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Evaluation Model of the Mental Health Education Effectiveness Based on Deep Neural Networks

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This research develops a deep neural network model called DNN-MHE to evaluate mental health education effects. A questionnaire survey collected data on 916 students' mental health knowledge, attitudes, and behaviors. DNN-MHE uses five fully connected layers to predict mental health metrics. Experiments demonstrate that DNN-MHE achieves 99.46% accuracy, outperforming RNN, CNN, and shallow MLP models. Ablation studies validate the impact of training iterations, number of neurons, and number of data samples on performance. Overall, DNN-MHE enables accurate and efficient analysis of mental health education with practical implications for improving university programs.

ACM CCS (2012) Classification: Computing methodologies → Machine learning → Machine learning algorithms

Keywords: deep neural network, mental health education, neuron numbers

1. Introduction

1.1. Research Background and Value

Mental health education is crucial for promoting the holistic growth and development of young students. It embodies the essential mission of higher education institutions to foster virtue and cultivate talent, as well as to enhance the quality of talent cultivation. Currently, with the development of the socio-economic landscape and influenced by numerous factors, the mental health issues of young students have increasingly become a focal concern for society at large, especially for universities. During the academic education period, students' ideological values, emotions, and behavioral abilities are not yet fully mature. Benjamin *et al.* highlight the maintenance of emotional wellbeing in law students and aim to present the results of a cross-sequential research [1]. Simultaneously, with the changes in the period and societal development, university mental health education faces new challenges and issues, which to a certain extent have diminished the practical effectiveness of mental health education in higher institutions. Among these, evaluating the effectiveness of mental health education is pivotal for further understanding the current state of students' mental health, improving their mental well-being, and strengthening the tangible outcomes of university mental health education. If we can utilize deep neural networks to evaluate the effectiveness of mental health education, it will greatly enhance the quality of talent cultivation in society.

Deep neural networks (DNN) [2–6] refer to a multi-layered neural network. It takes the output features of one layer as the input for the next layer for feature learning. By mapping features layer by layer, the features of the current spatial samples are mapped to another feature space, thereby learning a better feature representation for the given input. Compared to the first-generation neural networks (such as perceptrons), the advantage of DNN lies in its ability to address more complex data classification problems, such as those that are non-linearly separable. Neural networks have made significant breakthroughs in recent years, demonstrating powerful capabilities in many domains and are gradually being applied to the field of educational effect evaluation [7–10]. Mental health education, as an essential component of higher education, also requires indispensable quality assessments. However, traditional methods of evaluating the effectiveness of mental health education often exhibit strong subjectivity and lack unified evaluation standards. For example, the amount of data increases over time, and human resources in schools are limited, so traditional methods are inefficient in dealing with a large amount of student mental health data, and cannot dynamically predict and analyze the data as it increases, which leads to a failure to deal with the problems brought about by changes in the state of students' mental health in a timely manner. Therefore, utilizing deep neural networks for evaluating the effectiveness of mental health education can enhance the accuracy and efficiency of the assessments, providing educators with a better basis for decision-making, and consequently promoting the improvement of quality and effectiveness in university mental health education [11].

1.2. Literature Review on Related Research

Nowadays, mental health education plays a pivotal role in the daily learning and life of young students. How to efficiently evaluate the effects of mental health education for these students has garnered much attention from academic circles both domestically and abroad. For instance, Ma *et al.* [12] introduced a painting style classification model based on an improved convolutional neural network (CNN) [3] with the aim to enhance the accuracy of mental health therapy through art. This model effectively tackles the poor adaptability issue inherent in traditional classification methods, but still grapples with the computational challenges arising from handling large data volumes. With the expansion of university scales and increase in student's demands, mental health education struggles to cater to the individual needs of students promptly and effectively. To address this, Huang *et al.* [13], taking the identification of college students' mental disorders as an example, proposed a model based on convolutional neural networks. The goal was to offer consultation and support for college students' psychological counseling, but the model faced challenges in accurately predicting non-image data. Subsequently, to solve the low effectiveness when dealing with commonly used non-image datasets, Yao *et al.* [14], based on the backpropagation (BP) neural network [15], proposed a model regarding the relationship between college students' mental state and the pandemic. This model employed the multi-layer perceptron [16] commonly used for non-image datasets and optimized it using the BP algorithm. It eventually outlined various factors affecting the mental health of university students. However, the model only used a two-layer perceptron, leading to subpar prediction results. Overall, the existing deep learning methods are inadequate in dealing with mental health education problems. For example, CNNs are generally good for Euclidean data, such as images, RNNs are commonly used as neural networks to deal with sequential data, whereas shallow MLPs may bring low prediction accuracy. For this reason, there is an urgent need for a method that can efficiently deal with mental health data.

In summary, in the realm of mental health education, to better handle non-image data and enhance the predictive accuracy of existing models, this paper proposes a mental health education assessment model based on deep neural networks, called DNN-MHE. The DNN-MHE model increases the network depth with respect to the existing methods, leading to improved prediction results. Techniques like feature selection [17–19] and *k*-fold cross-validation [20–21] have been integrated into this model to counteract the overfitting issues that come with increased network depth. To sum it up, the main contributions of this paper are:

1. A scientific questionnaire survey targeting young students' mental health education issues was conducted for this study. Using the data obtained from the survey, a dataset for mental health education was created. It encompasses multiple aspects of mental health education issues, providing reference data for related research.

2. A mental health education model was introduced based on deep neural networks (DNN-MHE) that aims to improve the prediction efficiency of mental health education data. This model merges techniques from feature selection and k-fold cross-validation, effectively mitigating the overfitting issue within the network.
3. The study carries out extensive experimental evaluation of the model using the designed dataset. The experimental results demonstrate that DNN-MHE can significantly enhance the prediction accuracy of mental health education data. Additionally, through various ablation studies, the effectiveness of DNN-MHE is further verified.

2. Research Method and Process

2.1. Research Approach

This paper sets out from the perspective of the growth and development patterns of young students, the teaching laws of ideological and political education, and the moral development principle of "knowledge-emotion-action". We assess various groups of young students in terms of their awareness, recognition, and practice of mental health. Utilizing deep neural networks, we then evaluate the current effectiveness of mental health education, summarizing experiences and envisioning the future [14]. The research and evaluation mainly revolve around the following three dimensions:

1. Dimension one: Rational cognition of mental health [22]. This involves gauging the awareness of basic mental health knowledge, recognizing different categories of psychological abnormalities, and understanding the methods to improve individual mental health. The primary aim is to conduct a preliminary survey of different groups of young students regarding their understanding of mental health, intending to gain a comprehensive grasp of the current status of mental health education in higher institutions.
2. Dimension two: Ideological recognition of mental health [23]. This pertains to the survey of the recognition and effectiveness of mental health awareness. By examining different groups of young students, we aim to assess the evaluations of the current status and effectiveness of mental health education in various universities. This includes surveys on the recognition of special groups concerning mental health, awareness of psychological issues, and the current situation of mental health consciousness.
3. Dimension three: Behavioral practice of mental health [24]. This refers to the survey of the state and results of mental health practical capabilities. Through a comprehensive examination, we investigate the ability of different groups of young students in learning actions related to mental health education, adaptability to environments, interpersonal communication skills, and current status and results of career selection capabilities.

2.2. Research Methods

In this section, a combination of various research methods is used for establishing the basic concepts and theoretical framework, data collection, statistical analysis, model construction, and comparative studies with existing findings in related fields. The specific research methods are, as follows:

1. Literature review method [25]. Based on the research topic requirements and the main content of this empirical study, literature and documents are collected, sorted, and analyzed from databases like CNKI, the Marxism Library, government department related documents, as well as foreign databases such as Web of Science and Engineering Village Compendex. This helps lay a solid theoretical foundation for the empirical research in this paper.
2. Questionnaire survey method [26]. Following a preliminary literature analysis and drawing from existing research findings, this study designed a survey titled "Survey on the Effectiveness of Mental Health Education for Young Students." The primary method of data collection involved the use of a self-developed Likert scale to gather

extensive data. Subsequent steps include quantitative data analysis, constructing an effectiveness evaluation model, and analyzing data results. The goal is to offer suggestions and references for improving the strategies related to the mental health education of young students.

3. Computer Model Analysis Method [27]. Deep neural networks mainly comprise fully connected (FC) network structures, CNNs, and RNNs. Given that CNNs excel at processing Euclidean data like images, and RNNs are often used to handle sequential data, this study has chosen the FC neural network, which is better suited for predicting and assessing mental health data. We incorporate feature selection and k-fold cross-validation into the adopted network. On the one hand, the application of deep neural networks to the analysis of mental health education data incorporates a feature selection method, which selects features for the created data set in two ways, divided into basic information and cognitive information, which allows us to predict the mental health status of the students for different types of information, thus solving the shortcomings of the other methods that select all the information for prediction. On the other hand, the application of deep neural networks to the analysis of mental health education data incorporates the *k*-fold cross-validation method, which cross-validates the dataset to effectively assess the quality of the model, and thus can effectively avoid overfitting and underfitting.

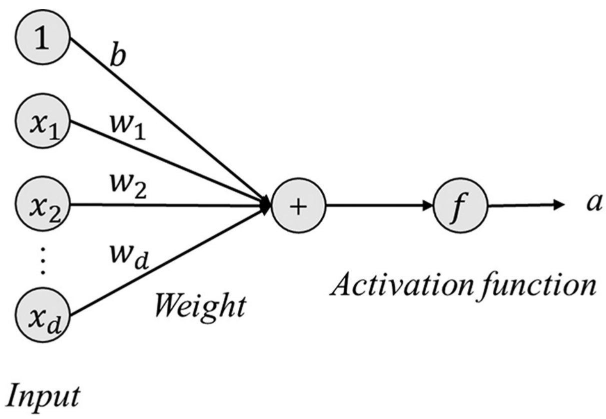

Figure 1. Typical neuron structure.

2.3. DNN-MHE

2.3.1. Basic Unit of DNN-MHE

The fully connected neural network (abbreviated as FCNN) is the fundamental structure of artificial neural networks, also known as the multilayer perceptron (MLP). In an FCNN, each neuron is connected to all the neurons in both the preceding and the succeeding layers, forming a densely connected structure. A typical neuron structure is shown in Figure 1. The calculation formula for the output of the neuron is shown in equation (1):

$$a = f\left(\sum_{i=0}^{d} x_i w_i + b\right) \tag{1}$$

In the formula, x_i represents the input signal from the upper layer, w_i represents the connection weight of each transmission signal, b represents the bias, $f(*)$ represents the activation function, and a represents the activity value of the neuron after the input signal passes through the activation function. Commonly used activation functions include the rectified linear unit [28], abbreviated as ReLU. It is a frequently used activation function in deep neural networks. The specific mathematical form is shown in equation (2).

$$ReLU(x) = f\begin{cases} x & x \geq 0 \\ 0 & x < 0 \end{cases} = \max(0, x) \tag{2}$$

2.3.2. Detailed Structure of DNN-MHE

The mental health education evaluation model designed in this paper is a structure of five layers, as shown in Figure 2. It is composed of an input layer, four hidden layers, and an output layer. Based on the dataset designed in this paper, a five-layer network structure is chosen to address the issue of low prediction accuracy in shallow network structures. On the one hand, the reason for choosing fully connected neural networks is because CNN is good at Euclidean data, such as images, and RNN is commonly used in neural networks that deal with sequen-

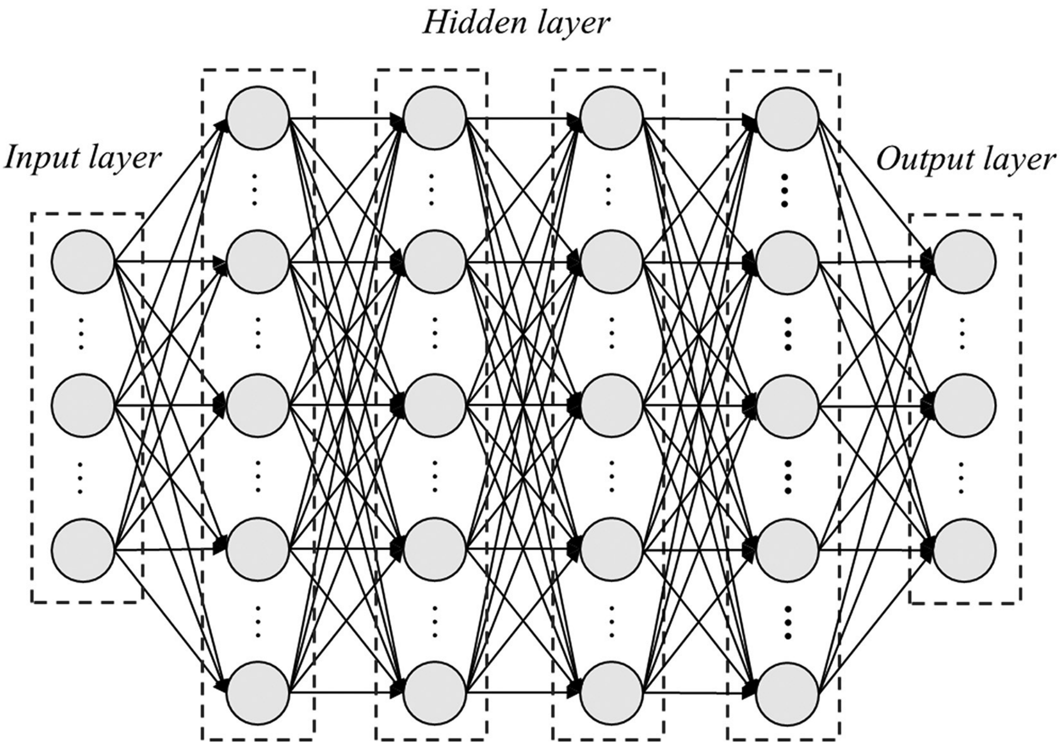

Figure 2. Structure Diagram of a Neural Network.

tial data, this paper chooses fully connected neural networks that are better at predicting and evaluating mental health data. On the other hand, the reason for choosing 5 fully connected layers is because the existing fully connected neural networks are shallow, such as 2–3 layers, which makes the prediction accuracy of the existing fully connected neural networks low, and too deep network architecture will bring the problem of overfitting and large amount of computation. Each layer of DNN-MHE has multiple neurons. When signals pass through the input layer to the hidden layers, the hidden layers transmit the processed data to the output layer, which then produces the result.

2.3.3. Implementation Process of DNN-MHE

Firstly, 80% of the data is chosen as training data and 20% as test data. The training data is put into DNN-MHE, and after processing by each neuron in the layers, the output result of each neuron in the hidden layers can be obtained through equation (1). To better measure the effectiveness of the model, the mean square error needs to be calculated using equation (3).

$$MSE(y, y') = \frac{1}{N}\sum_{i=1}^{N}(y_i - y'_i)^2 \tag{3}$$

Here, y is the actual value, and y_i' is the predicted value. By using the gradient descent algorithm, the connection weights and thresholds for each layer are adjusted, as shown in equations (4) and (5), until the desired accuracy or training time target is reached.

$$w := w - \alpha \frac{\partial J(w,b)}{\partial w} \tag{4}$$

$$b := b - \alpha \frac{\partial J(w,b)}{\partial b} \tag{5}$$

Here, := represents parameter updating, α stands for the learning rate which controls the step size, and $J(w, b)$ represents the cost function, which is another way of expressing the equation (3).

3. Overview of the Questionnaire Survey

In this study, a random sampling method was used to conduct a questionnaire survey among young students from various schools at different levels. A total of 931 valid questionnaires were collected. After data cleaning, 916 data entries were finalized [29]. The main content of the self-made questionnaire is, as follows:

1. Basic demographic information (basic information), as shown in Table 1. This primarily includes information on the respondent's gender, age, grade level, field of study, place of origin, whether they hold a student leadership position, whether they are an only child, and the educational level of their parents, among other details.
2. Survey content related to the effectiveness of mental health education (cognitive information), as shown in Table 2. Firstly, there's a section surveying the rational cognition of mental health, such as "changes in mental health." Following that, there's a section on the recognition status of mental health ideas, such as "existing psychological problems." Lastly, there's a section surveying the practice of mental health ideas and behaviors, like "interpersonal communication skills."

More details can be found, as follows:

1. Questionnaire design: This paper mainly investigates and evaluates the effect of mental health education in colleges and universities from the three dimensions of rational cognition of mental health, ideological recognition of mental health and behavioral practice of mental health.
2. Sampling techniques: This paper cleans up the data and eliminates abnormal data, and finally forms 916 valid questionnaire survey data and converts them into .csv files for follow-up processing.
3. Survey administration procedures: the score of each questionnaire item can be regarded as a data dimension, the questionnaire item summation score is regarded as a data dimension, then the input data of the neural network is a 26-dimensional data, and the output result is a one-dimensional data.

Table 1. Detailed data statistics on the survey questionnaire's basic information.

Project	**Gender**		**Average age**		**Grade category**		**Major**	
Classification	Male	Female	Male	Female	Undergraduate	Graduate	Humanities	Others
Number of samples	396	520	21.1		650	266	342	574
Project	**Student leaders**		**Only child**		**Source of students**		**Parental education**	
Classification	Yes	No	Yes	No	Country	Town	Undergraduate or below	Undergraduate and above
Number of samples	304	612	327	589	485	431	648	268

Table 2. Detailed data statistics on the respondents' cognition, recognition, and practice of mental health education.

Type	**Situation statistics**					
	Positive	**Percentage**	**Neutral**	**Percentage**	**Pessimistic**	**Percentage**
1	15	1.64%	37	4.04%	864	94.32%
2	47	5.13%	119	12.99%	750	81.88%
3	26	2.84%	137	14.96%	753	82.21%
4	9	0.98%	45	4.91%	862	94.10%
5	17	1.86%	79	8.62%	820	89.52%
6	33	3.60%	135	14.74%	748	81.66%
7	92	10.04%	193	21.07%	631	68.89%
8	123	13.43%	209	22.82%	584	63.76%
9	48	5.24%	154	16.81%	714	77.95%
10	44	4.80%	161	17.58%	711	77.62%
11	50	5.46%	170	18.56%	696	75.98%
12	36	3.93%	154	16.81%	726	79.26%
13	38	4.15%	168	18.34%	710	77.51%
14	59	6.44%	151	16.48%	706	77.07%
15	30	3.28%	133	14.52%	753	82.21%
16	54	5.90%	179	19.54%	683	74.56%
17	57	6.22%	195	21.29%	664	72.49%
18	57	6.22%	209	22.82%	650	70.96%

4. Experiments and Results

4.1. Implementation Details

In DNN-MHE, the backpropagation algorithm and the stochastic gradient descent method are used to update the network weights. The ReLU function is chosen as the activation function, with an initial learning rate set at 0.001. The total number of iterations is 300. 80% of the data is used for training the network, and the remaining 20% is for testing and validation. The model is trained using the data and undergoes 5-fold cross-validation, with the mean value taken as the final experimental result. It should be noted that during the validation process of DNN-MHE, this study employs four commonly used metrics for validation as described in formulas (6) to (9), which are precision, recall, F1 score, and accuracy [30–33].

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

$$F1score = \frac{2 \cdot P \cdot R}{P + R} \tag{8}$$

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{9}$$

Among them, *TP* represents the number of samples that are actually positive and are predicted as positive. *FP* represents the number of samples that are actually negative but are predicted as positive. *FN* represents the number of samples that are actually positive but are predicted as negative. *P* stands for Precision, *R* stands for Recall. *TN* represents the number of samples that are actually negative and are predicted as negative.

4.2. Experimental Results

This paper selects some classic neural network architectures for comparison to verify the effectiveness of DNN-MHE. As shown in Table 3, the accuracy score of DNN-MHE is 99.46%, the accuracy score of RNN is 95.99%, and the accuracy score of CNN is 95.64%. DNN-MHE is about 4 percentage points higher than both RNN and CNN. The accuracy score of MLP is 96.20%. Although the accuracy of MLP is higher than that of RNN and CNN, the current MLP used for mental health education is a shallow network architecture, which leads to its accuracy still needing improvement. In contrast, the accuracy score of DNN-MHE is 99.46%, which is about 3 percentage points higher than MLP. Similarly, the F1 score, precision, and recall of DNN-MHE have improved by 3 to 5 percentage points compared to RNN, CNN, and MLP. Especially, the precision of DNN-MHE is about 7 percentage points higher than MLP, and its recall is about 8 percentage points higher than RNN and about 11 percentage points higher than MLP. It is worth noting that when training DNN-MHE, the loss function can converge. As can be seen from Figure 3, when the number of iterations reaches 150, the training loss has basically converged.

Table 3. Comparative analysis of DNN-MHE with other methods on the collected dataset.

Method\Metric	Accuracy	F1 score	Precision	Recall
RNN	95.99%	96.38%	93.35%	89.44%
CNN	95.64%	96.68%	96.67%	94.69%
MLP	96.20%	89.48%	92.62%	86.89%
DNN-MHE	99.46%	98.57%	99.70%	97.50%

Table 4. Validation results of DNN-MHE on basic and cognitive information.

Type	Accuracy	F1 score	Precision	Recall
Basic information	89.13%	47.13%	44.57%	50.00%
Cognitive information	97.83%	94.39%	94.39%	94.39%
Basic + cognitive information	99.46%	98.57%	99.70%	97.50%

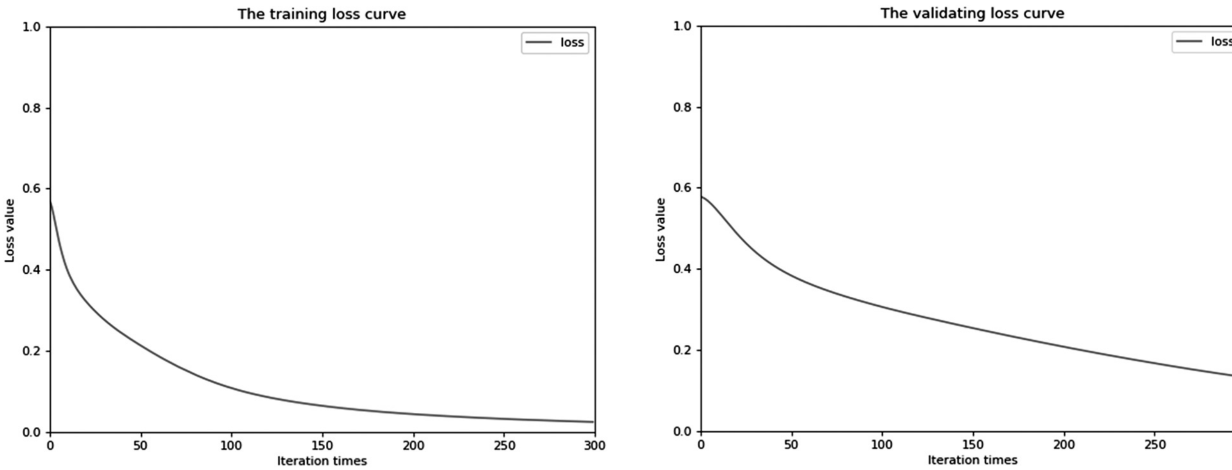

Figure 3. Variation curve of loss on the training set (left) and test set (right) with the number of iterations.

Moreover, when only using basic information for validation, the accuracy percentage obtained is 89.13%, and the F1 score, precision, and recall are 47.13%, 44.57%, and 50.00%, respectively. When only using cognitive information for validation, the accuracy percentage obtained is 97.83%, and the F1 score, precision, and recall are 94.39%, 94.39%, and 94.39%, respectively. When using all the information features for validation, the accuracy percentage obtained is 99.46%, and the F1 score, precision, and recall are 98.57%, 99.70%, and 97.50%, respectively. This indicates that if only basic information is available, the various prediction indicators are not very good. On the contrary, when the data is complete, the prediction effects of various indicators are quite good.

To validate the change in trend of DNN-MHE scores on the training set and test set with the number of iterations, the number of iterations is set to different values to verify the score of DNN-MHE under different situations. As seen from Figure 4, the model score on the training set continuously increases with the number of iterations. Upon validation, it was found that when the number of iterations is around 150, as the number of iterations increases, the model score of DNN-MHE on the test set remains stable.

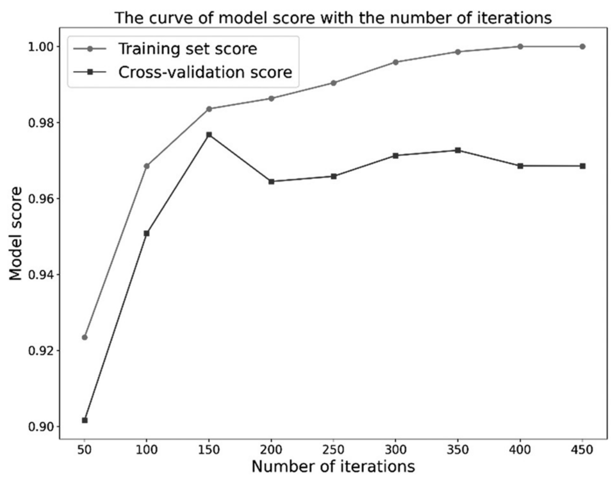

Figure 4. Trend of the DNN-MHE model scores on the training set and test set as the number of iterations changes.

To validate the trend of DNN-MHE scores on the training set and test set with changes in the number of neurons per layer, the number of neurons in each layer is set to different values to verify the scoring of DNN-MHE. As seen from Figure 5, the model score on the training set continuously increases with the increase in the number of iterations. The model score of DNN-MHE on the test set fluctuates significantly. This suggests that an increase in the number of neurons in each layer does not necessarily lead to an increase in model score, and a decline is also possible.

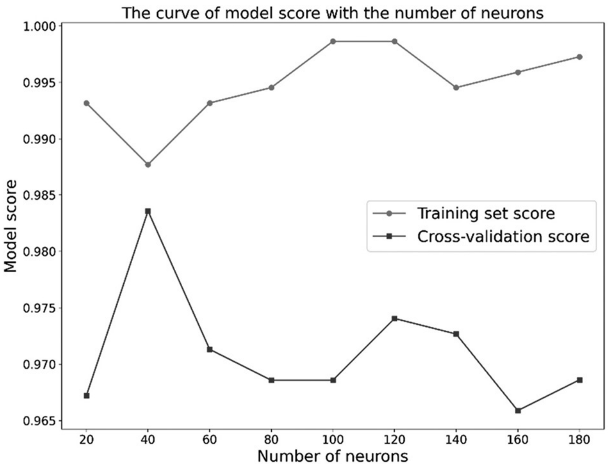

Figure 5. Trend of the DNN-MHE model scores on the training set and test set with changes in the number of neurons per layer.

4.3. Ablation Experiment

As is widely known, the performance of neural networks is influenced by the amount of data. To validate the performance of DNN-MHE on datasets of different sizes, the training dataset is proportionally divided into 10 parts for verification. As can be observed from Table 5, as the number of sampling points increases, both the mean of train scores (train_scores_mean) and the mean of validation scores (validation_scores_mean) continuously rise, while the standard deviation of train scores (train_scores_std) and the standard deviation of validation scores (validation_scores_std) roughly decrease. This indicates that the performance of the model is directly proportional to the number of sampling points. To understand the change in model performance with the variation of sampling points more visually, the trends of scores of DNN-MHE on training and test sets with the change in sample size are plotted. As shown in Figure 6, with the increase in sampling points, both train_scores_mean and validation_scores_mean keep rising. Once the number of sampling points reaches a certain threshold, the performance of the model approaches a plateau.

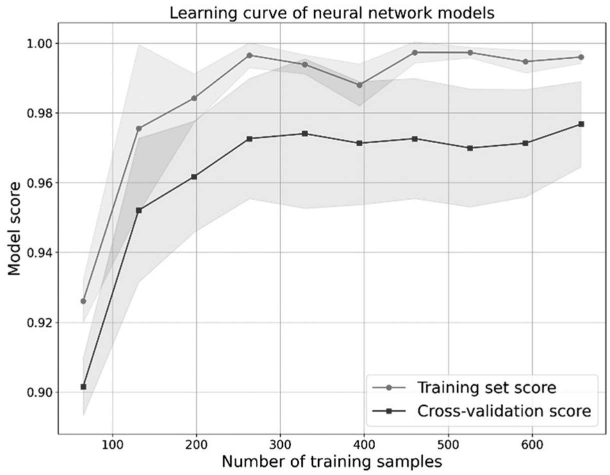

Figure 6. Trend of the DNN-MHE model scores on the training set and test set with changes in the number of sampled samples.

Moreover, the performance of neural networks is also influenced by the number of layers in the network, the number of neurons in each layer, and the number of iterations. Several experiments were conducted to validate the effect of these three factors on DNN-MHE. The results, as shown in Table 6 and Table 7, indicate that DNN-MHE is influenced by all three factors, and the impact does not follow a single trend. Specifically, on one hand, as shown in Table 6, when the number of neurons per layer remains constant, and as the number of layers in the network architecture increases, the accuracy scores of DNN-MHE on both the training and test datasets generally present a trend of first increasing and then decreasing. For instance, when the number of neurons is 40, with the increase in layers, the accuracy scores on the training and test sets rise from 98.50% and 96.99% to 99.32% and 97.81%, and then drop to 97.95% and 92.77%. When the number of layers remains constant, with the increase in the number of neurons per layer, the accuracy scores on both datasets gradually increase. For example, when the number of layers is 9, the accuracy scores of DNN-MHE on the training and test sets change from 89.89%

Table 5. Mean scores and standard deviations of DNN-MHE on training and test sets with variations in the number of sampling points.

Metric\ Sample Point	**65**	**131**	**197**	**263**	**329**	**394**	**460**	**526**	**592**	**658**
train_scores_mean	92.62%	97.56%	98.43%	99.66%	99.39%	98.81%	99.74%	99.73%	99.48%	99.60%
train_scores_std	6.15E-03	2.41E-02	6.98E-03	3.59E-03	2.72E-03	6.01E-03	3.04E-03	1.52E-03	3.24E-03	1.82E-03
validation_scores_mean	90.16%	95.21%	96.18%	97.27%	97.41%	97.14%	97.27%	97.00%	97.14%	97.68%
validation_scores_std	8.26E-03	2.06E-02	1.59E-02	1.72E-02	2.14E-02	1.77E-02	1.72E-02	1.69E-02	1.54E-02	1.22E-02

and 94.40% to 99.73% and 94.68%, and finally to 100.00% and 97.13%. On the other hand, as shown in Table 7, when the number of iterations for training and validation remains constant, with the increase in the number of layers, the accuracy scores of DNN-MHE on the training and test datasets might either decrease (*e.g.*, when iterations=50) or increase (*e.g.*, when iterations=250). This suggests that with relatively simple data, deeper network architectures might lead to overfitting. This could result in a decline in performance. Therefore, in the selection of the number of layers for DNN-MHE, choosing a network architecture with four hidden layers proved most effective. When the number of layers remains constant, as observed in Table 7, the performance of DNN-MHE typically improves with the increase in iterations. For example, when the number of layers is 7, the accuracy scores on the training and test sets change from 98.63% and 93.17% to 99.86% and 96.72%, and finally to 100.00% and 97.27%.

Table 6. Scores of DNN-MHE on the training and test sets with varying network depths and number of neurons per layer.

Layers\ Neurons	20	40	60	80	100	120	140	160	180
2	98.09%	98.50%	98.63%	98.77%	99.32%	98.63%	98.63%	98.91%	99.59%
	97.13%	96.99%	95.77%	96.86%	96.86%	96.58%	97.13%	96.18%	96.72%
3	98.22%	99.59%	99.45%	98.91%	98.91%	99.32%	99.45%	99.59%	99.18%
	95.90%	97.00%	96.72%	96.86%	96.59%	96.72%	97.40%	97.13%	97.27%
4	99.18%	98.77%	99.04%	99.32%	99.86%	99.86%	99.86%	99.86%	100.00%
	94.26%	96.58%	96.59%	97.13%	96.99%	97.54%	96.86%	96.86%	97.13%
5	97.54%	99.32%	99.86%	99.73%	99.86%	99.86%	100.00%	99.73%	99.86%
	95.35%	97.81%	96.45%	97.54%	96.86%	97.40%	97.40%	97.13%	97.81%
6	95.77%	99.59%	99.73%	99.86%	100.00%	100.00%	100.00%	100.00%	100.00%
	97.00%	97.68%	96.99%	95.77%	97.41%	97.13%	97.13%	97.13%	97.27%
7	98.63%	99.32%	99.86%	99.73%	99.86%	100.00%	100.00%	100.00%	100.00%
	93.17%	97.41%	96.72%	97.13%	96.72%	96.99%	97.00%	96.72%	97.27%
8	99.45%	99.45%	99.86%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
	91.94%	96.45%	96.58%	97.82%	96.31%	97.54%	97.68%	97.40%	97.54%
9	89.89%	96.72%	99.73%	99.86%	100.00%	100.00%	100.00%	100.00%	100.00%
	94.40%	94.67%	94.68%	97.68%	96.86%	97.00%	97.81%	97.54%	97.13%
10	98.09%	97.95%	89.89%	100.00%	100.00%	100.00%	100.00%	99.86%	100.00%
	91.40%	92.77%	96.58%	97.81%	95.63%	97.95%	96.86%	97.40%	96.72%

Table 7. Scores of DNN-MHE on the training and test sets with varying network depths and number of iterations.

Layers\ Iterations	**50**	**100**	**150**	**200**	**250**	**300**	**350**	**400**	**450**
2	94.54%	97.40%	98.22%	98.36%	98.91%	99.18%	99.45%	99.32%	99.32%
	91.67%	95.77%	96.45%	96.99%	96.45%	97.13%	96.72%	96.99%	96.72%
3	95.77%	94.40%	97.95%	98.22%	98.50%	99.32%	99.32%	99.59%	99.86%
	90.30%	95.90%	96.99%	97.13%	97.00%	96.72%	96.72%	97.00%	96.72%
4	90.98%	97.27%	98.22%	98.09%	99.45%	99.86%	100.00%	100.00%	99.73%
	89.89%	95.08%	96.99%	96.45%	96.58%	96.59%	96.72%	97.54%	97.54%
5	89.89%	96.45%	98.36%	99.73%	100.00%	99.45%	99.86%	100.00%	100.00%
	89.89%	91.94%	96.18%	96.86%	97.27%	96.45%	97.00%	96.99%	97.40%
6	90.57%	91.39%	98.77%	99.32%	99.86%	100.00%	100.00%	100.00%	100.00%
	89.89%	90.71%	93.71%	95.90%	97.54%	97.13%	97.00%	97.81%	96.99%
7	89.89%	97.13%	99.18%	98.36%	99.86%	99.86%	99.86%	100.00%	100.00%
	89.89%	91.66%	96.31%	96.04%	97.13%	97.41%	96.99%	97.68%	96.72%
8	89.89%	90.57%	92.35%	99.04%	99.86%	100.00%	100.00%	100.00%	100.00%
	89.89%	89.89%	92.48%	95.50%	97.54%	97.27%	97.54%	97.27%	97.00%
9	89.89%	97.13%	98.36%	98.77%	100.00%	100.00%	99.86%	100.00%	100.00%
	89.89%	89.89%	90.03%	93.17%	97.54%	97.81%	97.40%	96.99%	97.68%
10	89.89%	89.89%	97.54%	99.45%	99.59%	100.00%	99.86%	100.00%	99.86%
	89.89%	89.89%	90.30%	91.12%	97.27%	97.13%	97.27%	96.73%	97.54%

5. Conclusion and Policy Recommendations

In conclusion, the proposed DNN-MHE model provides an innovative approach for evaluating mental health education outcomes. Key results show that DNN-MHE attains over 99% accuracy in predicting metrics like knowledge, attitudes, and behaviors from the survey data. Comparisons demonstrate clear improvements over the existing neural network models. Ablation experiments further verify the model's robustness to variations in training parameters and data samples. This research has meaningful real-world applications by enabling universities to accurately and efficiently assess their mental health programs. Future work can explore model optimizations and extensions to other education domains. Overall, DNN-MHE is a valuable contribution towards data-driven tools for enhancing mental health education and student wellbeing.

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