score of 2, this student's mental health is categorized as "Normal," showing a balance of mild stress with effective coping and engagement strategies.

These examples illustrate how the factor analysis approach can be applied to our model to glean insights into the mental health of students.

3.2. **Dataset Description.** The dataset central to this study was meticulously compiled from an online platform dedicated to supporting the mental health of students in the Hangzhou province. This platform serves a dual purpose: providing a space for students to express their emotions and seek support, and facilitating the collection of data for research on mental health trends and indicators within this demographic.

Reflecting the diverse student population in Hangzhou, the dataset encompasses a wide range of demographic variables, including age, gender, academic level, and field of study. This diversity ensures that the findings of this research are not limited to a specific subgroup, but rather provide insights that are representative of the broader student community in the region. Additionally, the dataset includes comments that reflect a spectrum of mental health conditions, ranging from everyday stress and anxiety to more severe conditions such as depression and chronic stress. This comprehensive representation allows for a more nuanced analysis of mental health trends and the effectiveness of support mechanisms on the platform.

The comments were voluntarily provided by students who engaged with the online platform starting from January 2022 and concluding at the end of June 2022. To safeguard privacy and promote open expression, the comments were made anonymously. Participants were encouraged to articulate their emotional state in English, with the stipulation that their remarks be concise, limited to 300 characters. This brevity was designed to focus on the most impactful expressions of their current emotional well-being. In total, 23,325 comments were amassed during the collection period. The scoring process was overseen by psychological experts, who guided the labeling of each comment as either 'Stress' or 'Normal', based on the cumulative scores of these factors. This methodical categorization was crucial for the subsequent training and evaluation of deep learning models used in the study. For the purpose of training and evaluating deep learning models, the dataset was divided into two sets. The training set comprises 70% of the comments, while the remaining 30% for test set. Table 1 displays the precise distribution of the dataset.

Table 1. Dataset distribution.

Dataset	Stress	Normal
Train set	9535	6792
Test set	4087	2911

3.3. **Proposed Model.** Our proposed framework, as illustrated in Figure 1, is meticulously designed to assess the mental health status of students by analyzing their textual comments for stress indicators. This process incorporates several critical stages, each contributing to the comprehensive analysis and classification. The initial step involves

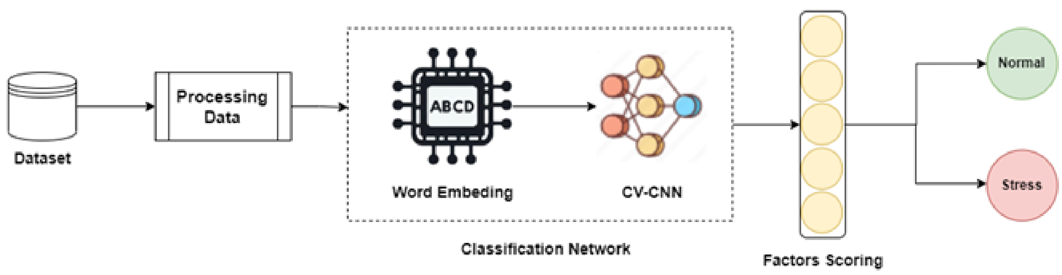

Figure 1. Proposed Framework

gathering raw textual data from the online student platform. This data then undergoes preprocessing, which includes cleaning (removing irrelevant characters), normalizing text, and breaking it into manageable units (tokens). This step is crucial to ensure data readiness for more advanced processing. Following preprocessing, the textual data is transformed into a numerical format using FastText word embedding [36]. This technique effectively encodes the semantic meanings of words into numerical vectors, essential for capturing the nuanced context within the language used by the students. The numerical vectors are then inputted into a Complex Value Convolutional Neural Network (CV-CNN) [37]. This network is adept at autonomously learning spatial hierarchies of features from the data, identifying key text patterns and features that are indicative of stress or a normal mental state. Utilizing the feature extraction capabilities of the CV-CNN, the system assigns a score to each comment based on the five predefined factors: Emotional Stability, Social Connectedness, Academic Engagement, Coping Strategies, and Physical Well-being. Each factor is scored on a scale from -5 to +5, with the cumulative score determining the overall mental health status. Finally, the total score from all five factors is summed to categorize each student's mental health status. Comments with a total score below 0 are classified as "Stressed," while those with a score from 0 to +5 are categorized as "Normal".

3.4. **Word Embeding Layer.** In FastText word embedding stage, we delve into the intricacies of region embedding by focusing on two primary models: the Context-Word and Word-Context region embeddings. The Context-Word region embedding is derived by considering the original word embedding of a central word and amalgamating it with the context units of all words within a specified region. The crawled words were processed to 300 dimensions output and the computation of this embedding involves a max pooling operation across the column dimension of the projected embedding matrix describe by the Formula (1)

$$r(i,c) = \max([\pi_{w_{i-c}}, \pi_{w_{i-c+1}}, ..., \pi_{w_{i+c-1}}, \pi_{w_{i+c}}]) \tag{1}$$

This process effectively captures the essence of the region embedding through a consideration of the projected embeddings of surrounding words. Turning to the Word-Context region embedding, we observe a distinct computational approach. Here, the projected word embedding $\pi_{w_{i+t}}$ for a word w_i and its embedding $e_{w_{i+t}}$ is obtained through an element-wise multiplication, represented as $\pi_{w_{i+t}} = K_{w_i} \odot e_{w_{i+t}}$. In this scenario, K_{w_i} denotes the local context unit of w_i, interacting with the embedding of w_{i+t} through element-wise multiplication.

Furthermore, the local context unit matrix K_{w_i} plays a pivotal role in this embedding process. Each column of this matrix is interpreted as a unique linear projection function, interacting with the embeddings of words in the local context. These projection functions are crucial in generating the projected word embeddings, which are the outcomes of applying these functions to the word embeddings. The relationship between the projected word embedding of w_{i+t}, denoted as $\pi_{w_{i+t}}$, and the $(c+t)$-th column in K_{w_i}, symbolized as $K_{w_{i+t}}$, is foundational in this context.

3.5. **Complex Value Convolutional Neural Network.** The architecture of Complex-Value Convolutional Neural Networks (CVCNN) is a sophisticated advancement in the field of deep learning, designed to process and analyze data more effectively by leveraging the mathematical intricacies of complex numbers. This architecture is an extension of the traditional CNN, with a key distinction in its ability to handle and process complex-valued data. The components and functionalities of the CVCNN architecture included:

Input Layer: Accepts 2-D matrices or channels of complex-valued data, catering to applications like signal and image processing where data naturally includes complex numbers.
Convolutional Layers: Utilizes complex-valued filters to perform convolutions, extracting crucial features and maintaining the intricate relationship between the real and imaginary components of complex numbers.
Activation Functions: Employs complex-specific functions such as complex ReLU or modReLU to apply non-linear transformations, preserving the complex data structure through the network.
Pooling Layers: Reduces the spatial dimensions of complex-valued feature maps while retaining essential features, managing the network's computational complexity.
Fully Connected Layers: Integrates extracted features into a comprehensive representation, handling complex-valued data for analysis or classification.
Output Layer: Translates processed complex-valued features into final outputs, which can be real or complex, leveraging the rich information for accurate predictions or classifications.

The architecture of CV-CNN is designed with inputs are treated as 2-D matrices or channels. It comprises an input layer, a series of convolutional and pooling layers, fully connected layers, and a final scoring layer which decipted in Figure 2. The input layer

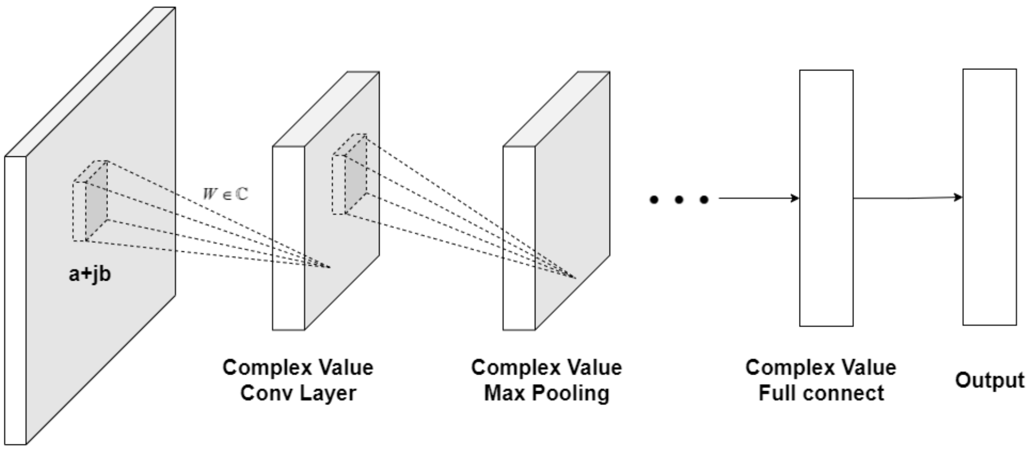

Figure 2. CV-CNN overall model

dimensions reflect the width, height, and depth (number of channels) of the image. In CV-CNNs, feature extraction starts with a convolutional layer followed by a pooling layer. The convolutional layer involves a set of complex-valued learnable filters that convolve local patches of the previous layer's feature maps, leading to complex output feature maps. The mathematical expression for the convolution operation is:

$$O_i^{l+1} = f(V_i^{l+1}) + j.f(\hat{V}_i^{l+1}) \tag{2}$$

$$V_i^{l+1} = \sum_{k=1}^{K} w_{ik}^{l+1} * O_k^l + b_i^{l+1} \tag{3}$$

where O_i^{l+1} are the output feature maps, w_{ik}^{l+1} represents the filter weights, O_k^l are the input feature maps, and b_i^{l+1} is the bias term. The symbol $*$ denotes the convolution operation, and $f()$ is activation function.

Pooling layers follow the convolutional layers and apply a downsampling operation, often using maximum or average pooling to reduce the spatial dimensions of the feature maps. This operation can be represented by the average pooling function:

$$O_i^{(l+1)}(x,y) = \mathrm{ave}_{u,v=0}^{g-1} O_i^{(l)}(x \cdot s + u, y \cdot s + v) \tag{4}$$

where g is the pooling size, s is the stride, and $O_i^{(l+1)}(x,y)$ is the output of the pooling operation at position (x,y).

The fully connected layers in the CV-CNN serve as integrators that compile the features extracted from previous layers, with each neuron connected to every neuron in the preceding layer. The final layer in our network produces a real-valued vector, where each dimension corresponds to one of the five key factors of mental health. Our framework employs a scoring mechanism where each factor is assigned a score from -5 to 5, reflecting the intensity and polarity of that aspect of mental health as derived from the student's comment.

CV-CNN uses complex backpropagation to optimize the weights and biases of a complex-valued convolutional neural network to reduce the discrepancy between the network's output and the desired target outcome for training data. The process involves the classic least-squared error function as the loss function E, and the network parameters are trained using Stochastic Gradient Descent (SGD) by minimizing this loss function during backpropagation.

For a set of training samples $\{X[n], T[n]\}_{n=1}^{N}$, where $X[n]$ is the n-th input data and $T[n]$ is the corresponding label, the complex-valued nature of both the input and label is taken into account. The classification error is expressed by the loss function E, calculated as:

$$E = \frac{1}{2N} \sum_{n=1}^{N} \sum_{k=1}^{K} \left[(\Re(T_k[n]) - \Re(O_k[n]))^2 + (\Im(T_k[n]) - \Im(O_k[n]))^2 \right] \tag{5}$$

The network parameters are updated iteratively with the following rules for weights and biases:

$$w_{ik}^{(l+1)[t+1]} = w_{ik}^{(l+1)[t]} - \eta \frac{\partial E[t]}{\partial w_{ik}^{(l+1)[t]}} \tag{6}$$

$$b_i^{(l+1)[t+1]} = b_i^{(l+1)[t]} - \eta \frac{\partial E[t]}{\partial b_i^{(l+1)[t]}} \tag{7}$$

Here, η is the learning rate, and the derivatives of the error with respect to the weights and biases are computed using the complex chain rule.

To calculate the complex gradients, the error gradient of the weights $\frac{\partial E}{\partial w_{ik}^{(l+1)}}$ is defined as:

$$\frac{\partial E}{\partial w_{ik}^{(l+1)}} = \frac{\partial \Re(E)}{\partial w_{ik}^{(l+1)}} + \frac{\partial \Im(E)}{\partial w_{ik}^{(l+1)}} \tag{8}$$

This is further expanded in terms of the real and imaginary components of the complex numbers involved. An intermediate quantity known as the "error term" $\delta_i^{(l+1)}$ is introduced to simplify the expression of the gradient:

$$\delta_i^{(l+1)} = -\frac{\partial \Re(E)}{\partial V_i^{(l+1)}} - j \frac{\partial \Im(E)}{\partial V_i^{(l+1)}} \tag{9}$$

Using the error term, the gradient of the loss function with respect to the weights is simplified as:

$$\frac{\partial E}{\partial w_{ik}^{(l+1)}} = -\delta_i^{(l+1)} \overline{O_i^{(l)}} \tag{10}$$

The bar denotes taking the complex conjugate of the output feature map from the previous layer l. This process is repeated for each layer in the network, from the output layer back to the input layer, updating the weights and biases to minimize the loss function and improve the model's performance on the training data.

3.6. **Data Adaption for CV-CNN.** In this section, we outline the transformation of textual data into a format that is suitable for CV-CNN. The word embeddings by FastText denoted as $E(w)$, is a dense vector of the form:

$$E(w) = [e_{w_1}, e_{w_2}, \ldots, e_{w_{300}}] \tag{11}$$

Each element e_{w_i} corresponds to a semantic feature same to a unique semantic dimension. The context of each word is considered by combining its embedding with those of its surrounding words to create a contextual vector c_w :

$$c_w = \frac{1}{2}\left[E(w) + E(\text{context}(w))\right] \tag{12}$$

This approach mirrors the method of constructing a coherency matrix in signal processing, where the relationship between embeddings is analogous to the interaction of polarized signals. Here, the coherency matrix for word embeddings, denoted as C, is formed by accumulating the outer products of the contextual vectors over a defined window of words, capturing both individual contributions and inter-word relationships:

$$C = \frac{1}{N}\sum_{i=1}^{N} c_w^i (c_w^i)^T \tag{13}$$

In this matrix, N is the number of contexts or the window size considered for each word, with the transpose operation denoting the creation of the outer product.

To adapt the data for the CV-CNN, we consider each word's embedding within its surrounding context to form a multi-dimensional tensor. This tensor is structured to represent the sequence and semantic nuances of words as they appear in textual data. By integrating the embeddings of a word with its contextual neighbors, we construct a rich, layered representation that captures the complexities of language, reflecting both the specific properties of individual words and the broader semantic patterns that emerge from their juxtaposition in text. Given a sequence of words $[w_1, w_2, \ldots, w_n]$, we construct the input tensor T to the CV-CNN using these contextual embeddings:

$$T = [c_{w_1}, c_{w_2}, \ldots, c_{w_n}]^T \tag{14}$$

In practical application, we structure the input tensor with dimensions $m_1 \times m_2 \times 300 = 5 \times 1 \times 300$, where $m_1 = 5$ represents a contextual window incorporating five words before and after the target word, and $m_2 = 1$ reflects the individual consideration of each word. Each word is represented by a 300-dimensional vector obtained from FastText embeddings. The network architecture incorporating input feeding of CV-CNN is depicted in Figure 3 and the training parameters of CVCNN are set as Table 2:

Table 2. Training parameters.

Parameter	**Value**
Optimizer	Adam
Weight_decay	3e-4
Learning rate	0.01
Dropout	0.8

4. **Experiment Results.**

```
Model: "CV-CNN"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 5, 1, 300)]       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 3, 1, 64)          57664
_________________________________________________________________
max_pooling2d_1 (MaxPooling2D) (None, 1, 1, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 1, 1, 128)         8320
_________________________________________________________________
max_pooling2d_2 (MaxPooling2D) (None, 1, 1, 128)       0
_________________________________________________________________
flatten_1 (Flatten)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 512)               66048
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0         (Dropout rate: 0.8)
_________________________________________________________________
dense_2 (Dense)              (None, 256)               131328
_________________________________________________________________
dropout_2 (Dropout)          (None, 256)               0         (Dropout rate: 0.8)
_________________________________________________________________
dense_3 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0         (Dropout rate: 0.8)
_________________________________________________________________
output_1 (Dense)             (None, 5)                 645
=================================================================
Total params: 244,901
Trainable params: 244,901
Non-trainable params: 0
_________________________________________________________________
```

Figure 3. Network structure of CVCNN

4.1. **Experiment Metric.** To measure the model's performance, we used standard metrics such as True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Table 3 presents the structure of the Confusion Matrix utilized for illustrating those metrics We calculated the mean accuracy as the quotient of correctly

Table 3. Confusion Matrix.

		Predict	
		Stress	Normal
Actual	Stress	TP	FP
	Normal	FN	TN

predicted instances to the total number of instances examined. This measure was used to determine the model's precision in predicting positive sentiments, while the recall metric assessed the fraction of positive instances correctly identified from the set of all actual positive instances. Additionally, we utilized the F1 score, a harmonized measure that merges precision and recall, to provide a more balanced evaluation of the model's predictive performance. These stringent evaluative criteria were implemented to scrutinize the capability of the model thoroughly. Equations (15) through (18) depict those criteria.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{15}$$

$$Precision = \frac{TP}{TP + FP} \tag{16}$$

$$Recall = \frac{TP}{TP + FN} \tag{17}$$

$$F1_{score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{18}$$

The selection criteria for the machine learning algorithms used for comparison were grounded on their relevance and widespread adoption in similar research contexts. The algorithms chosen represent a diverse spectrum of approaches, ensuring a comprehensive comparative analysis. This selection enables a robust evaluation of the CVCNN-MHFA model against established benchmarks, offering insights into its relative performance and areas of improvement.

4.2. **Experiment Setup.** The experimental setup for our study was conducted on a system equipped with an Intel Core i7-12700K CPU, offering high-performance processing capabilities. The computational tasks were accelerated using an NVIDIA GeForce RTX 3070 GPU, renowned for its efficiency in handling deep learning algorithms. The system was supported by 64GB of DDR4 RAM to facilitate the handling of large datasets and intensive computing tasks. For software, we utilized Python 3.8 for its rich ecosystem of data processing and machine learning libraries. The deep learning models were implemented and tested using the PyTorch 1.8 framework, chosen for its dynamic neural network graph and extensive library support, which allows for intricate model construction and seamless optimization.

4.3. **Experimental Results and Analysis.**

4.3.1. *Performance Analysis.* In the evaluation of our proposed framework, we analyzed the performance through a series of experiments. The training and testing losses across epochs of CVCNN-MHFA are presented in Figure 4. The graph delineates the trajectory

Figure 4. Training and test loss of CVCNN-MHFA

of model learning, capturing the reduction in loss as the model iteratively adjusts its parameters. Over 30 epochs, the CVCNN-MHFA utilized for the mental health factor analysis demonstrates a consistent decrease in the training loss, indicative of the model's improving accuracy in predicting the mental health status from the student comments. The test loss also follows a downward trend, although with some fluctuations, suggesting the model's generalizing capability when applied to unseen data. This balance between training and test performance is crucial for validating the model's effectiveness in real-world applications, ensuring it neither overfits to the training data nor fails to capture the underlying patterns necessary for accurate classification.

In Figure 5, we observe the performance metrics of CVCNN-MHFA, which showcases a robust performance. The Accuracy of the model stands at a commendable 94.56%, reflecting its reliable classification of the mental health states. Precision and Recall are notably high at 96.07%, and 94.54% respectively indicating a strong positive predictive value and capable of identifying the majority of true stress cases within the dataset. Furthermore, the F1 Score, at 95.3%, demonstrates the model's balanced precision-recall performance, affirming its effectiveness in the nuanced task of mental health classification.

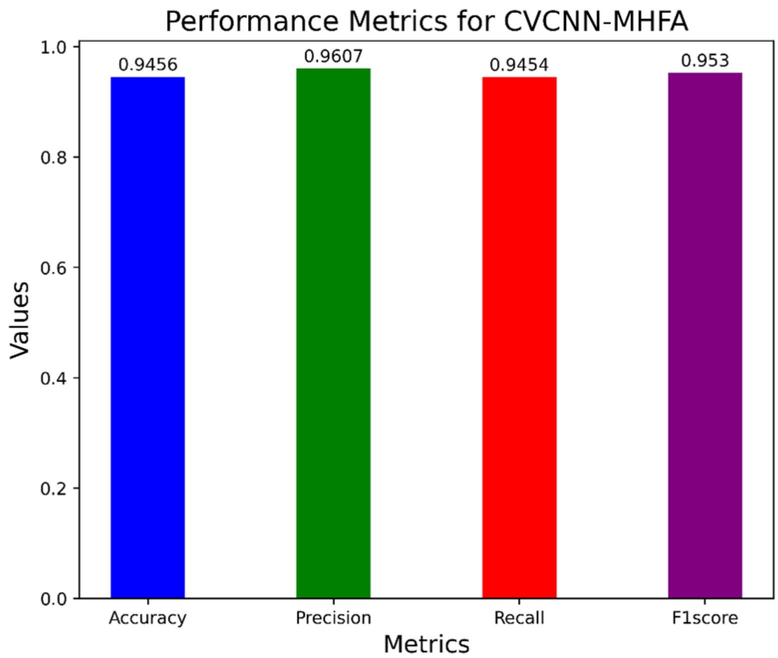

Figure 5. Performance metrics of CVCNN-MHFA

To evaluate the effectiveness of the CVCNN-MHFA model, a comparative analysis was performed between the proposed approach and 3 baseline models : Real-Valued Convolutional Neural Network (RVCNN), the Bidirectional Long Short-Term Memory (BiLSTM) and Deep Neural Network (DNN). The objective was to assess the respective outcomes of these models.

Figure 6 presents the Confusion Matrices for the CVCNN-MHFA model alongside the comparison models, offering a detailed visualization of each model's predictive performance. Table 4 provides a comparative analysis between CVCNN-MHFA with other prevalent methods in the domain of mental health assessment using deep learning. The

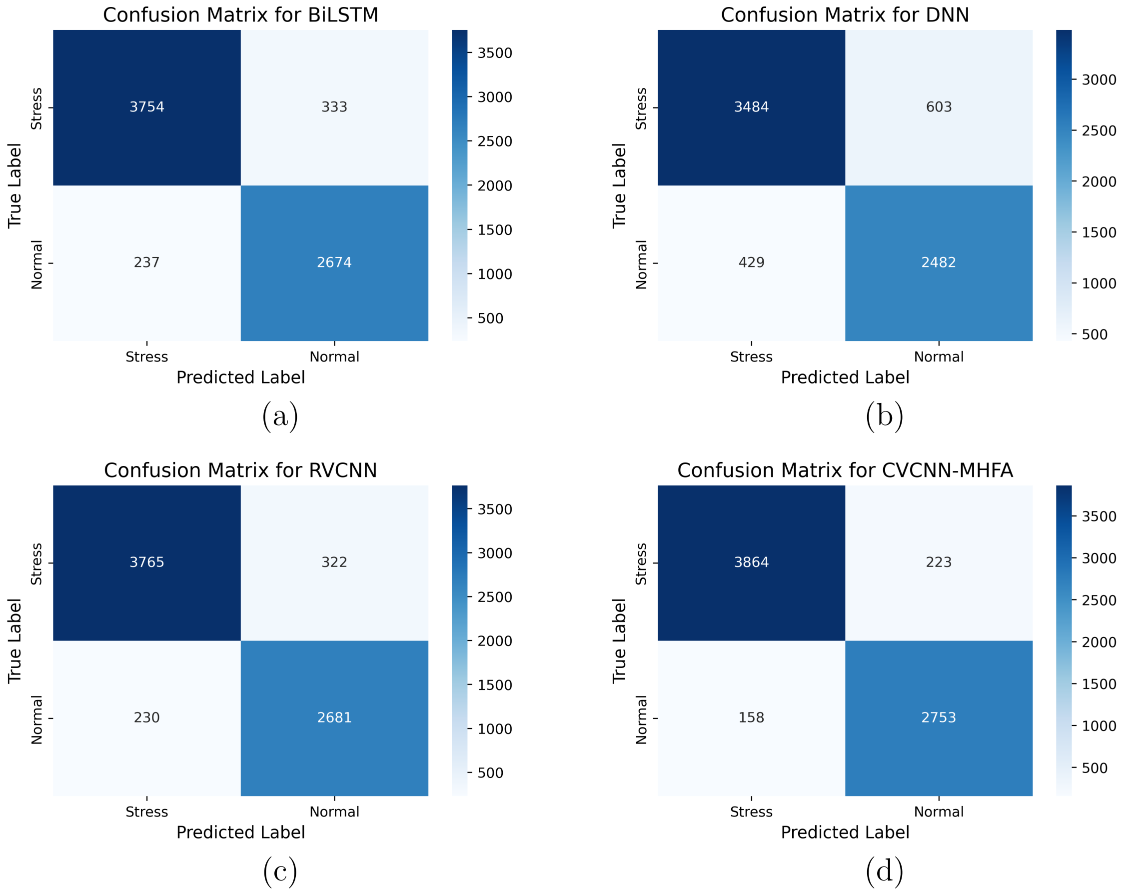

Figure 6. Confusion Matrix : a) BiLSTM , b) DNN , c) RVCNN , d) CVCNN

Table 4. Comparison outcomes of experiments

Methods	Acc	Precision	Recall	F1
CVCNN-MHFA	**0.9456**	**0.9607**	**0.9454**	**0.9530**
RVCNN	0.9211	0.9424	0.9212	0.9317
BiLSTM	0.9185	0.9406	0.9185	0.9294
DNN	0.8525	0.8904	0.8525	0.8710

CVCNN-MHFA outperforms the other considered models across all metrics, with an accuracy of 94.56%, precision of 96.07%, recall of 94.54%, and an F1 score of 95.30%. This superior performance can be attributed to the model's ability to capture complex patterns in the data, which are indicative of the nuanced nature of mental health conditions. In comparison, the RVCNN and the BiLSTM network show commendable results but fall short of the benchmarks set by CVCNN-MHFA. The RVCNN achieves an accuracy of 92.11% and an F1 score of 93.17%, while the BiLSTM model is close with an accuracy of 91.85% and an F1 score of 92.94%. These results suggest that while RVCNN and BiLSTM are effective for text classification tasks, the complex value computations of CVCNN-MHFA provide a significant advantage in capturing the intricate features necessary for mental health analysis. DNN while still a powerful tool for pattern recognition, lags in this application, with an accuracy of 85.25% and an F1 score of 87.10%. The comparative underperformance of the DNN model could be due to its less sophisticated handling of the sequential and contextual nature of textual data, which is crucial in interpreting emotional expressions and sentiments accurately. These comparative results underscore the effectiveness of our proposed CVCNN-MHFA framework in the context of mental health status classification from textual comments.

The CVCNN-MHFA model's robust performance in classifying mental health conditions offers significant practical benefits in educational settings. Its early detection capabilities can facilitate timely intervention and support, guiding the development of tailored mental health programs. Insights from the model can inform resource allocation, ensuring that support services are available where most needed. Additionally, its continuous monitoring can assist in evaluating the effectiveness of mental health initiatives, promoting a proactive approach to student well-being. Integrating such a data-driven model can also aid in reducing stigma and fostering an environment where mental health is openly addressed, making the CVCNN-MHFA model a valuable asset for creating supportive and responsive educational landscapes.

4.3.2. *Statistical Analysis.* This section provides a quantitative measure of the model's predictive accuracy compared to expert assessments. In Table 5 and Figure 7, which includes 4087 comments labeled "Stress" by experts, the scores across the five factors: Emotional Stability (ES), Social Connectedness (SC), Academic Engagement (AE), Coping Strategies (CS), and Physical Well-being (PW), reveal a close correspondence between the experts' scores and the CVCNN-MHFA's predictions.

Table 5. Comparison of factors score on comments labeled "Stress"

Source	**ES**	**SC**	**AE**	**CS**	**PW**
Expert's Score	-4090	-4089	-4172	-4019	-3894
Model's Score	-4123.16	-3953.12	-4254.68	-3913.17	-3703.47

There are noticeable variances in certain factors, the model predicts a slightly higher level of stress in Emotional Stability (ES) and Academic Engagement (AE) with scores of -4123.16 and -4254.68 respectively, compared to the experts' scores of -4090 and -4172. Conversely, the model attributes a lesser degree of stress in Social Connectedness (SC) and Physical Well-being (PW) with scores of -3953.12 and -3703.47, which are higher than the experts' scores of -4089 and -3894, indicating that the model perceives less stress impact in these areas.

In contrast, Table 6 and Figure 8, showcases the scores for 2911 comments labeled "Normal." Here, the experts' scores tend to be more positive, as expected, across all factors, indicating a general state of well-being. The model's scores largely align with the experts' assessments, particularly in Social Connectedness (SC) and Academic Engagement (AE), where the scores are very close or even exceed the experts' with 2958.14 and 2747.97 respectively, compared to 2943 and 2659. This suggests the model's effectiveness in recognizing normalcy in these areas. However, the model exhibits a lower score in Emotional Stability (ES) and Coping Strategies (CS), as well as Physical Well-being (PW), with 2393.26, 2389.76, and 2762.93 respectively, against the experts' 2579, 2675, and 2998, indicating a slightly conservative estimation of normalcy in these factors.

Table 6. Comparison of factors score on comments labeled "Normal"

Source	**ES**	**SC**	**AE**	**CS**	**PW**
Expert's Score	2579	2943	2659	2675	2998
Model's Score	2393.26	2958.14	2747.97	2389.76	2762.93

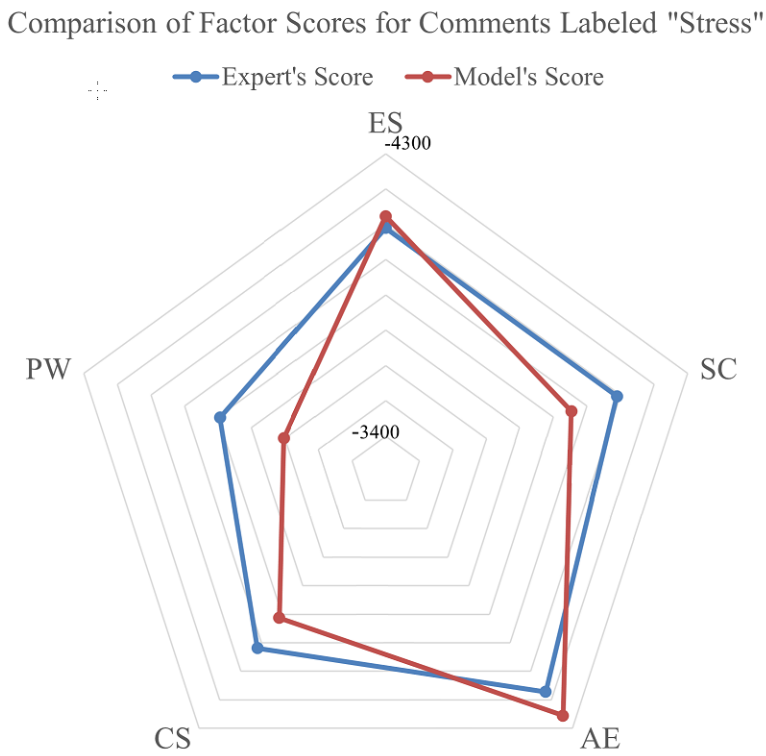

Figure 7. Comparison of factors score for comments labeled “Stress”

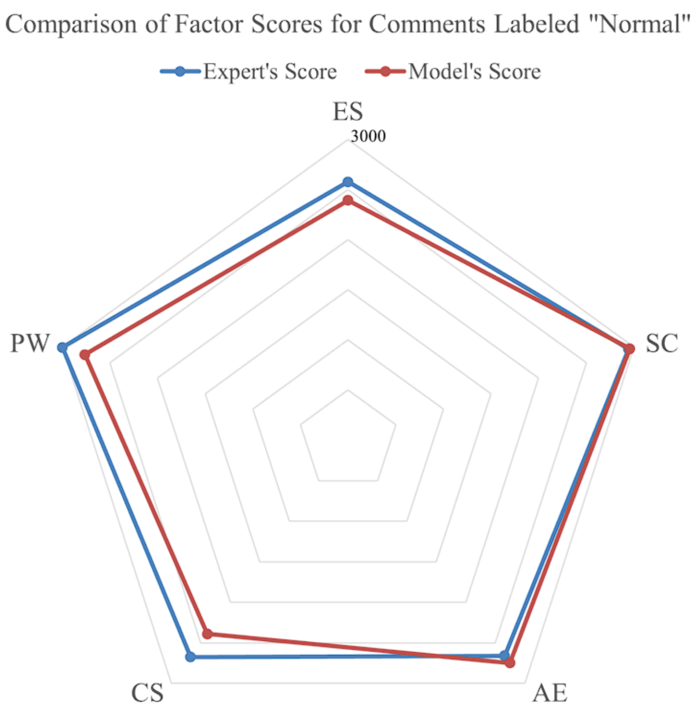

Figure 8. Comparison of factors score for comments labeled “Normal”

The comparative analysis underscores the understanding of the model in differentiating between ”Stress” and ”Normal” states. It also highlights areas where the model’s predictions deviate from the experts’, providing insights into potential areas for refinement. The overall consistency between the model’s scores and the experts’ scores across a majority of factors reaffirms the reliability of the CVCNN-MHFA in assessing mental health status, with the noted variations suggesting opportunities for further model tuning to enhance alignment with human expert evaluations.

Throughout this research, we navigated the complex landscape of mental health concerns and their diverse expressions across different demographics, contending with the potential for bias in data labeling and the inherent 'black box' nature of our AI model that could affect both interpretability and generalizability. To mitigate these issues, we not only diversified our dataset and integrated expert oversight into our methodology but also recognized the need for future studies to further enhance demographic inclusivity, adopt consensus labeling, and improve model transparency. Additionally, by embracing the multi-dimensional aspects of mental health, there is a substantial opportunity for future research to integrate multimodal data, thereby refining the model's predictive accuracy and keeping pace with the rapidly evolving language of mental health discourse, especially prevalent on social media platforms.

Simultaneously, the prospect of integrating our CVCNN-MHFA model with the existing mental health support frameworks within educational institutions offers a pathway to bolster student well-being. This integration promises to enable real-time monitoring and nuanced analysis of student sentiments, equipping educators and mental health professionals with critical insights that can be leveraged to identify students in need and initiate appropriate interventions promptly. Such a synergistic approach, which aligns the model's advanced capabilities with current support mechanisms, promises to forge a data-driven, responsive support network that caters to personalized student care pathways. As we look ahead, ensuring the seamless interoperability of AI models with educational databases and support systems, while rigorously upholding privacy and ethical standards, will be vital in advancing the frontier of AI in educational mental health services.

5. **Conclusion.** In this study, we have developed and validated a Complex Value Convolutional Neural Network (CVCNN-MHFA) tailored for the assessment of student mental health, analyzing textual comments for signs of stress and well-being. Our experimental results reveal that the CVCNN-MHFA model outperforms traditional models, exhibiting high accuracy, precision, recall, and F1 score, which suggests a robust capability in identifying mental health conditions from text. While there are minor discrepancies between the model's predictions and expert evaluations, particularly in factors such as Emotional Stability and Social Connectedness, these differences offer valuable insights for refining the AI framework. Radar charts vividly illustrate the model's performance, providing a clear visual confirmation of its predictive power.

This research marks a significant leap in mental health assessment by leveraging AI's nuanced capabilities, notably in deciphering complex textual patterns indicative of mental states. The CVCNN-MHFA model's success highlights AI's potential to elevate the precision and efficiency of mental health diagnostics, promoting scalable and sensitive wellness monitoring. This study not only furthers AI's technical prowess in mental health but also fosters more tailored, data-driven support systems, particularly vital amidst escalating mental health concerns in educational settings. Looking ahead, the model's evolution—with a focus on refining parameters, boosting interpretability, and integrating multimodal data—promises to enrich AI's role in mental health intervention, opening new avenues for research and practical application. Future work will focus on fine-tuning the model's parameters, enhancing its interpretability, and exploring the integration of multimodal data to enrich the framework's sensitivity and applicability, thereby broadening the horizons of AI in mental health assessment and intervention.

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