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A Deep Learning Model-Based Approach to Predicting Mental Toughness in College Students

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Abstract. *College students today deal with several difficulties including academic pressure, social adaptability and personal growth that combined influence their psychological resilience in the constantly changing social scene. Maintaining the psychological health and academic performance of college students depends critically on psychological resilience—that is, an individual's capacity to adapt favorably in the face of stress, obstacles, and adversity. But conventional approaches of gauging mental toughness depend on scale assessments and questionnaires, which are constrained by people's subjective assessments and make it challenging to dynamically depict variations in mental toughness. This work suggests a hybrid model, GDM-Resilience, which combines graph neural networks with deep multimodal learning to handle multi-source data more thoroughly and flexibly, and to raise the accuracy and applicability of prediction, thereby overcoming these constraints. By means of the multimodal data fusion technique, the GDM-Resilience model accomplishes great fusion of the several feature dimensions of mental toughness data. The aspects of mental toughness were predicted using a multi-label classification technique; hyperparameter optimisation and ablation studies were conducted to validate it. More precisely and practically than the conventional approaches, the experimental results show that the model performs well in integrating multimodal data and capturing the multidimensional features of mental toughness, so offering an efficient technical means for mental health support and tailored educational intervention.*
Keywords: mental toughness prediction; student mental health; graph neural network; deep multi-modal learning.

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1. **Introduction.** Psychological resilience among college students has lately become a major focus of study [1]. Maintaining the psychological health and academic success of college students depends on psychological resilience—that is, an individual's capacity to adapt favorably in the face of stress [2], obstacles [3], and adversity [4]. Under the several effects of academic stress, social adaptability, and personal development needs, the need of strategies to evaluate and improve the resilience of college students has become progressively critical. More thorough, data-driven approaches are desperately needed, nevertheless, since conventional evaluation techniques sometimes find it difficult to adequately depict the intricacy of psychological resilience [5].

1.1. **Related work.** Concerning mental toughness evaluation, conventional approaches have depended on scales and questionnaires. Usually used to evaluate a person's emotional control, stress coping, social support, and other aspects, these techniques are developed by psychologists. These conventional approaches, however, depend on self-reports from individuals, which are prone to personal opinions and challenging to dynamically portray changes in mental toughness in various environments.

Data-driven approaches have progressively been included into mental toughness prediction studies using machine learning and deep learning techniques [6]. Early research mostly focused on feature engineering, building prediction models through feature selection, data preparation and other processes, such Support Vector Machine (SVM) [7], Random Forest (RF) and other conventional machine learning techniques [8]. Although these techniques have made considerable improvement in prediction accuracy, their performance is still limited when handling multidimensional and complicated data, particularly in terms of perhaps catching potential correlations in mental toughness.

Deep learning techniques have progressively evolved in recent years into a research hotspot for mental toughness prediction. By use of models such Deep Neural Network (DNN), scientists aim to capture the intricate interactions between mental toughness traits and enhance the generalization capability of prediction models [9]. Graph neural networks (GNN) have especially shown notable performance in complicated relational data including social network analysis and recommender systems as well as in a limited number of applications to model and predict mental toughness [10]. Furthermore, progressively rising application of Multi-Modal Learning in the field of psychology is Researchers can build more thorough resilience prediction models by combining several data sources, including physiological signals, behavioural data, and questionnaire results.

The present research has certain flaws, though: most of the techniques are challenging to efficiently combine several data sources, which results in a lack of comprehensiveness in the prediction results; on the other hand, although the deep learning models are great in improving the prediction accuracy, their complexity usually increases the difficulty of the model training, which may affect the practicality of the model. This research thus suggests "GDM-Resilience", a hybrid model combining GNN and Deep Multi-Modal Learning (DMML) [11], to handle multi-source data more comprehensively and flexibly, and to further increase the accuracy and application of college students' mental toughness prediction.

1.2. **Contribution.** To address this background, our work introduces a novel recommendation model, "GDM-Resilience". The key contributions of our model are as follows:

(1) **Multimodal data fusion strategy.** To get the deep fusion of several feature dimensions of mental toughness data, multimodal learning technology was included into the model. By means of joint modeling of data from several sources, the GDM-Resilience model may more fully represent students' performance in all spheres of

mental toughness, so guaranteeing the correctness and comprehensiveness of the assessment results.

(2) **Multi-label classification method applied to mental toughness.** The model achieves a multi-dimensional representation of individual psychological states by being able to predict the dimensions of mental toughness in a multi-label classification way, therefore differentiating it from earlier studies that only concentrate on one toughness dimension. This function has great application potential and can assist researchers in the domains of education and mental health to more precisely determine the particular performance of individuals on several levels of mental toughness.

(3) **Hyper-parameter optimisation and ablation experimental validation.** This work systematically performs hyperparameter optimization of the model and analyzes the effects of various modules on the prediction accuracy by ablation experiments, so revealing the functions performed by each module in the model and offering a basis for additional improvement of the mental toughness prediction model.

2. Theoretical analysis.

2.1. Deep learning models.

Deep learning is a machine learning method based on multi-layer neural networks that allows efficient modeling of complicated data patterns by layer-by-layer feature extraction. On picture and time-series data, classical models including Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) perform well [12]; but, CNNs and RNNs are not very good in tasks requiring the natural correlations and multimodal aspects of the data.

Consequently, in this work we select graph neural networks and deep multimodal networks, better appropriate for the prediction of mental toughness. While DMML can combine data from several modalities, such textual, scale and behavioral data, GNN can learn structural relationships between individuals using the information of nodes and edges. These models enable a thorough knowledge of mental toughness [13].

With graph-structured data, particularly data including relationships between nodes, GNN is appropriate; its structure is shown in Figure 1.

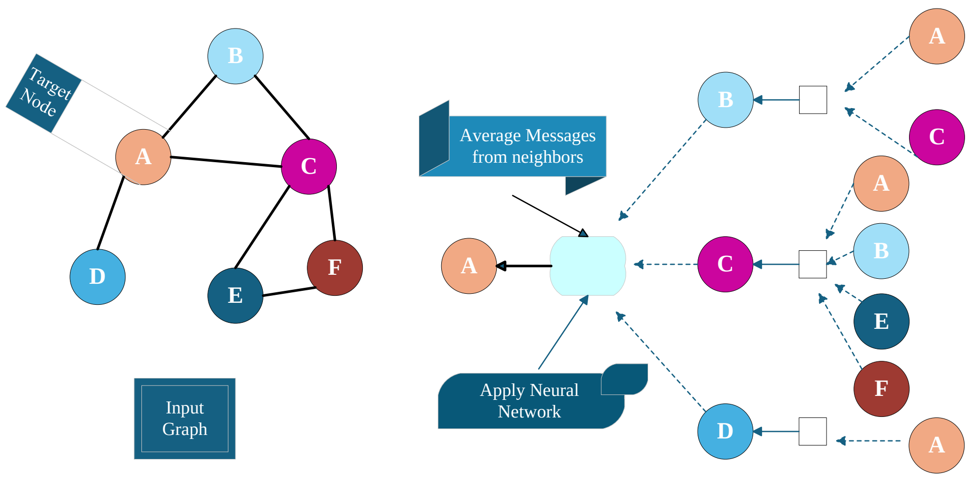

Figure 1. Classification of GNN nodes

Consider a student feature graph $G = (V, E)$, in which V represents nodes (students) and E represents edges (inter-student interactions).

(1) Initializing node characteristics. Assume that every node i starts with mental toughness connected features:

$$h_i^{(0)} = x_i \tag{1}$$

where x_i is the input feature vector of node i.

(2) Neighborhood aggregation [14]. Feature aggregation of node i at the kth layer using information from its neighbour nodes $N(i)$:

$$m_i^{(k)} = \sum_{j \in N(i)} W^{(k)} h_j^{(k)} \tag{2}$$

where $W^{(k)}$ is the weight matrix of the current layer.

(3) Node update. The information of the node itself is combined with the neighborhood aggregation results to update the node features:

$$h_j^{(k+1)} = \sigma\left(W^{(k)} h_j^{(k)} + m_i^{(k)}\right) \tag{3}$$

where σ is the activation function (e.g., ReLU).

(4) Aggregation with several layers. Proceed as above for several layers so that the node features can acquire the information of far-off adjacent nodes and acquire the node features of the last layer K:

$$h_i^{(K)} = \text{Aggregate}\left(h_i^{(K-1)}, \sum_{j \in N(i)} W^{(K-1)} h_j^{(K-1)}\right) \tag{4}$$

(5) Graph worldwide depiction. Combine the node features to create a global graph representation h_G:

$$h_G = \text{Readout}\left(\{h_i^{(K)} \mid i \in V\}\right) \tag{5}$$

(6) Output from classification or regression [15]. Pass h_G to the fully-connected layer to get the output y for prediction of mental toughness:

$$y = W_G h_G + b \tag{6}$$

(7) Loss purpose. Reducing mean square error loss or cross entropy loss (selected in line with task type):

$$L = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{7}$$

where y_i is the true value and $\hat{y}_i$ is the predicted value.

In the mental toughness prediction challenge, I have to incorporate several psychological traits, behavioural data, and other unstructured material (text and images) in addition to mine the relational networks among students. While for a thorough knowledge of mental toughness it is essential to use additional sources of data to build a more accurate prediction model; GNN is appropriate for capturing complicated interactions and propagation patterns across student nodes. DMML thus aggregates data from several modalities to enable cross-modal fusion of information [16], see Figure 2.

(1) Extensive feature extraction modally. Every modality's raw data X_i undergo independent feature extraction networks to derive the feature representation H_i:

$$H_i = f_i(X_i), i = 1, 2, \ldots, m \tag{8}$$

(2) Modal feature mapping in two directions. Maps elements into the same dimensional space for fusion:

$$\tilde{H}_i = W_i H_i \tag{9}$$

where W_i is the weight matrix used to map H_i to the unity dimension.

(3) Multimodal feature splicing. Various modalities' features are combined to create a joint representation:

$$H_{\text{concat}} = [\tilde{H}_1; \tilde{H}_2; \ldots; \tilde{H}_m] \tag{10}$$

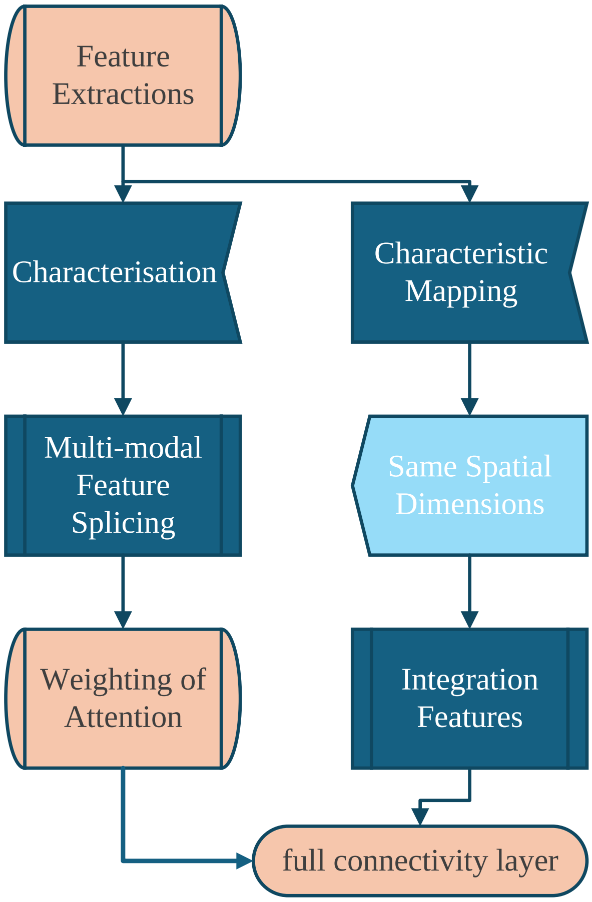

Figure 2. DMML fusion data process

(4) Many systems of attention. Determine the attentional weights of every modality to record the interactions among them:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{11}$$

where Q, K and V are the query, key and value matrices for different modal features and d_k is the scaling factor.

(5) Fusion function creation. Form a fusion representation with modal properties changed with attention weights:

$$H_{\text{fusion}} = \sum_{i=1}^{m} \alpha_i \tilde{H}_i \tag{12}$$

where α_i is the attention weight of the ith modality.

(6) Layer prediction for full connection. The prediction results are obtained by passing the fusion feature H_{fusion} into the fully linked layer:

$$y = W_{\text{fusion}} H_{\text{fusion}} + b \tag{13}$$

At last, the prediction error was computed with mean square error or cross-entropy loss.

Overall, GNN and DMML both show special ability in mental toughness prediction. By means of network of interactions among students, GNN efficiently reflects the function of social influence and collective behavior on individual mental toughness. Conversely, by combining information from many data modalities, DMML offers a richer picture of features. Thus, the choice of these two models to offer a technical basis for mental toughness prediction will enable us to acquire understanding of the several elements influencing college students' mental toughness in a challenging educational environment, so offering empirical data for the development of educational interventions and support strategies.

2.2. **Predictors of mental resilience.** The capacity of a person to stay well-adjusted and psychologically healthy in the face of stress, hardship and challenges is known as mental resilience. Given that mental toughness directly influences students' learning performance and mental health, its prediction is very crucial in educational environments—especially in college populations [17]. Thus, the creation of efficient predictive models of mental toughness will enable teachers to offer specific assistance and interventions.

Gathering pertinent information comes first in the prediction of mental toughness. Typical data sources include:

(1) Standardised mental toughness scales—such as Connor-Davidson Resilience Scale—are used in questionnaires to evaluate pupils' mental toughness.
(2) Behavioural data. Information on students' learning behaviours, engagement, etc. is captured through learning management systems.
(3) Physiological data. Should such signals be accessible, heart rate and brain waves (EEG) can be recorded.

Feature selection guarantees the most relevant information is used during model training, so it is the secret to data preparation. Usually used feature selection techniques are the following:

(1) Information Gain.

$$\mathrm{IG}(Y, X) = H(Y) - H(Y|X) \tag{14}$$

where $H(Y)$ is the entropy of the target variable, and $H(Y|X)$ is the conditional entropy of the target variable Y given the feature X.

(2) Pearson Correlation Coefficient. It computes the target variable's linear correlation with the characteristics using this formula:

$$r = \frac{\sum(X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum(X - \bar{X})^2 \sum(Y - \bar{Y})^2}} \tag{15}$$

where $\bar{X}$ and $\bar{Y}$ are their means; X and Y are respectively the observed values of the feature and goal variables. Features having high absolute relevance for modeling can be chosen by computing the correlation coefficient r.

Feature significance is another often used feature significance scoring system computed as:

$$\mathrm{Score}(f) = \frac{1}{NT} \sum_{t=1}^{NT} \Delta G_{\mathrm{init}} \tag{16}$$

where NT is the number of trees and ΔG_{init} is the change in the Gini index after the introduction of the feature f in the tree t.

By means of efficient data preparation and feature selection, the mental toughness prediction model can fully exploit multivariate data including physiological signals, questionnaire findings, and behavioral data of students. First, by means of techniques including information gain and correlation coefficient, we may find features strongly associated with mental toughness, so lowering model complexity and enhancing prediction accuracy. Model-based feature selection, such relevance score, guarantees even more the validity and dependability of the chosen features. These actions not only set the groundwork for model construction but also give great support for next deep learning model training. Thus, the building of an accurate prediction model of mental toughness not only helps teachers to recognize pupils' psychological requirements in a timely manner, but also offers a scientific basis for the development of tailored interventions and support measures.

3. Construction and implementation of a deep learning model based prediction model for college students' mental toughness: GDM-Resilience.

3.1. **Model construction.** Effective integration of several kinds of information is the secret to model creation in the prediction of mental toughness. This work blends GNN and DMML to build a complete deep learning model so that full use of graph-structured data and multimodal information may be made. The model's architecture consists of several layers, each with a particular purpose to attain precise estimate of mental toughness.

(1) **Input layer.** Receives data from several sources, including physiological signals, learnt behavioural data, and textual data from psychometric tests [18]. Every modality's data are normalised and converted in this layer into a format fit for next usage.

(2) **Feature extraction layer.** Long short-term memory network (LSTM) processing of the psychological assessment's textual data results in temporal features extracted [19]. The pertinent ratio is:

$$h_t = \mathrm{LSTM}(x_t, h_{t-1}) \tag{17}$$

where x_t is the input text feature and h_t is the hidden state at the current moment.

Graph feature extraction uses a graph neural network to replicate the structure of the student social network, therefore extracting node and edge features from the graph. The layer's recipe calls for:

$$H^{(l+1)} = \sigma(\tilde{A}H^{(l)}W^{(l)}) \tag{18}$$

where $\tilde{A}$ is the normalised adjacency matrix and $H^{(l)}$ is the feature representation of the lth layer.

(3) **Feature fusion layer.** Extensive feature representation is produced by fusing elements taken from text and graph structures. One can weigh the fusion technique either concatenation using the formula or weighted average:

$$H_{\text{fused}} = \mathrm{concat}(H_{\text{text}}, H_{\text{graph}}) \tag{19}$$

where H_{text} and H_{graph} are the outputs of text and graph features respectively.

(4) **Full connectivity layer.** Feature integration runs across the whole connected layer following feature fusion. Equipped with Equation (20), this layer can learn more intricate nonlinear relations.

$$H_{\text{fc}} = \sigma(W_{\text{fc}}H_{\text{fused}} + b_{\text{fc}}) \tag{20}$$

where W_{fc} is the weight of the fully connected layer and b_{fc} is the bias.

(5) **Output layer.** It is set as a regression or classification layer depending on the aim of mental toughness prediction. Should a regression problem exist, the output layer formula is:

$$y = W_{\text{out}}H_{\text{fc}} + b_{\text{out}} \tag{21}$$

where y is the predicted mental toughness value.

The fusion model will be trained with the training set following construction of the model. A back-propagation method optimizes the model parameters throughout the training process therefore enhancing the generalization and accuracy of the forecasts.

3.2. **Model training and optimisation.** A mental health assessment program at a college in the Southeast produced the predictive dataset of mental toughness used in this work. To gather information from college students in a variety of grades and disciplines, the initiative incorporated surveys, interviews, and laboratory tests. As Table 1 shows, 600 samples in all encompassed many student traits in the areas of mental toughness, social support, and emotional condition [20].

Table 1. Feature Information

Feature Name	**Feature Type**	**Description**
Age	Continuous	The age of the student, measured in years
Gender	Categorical	The gender of the student (Male/Female)
Resilience Score	Continuous	Score obtained from the resilience assessment tool, range 1-7
Social Support	Continuous	Student's self-assessment of social support, range 1-10
Emotional State	Continuous	Student's emotional state rating, range 1-10
Academic Pressure	Continuous	Student's perceived academic pressure rating, range 1-10
Self-efficacy	Continuous	Student's confidence in their abilities, range 1-10
Coping Strategy	Categorical	The coping strategies used by students under pressure (Positive/Negative)

The dataset was split using an 80/10/10 ratio into training, validation, and test sets prior to model development. Model training uses the training set; hyperparameter tuning uses the validation set; final model evaluation comes from the test set.

Mostly, model training consists in parameter initialisation, forward propagation, loss computation and reverse propagation. Parameter updates for the built deep learning models either use Adam optimiser or Stochastic Gradient Descent (SGD) [21]. The main phases of the training process include in this:

Appropriate initialisation techniques—such as Xavier or He initialisation—help to determine model weights so as to prevent gradient vanishing or explosion events [22].

Forward propagation generates the expected output by layer by layer passing the input data across the network levels. While for DMML it entails the fusing of several modal data, for GNN the forward propagation procedure also consists in aggregation and propagation operations of node features. Using a loss function—e.g., mean square error MSE or cross-entropy loss—the gap between the model predictions and the actual labels is determined.

Backpropagation uses the chain rule to determine the gradient of the loss function with regard to every parameter, therefore adjusting the model parameters depending on the learning rate. The parameter update formula for optimisers like Adam is:

$$\theta = \theta - \frac{\alpha}{\sqrt{v_t} + \epsilon} \cdot m_t \tag{22}$$

where θ is a model parameter, α is the learning rate, m_t and v_t are the estimates of the first and second order moments, respectively, and ϵ is a small constant to avoid a zero denominator.

3.3. **Model evaluation and adjustment.** Following training, the model is assessed from a test set. The judgment of model performance depends on the evaluation criteria used; so, the following are some of the key ones applied in this work.

(1) The model's performance in the categorization of mental toughness levels—that is, high, medium, low—is evaluated using accuracy [23]. Formula for calculating accuracy is:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{23}$$

where True Positive (TP) is the genuine case; True Negative (TN) is the genuine negative case; fake Positive (FP) is the fake positive; False Negative (FN) is the false negative.

(2) Since it combines accuracy and memory, the F1 score is absolutely vital for unbalanced classification problems [24]. The pattern is:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{24}$$

where Precision and Recall measure the accuracy of the model and the ability to identify positive samples, respectively.

(3) For multi-label classification problems, mean average precision (mAP) evaluates the average model performance over several categories and is appropriate for multi-dimensional analysis in mental toughness evaluation [25].

Calculated for every category, the AP value—average precision—is the area under the precision-recall curve and can be stated as:

$$AP = \sum_{n=1}^{N} (\text{Recall}_n - \text{Recall}_{n-1}) \cdot \text{Precision}_n \tag{25}$$

Then, mAP is the average of all category AP values:

$$mAP = \frac{1}{C} \sum_{c=1}^{C} AP_c \tag{26}$$

where C is the number of categories.

(4) Area under the AUC-ROC curve: Plotting with the false positive rate (FPR) as the horizontal axis and the true positive rate (TPR) as the vertical axis, AUC (Area Under the Curve) gauges the area under the receiver operational characteristic curve (ROC) [26]. For varying degrees of mental toughness, the model's discriminating capacity increases with increasing value of the AUC [27]. One may represent the AUC value as the area under the ROC curve and is computed as the area under the ROC curve and can be written as:

$$AUC = \int_0^1 TPR(FPR) d(FPR) \tag{27}$$

These evaluation criteria enable a thorough performance analysis of the model to guarantee its accuracy and efficacy in activities involving mental toughness prediction. Should performance on the test set fall short, additional changes depending on the assessment findings—such as modifying the model structure, choosing alternative features, or experimenting with other hyperparameter values.

4. **Performance testing and analysis.** In order to verify the validity of the proposed GDM-Resilience model, we design and implement three key experiments, which include basic performance evaluation, performance optimization, and component analysis.

4.1. **Multi-labelling classification experiment.** One can see mental toughness as a complicated concept spanning several spheres including social support, stress management, and emotional control. Using these features as multi-label outputs helps students to evaluate and comprehend their mental toughness more fully. In this experiment, each sample corresponds to several labels reflecting students' performance on several levels of mental toughness; the dataset used comprises several elements connected to mental toughness. With the particular features provided in Table 2, the dataset will comprise the responses of the questionnaire and the scores of the pertinent psychological tests:

Table 2. Psychographic labelling

Feature	**Description**
Emotional Regulation	Scores on emotional regulation ability
Stress Coping	Scores on coping with stress
Social Support	Assessment of social support network
Resilience Score	Overall resilience assessment score
Anxiety Level	Assessment of anxiety levels
Depression Level	Assessment of depression levels

The experimental results are shown in Figure 3:

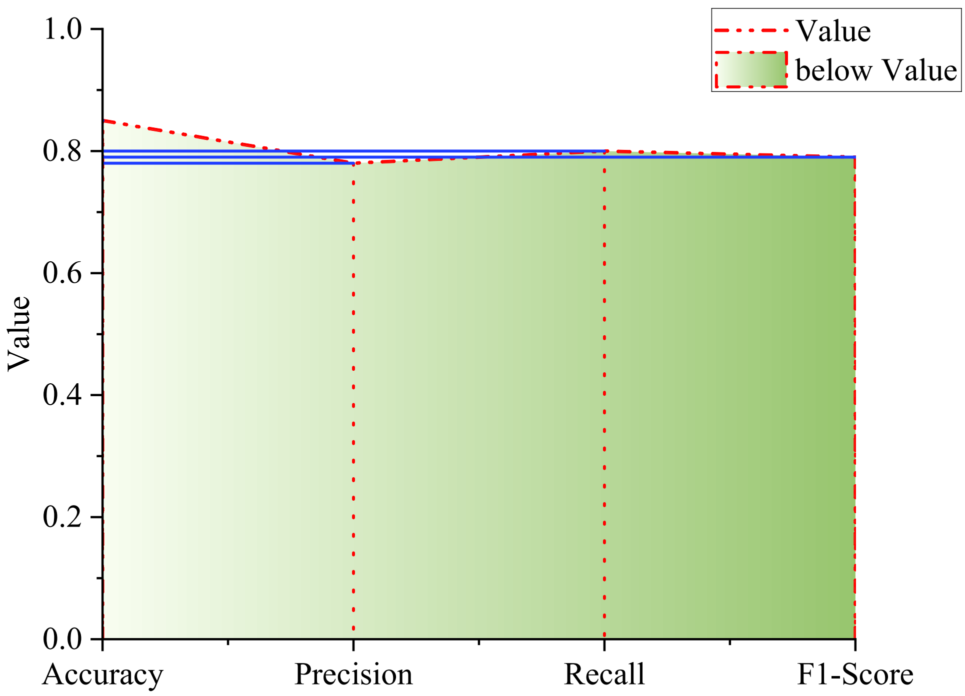

Figure 3. Experimental results of multi-label classification

The model shows strong predictive capacity in numerous aspects, according the results. With an overall accuracy of 85%, the model made 85% of its predictions compatible with the actual labels in all the samples. Reflecting a strong identification capacity, the recall rate was 80% and the precision rate was 78%, thereby suggesting the dependability of the model in predicting positive samples; the model was able to identify 80% of the actual mental toughness samples. With an F1 score of 0.79 the model achieved an excellent mix between completeness and accuracy. Furthermore, Table 3 shows the correlation analysis results, which show a strong positive correlation between social support and emotion regulation and a 0.65 correlation between emotion regulation and stress coping—that is, between these two dimensions. These results imply that multi-label categorization not only fairly evaluates mental toughness but also exposes the natural links among several aspects.

Table 3. Results of correlation analysis

Metric	**Value**
Resilience Score	Predicted: 75, True: 70
Anxiety Level	Predicted: 4, True: 5
Depression Level	Predicted: 3, True: 2

4.2. **Hyperparameter optimisation experiments.** This work investigated the effect of various hyperparameter values on model performance by means of hyperparameter optimization trials. We sought the best configurations to improve the predictive capabilities of the GNN and DMML fusion model by adjusting the critical hyperparameters (e.g., learning rate, batch size, and number of hidden layer units). More especially, the following hyperparameters were chosen for optimization:

- Learning Rate: A parameter that affects the speed of convergence of the model.
- Batch Size: Every training's total sample count.
- A parameter regulating the model's complexity is the number of hidden units.

In our tests, we hyperparameter adjust using "Grid Search". Figure 4 displays the particular experimental results:

We discovered by means of analysis of the trial results for various hyperparameter combinations that a configuration with a learning rate of 0.001, a batch size of 32, and a number of hidden layer units of 128 performs best. The accuracy of the model achieves 87% in this environment; the precision and recall are likewise much enhanced at 80% and 81%, respectively. These findings show that the model performance is much influenced by the hyperparameter choice; so, the suitable learning rate and batch size can help to increase the predictive capacity of the model. Furthermore, by maximising the hidden layer units, the model's complexity is rather under control, therefore preventing the overfitting phenomena. All things considered, the hyperparameter optimization studies offer great encouragement for ongoing enhancement of the model performance.

4.3. **Ablation Experiments.** This work uses ablation experiments to progressively remove important components from the model, therefore assessing the relevance of every component to the performance of multi-label classification. We initially construct a whole model integrating GNN with DMML and track the benchmark results. Different model characteristics and network layers were then methodically eliminated in order to track model performance at every level. Figure 5 displays the experimental outcomes.

With an accuracy of 85% and a mAP value of 0.76, the baseline model shows in the experimental data to be generally performing well in the multi-label mental toughness prediction test. The accuracy plummeted to 75% and the mAP to 0.65 when the graph neural network was deleted, therefore demonstrating the significance of the GNN in collecting structural elements of the data. Eliminating the deep multimodal network lowered the model accuracy to 77% and mAP to 0.70, thereby underlining the need of DMML in handling various input data.

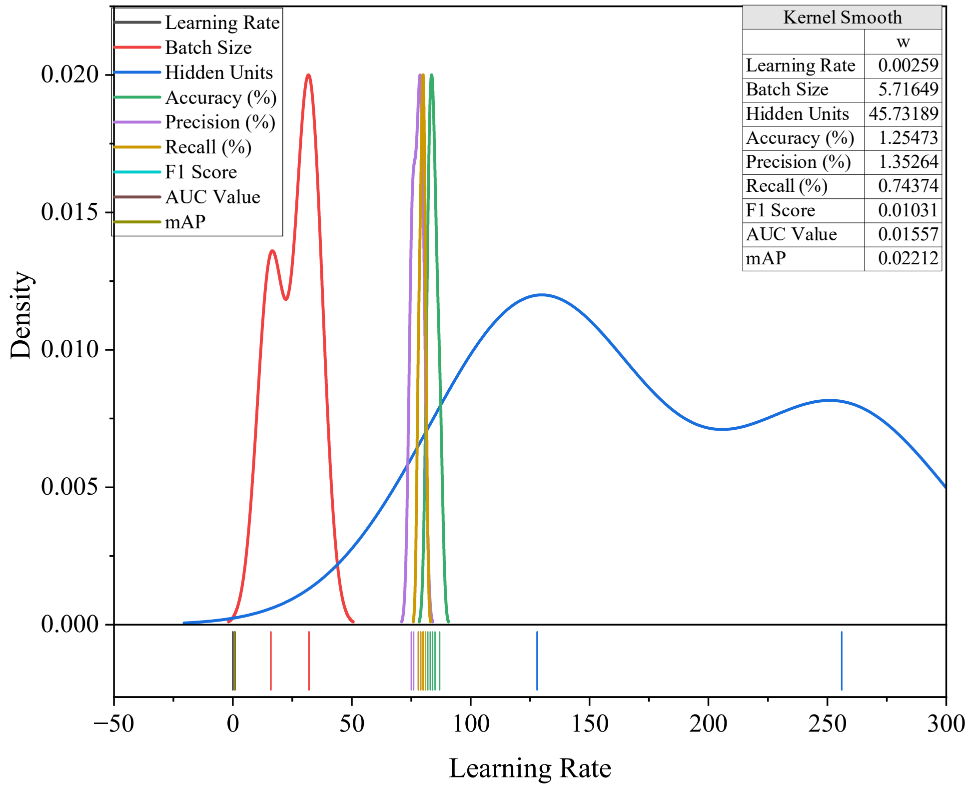

Figure 4. Experimental results of hyperparameter optimisation

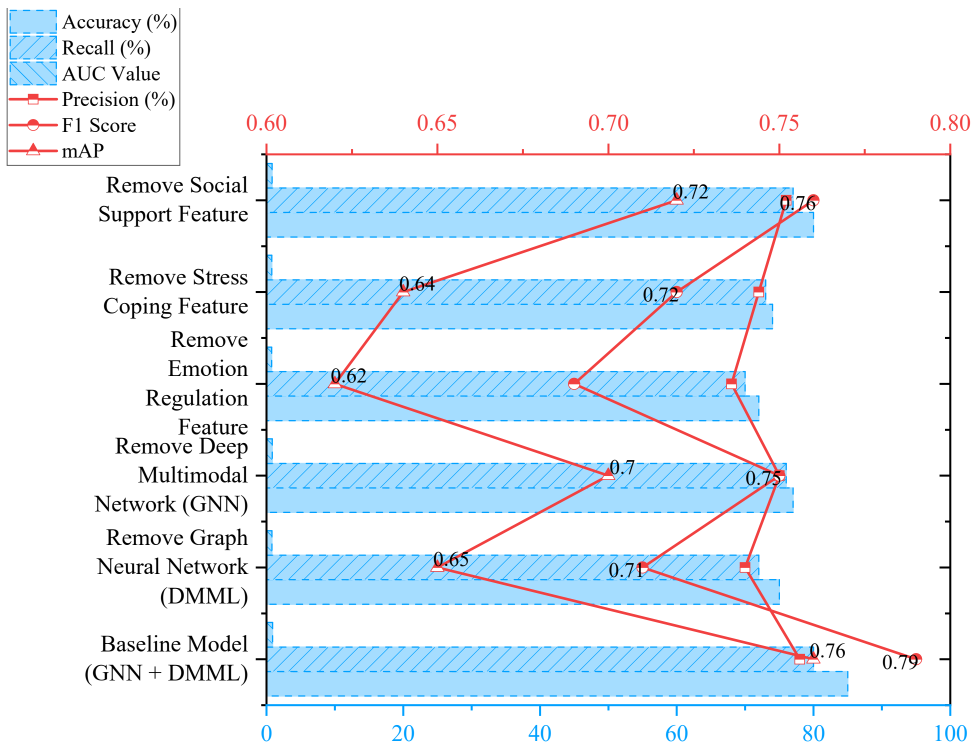

Figure 5. Results of ablation experiment

Eliminating elements connected to emotional regulation in the study of accuracy and recall reduced the accuracy from 78% to 68% and the recall from 80% to 70%. This implies that the accuracy of mental toughness prediction depends on the ability of emotion control; hence, its mAP value dropped to 0.62, so demonstrating the detrimental effect of eliminating this ability on model performance. Eliminating the stress coping mechanism produced an F1 score of 0.72 and a mAP of 0.64, therefore demonstrating the significance of this function for model performance.

Eliminating the social support element caused model accuracy to drop to 80%; yet, the mAP stayed at 0.72, implying that the feature helped to somewhat preserve stability and explanatory power of model performance.

All in all, the ablation studies shed light on the function of every model component and feature in the multi-label classification task. This offers a foundation for next studies and vital new perspectives on maximizing mental toughness prediction algorithms.

5. **Conclusion.** In this work, the GDM-Resilience model is suggested to combine GNN and DMML in order to attain multidimensional prediction of college students' mental toughness. More accurate and relevant than conventional approaches, the experimental results reveal that the GDM-Resilience model performs exceptionally in integrating multimodal data and catching multidimensional characteristics of mental toughness. The model uses multi-label classification to evaluate individual performance on several levels of mental toughness, therefore offering a useful technical instrument for mental health support and customized educational intervention.

There are still certain constraints even if this study has made great development in the prediction of mental toughness of college students. First, especially in situations including physiological signals, questionnaire data, and behavioural data, multimodal data collecting is expensive and technically difficult; it is also prone to data inconsistencies, missing or noise, which could so reduce the predictive power of the model. Mental toughness, as an integrated construct of emotions and behaviors, has a fluctuating and unstable state and is challenging to fairly depict an individual's long-term psychological development trajectory by depending just on one-time data collecting, a constraint that may also affect the generalizability of the model.

Furthermore, the GDM-Resilience model integrates GNN and DMML, so its computational complexity is substantial and training and prediction call for significant computer resources. Should the model be implemented in settings with limited resources—such as mobile or embedded systems—it could be challenging to satisfy the needs of real-time mental health assessment, therefore restricting the useful application scenarios of the model. Improper handling of the data fusion could result in information loss or noise interference, therefore influencing the stability and accuracy of the model.

Future studies can be enhanced and broadened in the following ways to solve the aforesaid constraints:

(1) Enriching data collection methods. Future research can use other types of data sources, like behavioral data, voice data, text logs, etc., so enhancing the capturing of mental toughness traits. Furthermore, individual time-series data can be established by means of long-term longitudinal data collecting, so enabling the capture of the law of mental toughness over time and improve the dynamic responsiveness of the prediction model.

(2) Optimise model structure and lightweight deployment. To ensure that the model can also operate effectively on mobile devices and to lighten the GDM-Resilience model to fit application situations with limited resources, we can try to incorporate model compression and distillation approaches in the future. Simultaneously, an

adaptive model optimisation technique is implemented to dynamically modify computational resources depending on various data volumes and application scenarios thereby improving the model's practicability and popularity.

(3) Personalised mental toughness assessment. Individual differences abound in mental toughness; hence, in the future, tailored elements can be included into the model building process along with students' basic knowledge, background information, etc., so differentiating the prediction of various students' mental toughness status and so provide more focused support for individualized educational interventions.

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