Journal of Network Intelligence ©2025 ISSN 2414-8105
Taiwan Ubiquitous Information Volume **10**, Number **3**, August **2025**

Intelligent Diagnosis of Depression Based on Generative Adversarial Network and Convolutional Neural Network

Pin-Jie Liu*

School of Computer Engineering
Guangzhou Huali College
Guangzhou 511325, P. R. China
liupinjie0922@163.com

Guang-Yu Zhai

School of Economics and Management
Lanzhou University of Technology
Lanzhou 730050, P. R. China
zhaigy12@lzu.edu.cn

Guang-Yao Zhang

Faculty of Engineering and Information Technology
INTI International University
71950 Jurai Newtown, Negeri Sembilan, Malaysia
sv8692@163.com

*Corresponding author: Pin-Jie Liu
Received August 8, 2024, revised January 9, 2025, accepted April 26, 2025.

Abstract. *Electroencephalography (EEG) is used as a quantitative measurement tool for depression because of its high temporal resolution, low cost, and ease of setup. Deep learning algorithms are currently used in a variety of ways on EEG, including the diagnosis and classification of depression. However, these methods suffer from poor EEG image quality and inadequate feature extraction. Thus, this article designs an intelligent diagnosis method for depression relied on Generative Adversarial Network (GAN) and Convolutional Neural Network (CNN). Firstly, to ensure the authenticity and integrity of the EEG image, the GAN encodes the real EEG, the generator takes the EEG encoding as input, and the discriminator discriminates between the real EEG and the generated EEG in order to motivate the generator to produce high quality EEG images. The optimized multi-channel CNN is then adopted to capture the deep characteristics of the EEG and expand the receptive field by successively using dilated convolution with different null rates. A hybrid attention mechanism is used to enhance the characteristics of EEG from channel and space, and finally the classification diagnosis results are output by Softmax classifier. Experimental outcome on the publicly available dataset MODMA imply that the classification accuracy of the designed method is 92.56%, which is an improvement of 14.15%, 10.27%, 3.62%, and 5.85% compared to the other four methods, respectively, proving the superiority of the suggested method for the classification and diagnosis of depression.*

Keywords: Depression diagnosis; Generative adversarial network; Convolutional neural network; Channel attention mechanism; Spatial attention mechanism

---

1. **Introduction.** Depression is one of the most common mental illnesses in current world, which both interrupts patients' lives and has a great effect on economic development and social stability [1]. Therefore, depression diagnosis and efficacy prediction have received increasing attention from all sectors of society. At present, depression is mainly diagnosed based on scale enquiry, doctor's questioning and clinical observation, which can be affected by the large differences in patients' clinical symptoms, doctor's professional level and patients' subjective factors, which brings challenges to accurate diagnosis [2]. In the treatment of depression, the choice of medication for patients depends on the clinical diagnosis of the doctor, and this kind of consultation brings inconvenience to the patients and may even cause them to resist. Therefore, it is essential to find an appropriate and effective way to diagnose depression.

1.1. **Related Work.** Electroencephalographic (EEG) signals contain a large amount of physiological information of the patient, which can effectively respond to the abnormal EEG information implied by the cerebral cortex, and meanwhile has the advantages of high secular declaration, low cost, and easy to set up [3], which has been gradually used to assist in the diagnosis of depressive disorders [4, 5]. Traditional research has adopted machine learning models to diagnose depression. Jayawardena et al. [6] extracted relevant features for depression diagnosis based on denoising the raw EEG data by independent component analysis and input these features into logistic regression and plain Bayes for depression diagnosis. Srinivasan et al. [7] used genetic algorithm and sequential feature selection of EEG features and finally used Support Vector Machine (SVM) for depression classification. Chikersal et al. [8] used a minimum redundancy-maximum related characteristic alternative method to choose the most relevant features from the features extracted from the EEG and used the K-nearest neighbours method to predict the outcome of patients treated with repetitive transcranial magnetic stimulation.

Compared with the traditional machine learning methods mentioned above, deep learning algorithms extract EEG features directly from preprocessed data, avoiding the workload of extracting EEG features manually in large quantities, and more and more researchers have applied Deep Learning (DL) to the diagnosis of depression [9, 10], especially the Convolutional Neural Network (CNN), which is with the ability of adaptive studying and does not require manual selection of feature sets, can effectively shorten the experimental process. Acharya et al. [11] used CNN for EEG classification, which can adaptively learn from the input EEG images and differentiate the EEGs of disappointed and common subjects. Lin et al. [12] adopted 1D-CNN combined with the attention mechanism for the diagnosis of depression, but the diagnostic efficiency was not high due to the unclear contours of the EEG images. De Melo et al. [13] diagnosed depression based on C3D model and extracted the spatio-temporal features of EEG and used mean pooling to fuse the extracted features to improve the diagnostic accuracy. Kour and Gupta [14] used CNN and LSTM for EEG detection which was used to diagnose clinical depression and achieved good diagnostic results. Uyulan et al. [15] applied GoogLeNet [16] and Inception-Net [17] to the MODMA dataset for depression identification, but the samples were of low quality and suffered from overfitting.

In the DL models mentioned above, the existence of the small sample problem restricts its own development, and the expansion of small sample data will significantly improve the classification accuracy. But the expanded samples also have problems such as poor quality, lack of diversity, overfitting, etc. GAN can address this issue well. Zhao et al. [18] suggested a GAN relied on functional network connectivity for distinguishing patients with depression. In this model, a generator is required to generate a false EEG matrix, and a discriminator is required to identify the true or false EEG matrix and give the category to which the EEG matrix belongs. Fu et al. [19] used a generative adversarial network to achieve learning from a large number of unlabelled EEG signals and to perform a depression diagnosis task, but the feature extraction of the original generator was poor, resulting in inefficient diagnosis.

1.2. **Contribution.** As can be seen from the above, a variety of solutions have been proposed for the research of depression diagnosis. However, most of the researches suffer from the problems of blurred details and insufficient feature extraction in raw EEG images. To cope with the above issues, this paper designs an intelligent diagnosis method for depression based on GAN and CNN. Firstly, to improve the quality of the EEG image, the generator of the GAN is regarded as a variational self-encoder, which obtains the hidden spatial information of the input EEG after encoding, and generates a new picture via the decoder. A discriminator is used to discriminate among the true picture and the generated picture, which prompts the generator to produce a more realistic image. On this basis, multi-channel CNN is adopted to capture the deep characteristics of EEG, and expansion convolution is added to focus on the global contextual information, expanding the sensory field without increasing the computation; hybrid attention is used to enhance the characteristic extraction ability of the network, extracting the characteristics of the EEG image hidden in the complex background and suppressing irrelevant features. Finally, the classification diagnosis results are output by Softmax classifier. The experimental outcome indicates that the designed method achieved a better classification effect in the diagnosis of depression in terms of three indicators: accuracy, sensitivity and specificity.

2. Theoretical Analysis.

2.1. **Convolutional Neural Network.** CNN can categorize the input data of a translation constant manner according to a hierarchical framework, with features such as weight sharing and local connectivity [20]. Compared with traditional neural networks, CNN not only decreases the amount of weights, which makes the network simple to improve, but also decreases the model's complexity and the threat of overfitting. CNN with multiple obscured levels has excellent representation learning capability, and the feature information it learns better reflects the necessary features of the information, that is beneficial to the categorization and visualization of the model. The general model of CNN is implied in Figure 1.

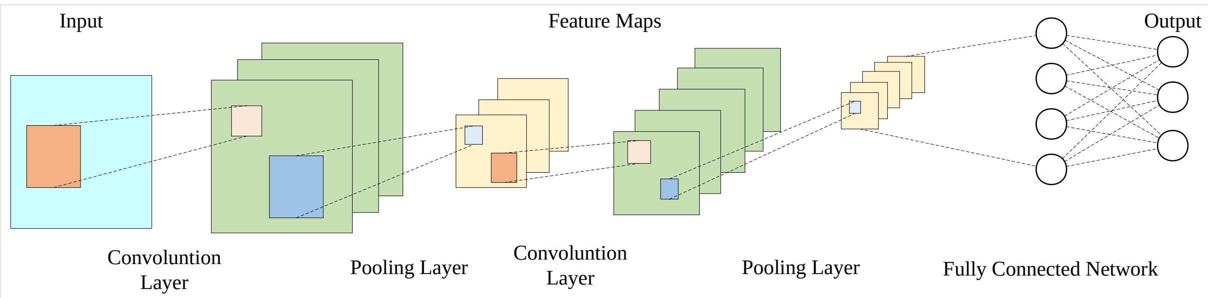


Figure 1. The framework of CNN models.

The convolutional level uses convolutional kernels to capture characteristics, and includes various convolutional kernels, every neuron is linked to a native region of the former level, which is denoted as the "assimilative field", and the magnitude of the region relies on the magnitude of the convolutional kernel. Convolution is defined as implied in

Equation (1), where $p \times q$ is the magnitude, v is the weight, w is the picture's grey value, and the bias a is augmented after the convolution, and f is the activation operation.

$$z_{x,y} = f\left(\sum_{i}^{p\times q} v_i w_i + a\right) \tag{1}$$

Pooling level is an operation used for downsampling, its chief purpose is to decrease the magnitude of the characteristic map, often use the maximum pooling (Max Pooling), which is a function of Equation (2), where $0 \le m \le M, 0 \le n \le N$.

$$f = \max(x_{m,n}, x_{m+1,n}, x_{m,n+1}, x_{m+1,n+1}) \tag{2}$$

The fully connected level links the neurons of the previous levels, captures the feature combinations and afterwards tiles them into vectors as inputs to the final classifier, and the output level is an universal pattern of logistic regression, that is able to achieve the multi-categorization problem, generally using the Softmax function [21].

2.2. **Generating Adversarial Network.** GAN consists of two competing generators (G) and discriminators (D) designed to learn real data distributions and generate fake data with similar distributions [22]. Both G and D try to improve various and opposite target functions in a zero-sum game to seek a universal equilibrium, which is very suitable for solving problems with insufficient samples and low quality. The basic framework of GAN is implied in Figure 2.

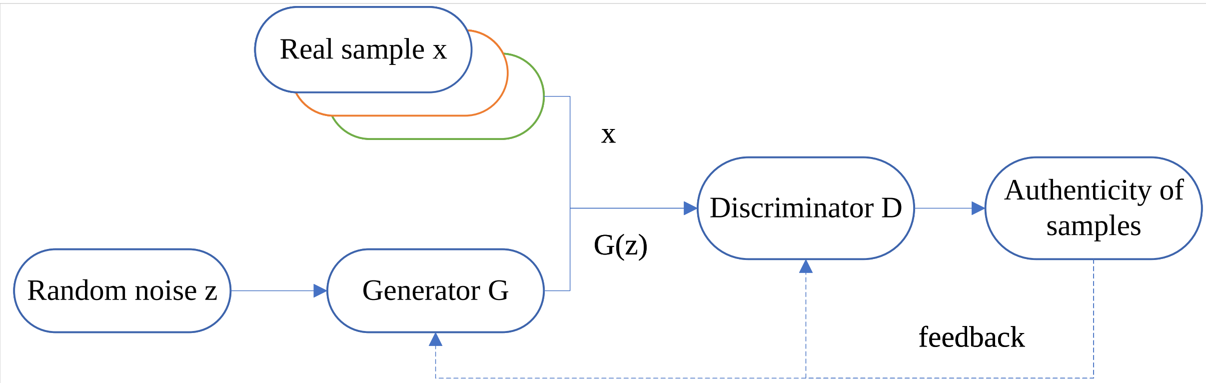


Figure 2. The basic framework of GAN.

In a GAN, x is the data captured from the true data allocation p_{data}, the noise vector z comes from a Gaussian previous allocation p_z with zero mean and unit deviation, and p_g denotes the distribution of G over the x. The potential vector z is passed as input to G, which then outputs an image $G(z)$. The goal is to make $G(z)$ as close as possible to $D(x)$. Besides, D also tries to prevent itself from being spoofed by G. Typically, D is a binary classifier, $D(x) = 1$ when $x \sim p_{data}$, and $D(x) = 0$ when $x \sim p_g$.

The target function of the GAN attempts to match p_{data} with p_g. The parameters of G and D are represented through θ_G and θ_D, separately, and θ_G is optimized so that D cannot distinguish between G generating false samples and true samples. The process can be expressed as training θ_G to minimise the loss and training θ_D to maximize the loss with the following objective function:

$$\min_{\theta_G}\max_{\theta_D} V(G,D) = \mathbb{E}_{x\sim p_{data}}[\log D(x)] + \mathbb{E}_{z\sim p_z}[\log(1 - D(G(z)))] \tag{3}$$

3. EEG Image Generation Based on GAN.

3.1. **Design of the Generator.** Intending to the issues that the EEG generation method requires a large number of datasets for training and the generated images are not clear in outline, an optimized GAN is used to achieve the image generation. A variational self-encoder is introduced, and the mean and variance of the input image data are obtained through the encoder, which transforms the hidden variables corresponding to the images into a standard Gaussian distribution, and then generates high-quality EEGs through the generator, which facilitates the subsequent classification and diagnosis of depression.

The EEG image generation model consists of a discriminator D and a generator G, which is regarded as a variational self-encoder that encodes the hidden spatial information of the input picture and generates a new picture through a decoder. The encoder extracts physical features by encoding the real EEG from the training dataset and mapping out the real image into a latent space. The G takes the EEG encoding as input with a view to generating images that can not be correctly discriminated by the D. The D discriminates among the real picture and the generated picture, determining whether it belongs to the real image or the G-generated image. To avoid the disadvantage of too large a gap in the discriminative effect, randomness technology is added to the GAN, which improves the stability and robustness of the D, and obtains better discriminative effect, while prompting the G to generate a more realistic image.

Let the real sample of EEG be x, which is encoded by the encoder to obtain the mean λ and variance σ. A random eigenvector a is constructed using the standard normal distribution:

$$a = \lambda^2 + \sigma^2\ N(0, I) \tag{4}$$

The G gets the sample as x' and the D outputs the result as goes through the G and the process can be described as below:

$$G:\ x' = g(z, \theta_g), \quad y \in [0, 1] \tag{5}$$

where $g(\cdot)$ is the generating function and θ_g is the G's parameter, after the EEG input from the D, the original EEG image and the generated image are X' and X, respectively, and the process is as in Equation (6):

$$X' = D_f(x', \theta_f), \qquad X = D_f(x, \theta_f) \tag{6}$$

According to Equation (6), the output after the D can be obtained as below:

$$y = \begin{pmatrix} D(x) \\ D(x') \end{pmatrix} = \begin{pmatrix} D(x) \\ D(G(z)) \end{pmatrix} \tag{7}$$

The meaning of $D(x)$ is the probability of discriminating the sample x correctly, then $(1 - D(x))$ is the probability of discriminating it as an incorrect sample. The whole input data of GAN network is either real or generated images, when the network reaches the equilibrium, the probability of $D(x)$ will be close to 0.5, and then, according to the definition of Equation (7), the error function is established as shown below:

$$\min \left\{ - \left[\sum_{x \in p(x)} \log(D(x, \theta_d)) + \sum_{x' \in p(x')} \log(1 - D(x', \theta_d)) \right] \right\} \tag{8}$$

where $D(x')$ is the distribution obeying the noise in the generator and θ_d is the internal parameter of the D.

The G adjusts the weight size of the network through the back propagation method, in order that the pseudo-image is constantly near to the true sample picture, the loss function of the discriminative model will constantly become smaller and smaller, and the loss function of the generative model will constantly become larger and smaller, and over time, the network will eventually be balanced by maximizing the entropy of the noise distribution, i.e., maximizing the Equation (9):

$$\max_{\theta_g} \sum_{x' \in p(x')} \log(D(x')) \tag{9}$$

3.2. **Design of the Discriminator.** Let $p_{data}(x)$ and $p_g(x)$ denote the real EEG samples and the optimized G-generated EEG samples respectively. Both the discriminative network and the generator network have their own loss functions, but the GAN consists of both of them, so the loss function is modified according to the following equation:

$$V(D,G) = \int p_{data}(x) \log(D(x))dx + \int p_g(x) \log(1 - D(x))dx \tag{10}$$

During the training process, $p_{data}(x)$ and $p_g(x)$ need to be infinitely close. In the optimization of Equation (10), it is essential to iterate D and G separately. When training D, the real EEG is mixed with the generated EEG and fed into D as input, D will give the result "0" or "1" and adjust the network parameters according to the output value; when training the generator, D will give the discriminative result and feedback the difference to G to adjust the parameters, and so on until the two networks reach stability. When optimizing D, it is also necessary to minimize the cross-entropy operation [23], as shown below:

$$V(D,G) = \frac{1}{2} \int_x p_g(x) \log(1 - D(x))dx - \int_x p_{data}(x) \log(D(x))dx \tag{11}$$

Equation (11) is a typical statistical distribution problem with the following optimal solution:

$$D^*(x) = \frac{p_{data}(x)}{p_{data}(x) + p_g(x)} \tag{12}$$

Since both $p_{data}(x)$ and $p_g(x)$ denote the probability magnitude, in practice, $p_{data}(x)$ and $p_g(x)$ must be a real number between (0,1]. Therefore, the objective function must be differentiable everywhere in the continuous space, and according to the first-order derivation rule, the objective function $V(D,G)$ obtains the minimum value at Equation (12). When G is fixed, D already has the optimal solution and D achieves the best performance.

4. Intelligent Diagnosis of Depression Based on GAN and CNN.

4.1. **Multi-channel CNN-based EEG Feature Extraction.** After obtaining the above generated images of EEG, this article designs an intelligent diagnosis approach for depression based on GAN and CNN. Firstly, multi-channel convolution is applied to capture the deep characteristics of the EEG picture and expand the sensory field by successively using dilated convolution with different null rates. Then the extracted features are mapped to the hybrid attention module for feature enhancement, which is assigned from both channel and spatial dimensions, and finally classified and diagnosed by Softmax classifier.

This article combines multi-scale feature extraction [24] and dilation convolution on the basis of traditional CNN to extract features from the generated EEG images in the following steps.

(1) Shallow feature extraction. Firstly, the shallow feature f_s of the EEG image after GAN generation is extracted using 3×3 convolution as implied in Equation (13), where X denotes the generated EEG image.

$$f_s = \mathrm{Conv}_{3\times3}(X) \tag{13}$$

(2) Deep feature extraction. The shallow features are sequentially passed through Dilated Convolution (DCB) and Multi-scale Feature Extraction (MFEB), where three scale convolution kernels of sizes 3×3, 5×5 and 7×7 are used to extract the deeper features of the EEG image in MFEB, and the deeper features are denoted by Equation (14):

$$f_i = \mathrm{Conv}_{i\times i}(f_s), \quad i = 3, 5, 7 \tag{14}$$

Then, the three features of different scales are superimposed through channels to gain the final characteristic F, as implied in Equation (15):

$$F = \sum_{i=3,5,7} f_i \tag{15}$$

Expanded convolution allows the convolution kernel to better capture the feature information of the input image. The computation of its receptive field is implied in Equation (16) and Equation (17):

$$p' = p + (p-1) \times (b-1) \tag{16}$$

$$R_{p+1} = R_p + (p'-1) \times \prod_{p=1}^{k} S_p \tag{17}$$

where p is the convolution kernel magnitude; b is the void rate; S_p denotes the stride of the p-th layer; R_{p+1} denotes the sensory field of the current level.

4.2. **Feature Enhancement Based on Hybrid Attention.** A mixed attention method uniting channel attention [25] and spatial attention [26] is introduced to distribute weights to the characteristics from both channel and spatial dimensions, as implied in Equation (18) and Equation (19):

$$M_c(F) = \sigma\big(\mathrm{MLP}(\mathrm{AvgPool}(F)) + \mathrm{MLP}(\mathrm{MaxPool}(F))\big) \tag{18}$$

$$M_s(F) = \delta\big(f([F_{avg}, F_{max}])\big) \tag{19}$$

4.3. **Classification Diagnostics and Loss Functions.** The generated EEG image X undergoes the process of forward propagation through the multiscale convolutional and hybrid attention layers and updates the weights and biases through back propagation, as formulated in Equation (20):

$$y^l = f\big(M_s(M_c(K_M * X^{l-1} + c^{l-1}))\big) \tag{20}$$

where X^{l-1} denotes the input of level $l-1$; c^{l-1} denotes the bias; $f(\cdot)$ denotes the ReLU activation.

The loss function uses the cross-entropy loss function:

$$L = \frac{1}{N} \sum_i \big[- y_i \log(p_i) - (1-y_i)\log(1-p_i)\big] \tag{21}$$

where N stands for the amount of instances, y_i stands for the category of instance i.

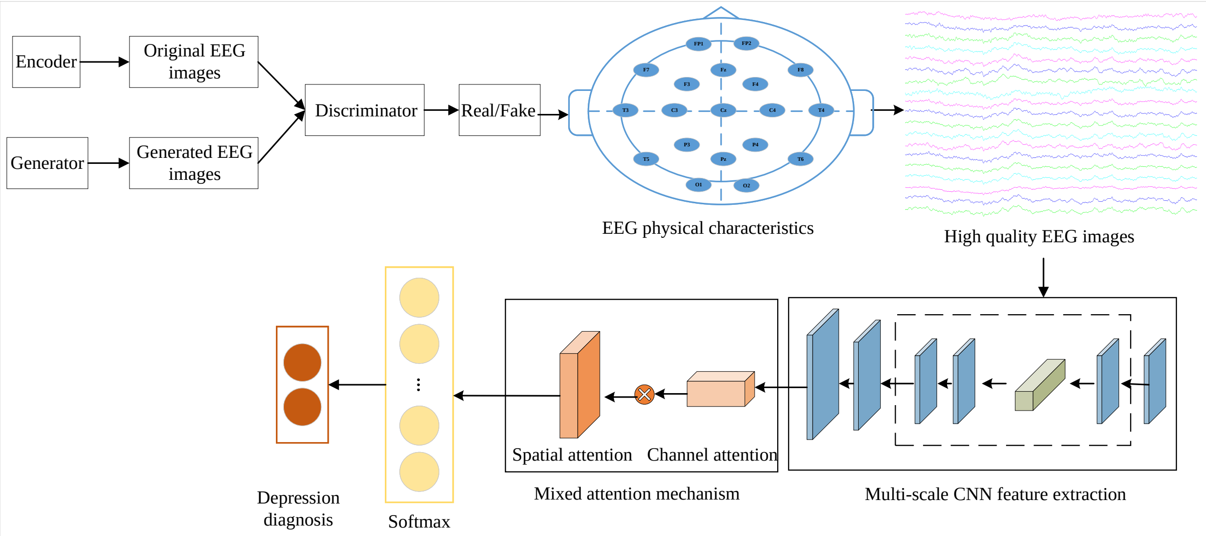


Figure 3. The whole of the proposed diagnostic approach to depression.

Finally, the features enhanced by the hybrid attention mechanism are concatenated by a fully connected level and the final outcome is classified by a Softmax classifier:

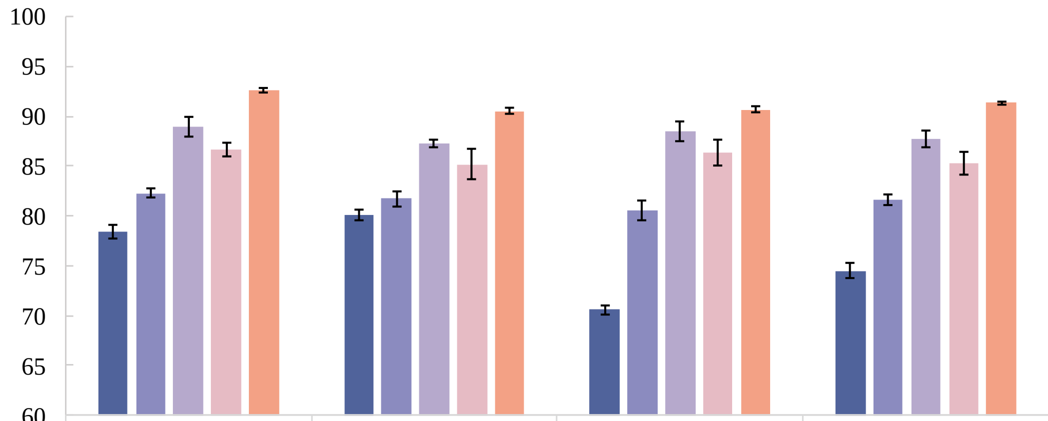
$$\text{Softmax}(z_i) = \frac{\exp(z_i)}{\sum_j \exp(z_j)} \tag{22}$$

5. Experiments and Analysis of Results.

5.1. Classification Performance Analysis. The experiments of the article were generated by running the programs on a Lenovo laptop computer with Windows 10 64-bit operating system, Intel (R) Core (TM) i7-10875H@2.30 GHz CPU, Nvidia GeForce RTX 2060 GPU, and 16GB RAM. Data processing and augmentation was implemented via Python, and CUDA was adopted for promoted calculation during training.

The experimental data used were obtained from the publicly available dataset MODMA, which consisted of 30 patients with depressive disorder and 28 healthy controls. Each participant was enrolled from the University of Science Malaysia (HUSM), and 5-minute EEG data were collected from depressed patients and healthy controls at the hospital outpatient clinic in a closed-eye resting state, resulting in a final set of 17,400 pre-processed samples. The experiment divided each dataset into 90% training set and 10% testing set, the amount of training instances in every epoch was 32, the amount of training epochs was 50, and the studying rate was set at 0.001.

This article explores the classification performance of five different models (1D-CNN [12], C3D [13], GO-INC [15], GANE [19], and the proposed method, GAN-CNN) for the diagnosis of depression in the MODMA dataset, with the performance metrics of Accuracy, Sensitivity, Specificity, and Modified Accuracy (M_Accuracy). Figure 4 demonstrates the experimental outcome of the designed method and the comparison model over the full frequency band. GAN-CNN obtains better categorization performance in all four evaluation metrics compared to another four DL models, with classification accuracy, sensitivity, specificity and corrected accuracy of 92.56%, 90.48%, 90.68% and 91.32%, respectively. Compared with 1D-CNN, C3D, GO-INC, and GANE, the classification accuracy of GAN-CNN is improved by 14.15%, 10.27%, 3.62%, and 5.85%, respectively. Furthermore, compared with the comparison method, GAN-CNN has the smallest standard deviation in all



	Accuracy (%)	Sensitivity (%)	Specificity (%)	M_ Accuracy (%)
1D-CNN	78.41	80.14	70.57	74.51
C3D	82.29	81.76	80.49	81.63
GO-INC	88.94	87.22	88.46	87.71
GANE	86.71	85.17	86.38	85.29
GAN-CNN	92.56	90.48	90.68	91.32

Figure 4. Comparison of categorization performance of various depression diagnostic methods.

four assessment metrics, and achieves the smallest standard deviation of 0.08% in the accuracy rate, which further indicates that GAN-CNN has stronger robustness in depression diagnosis using EEG data.

The above experimental results show that the GAN-CNN generates high-quality EEG images by GAN and can effectively extract potential features between EEG channels using channel CNNs, which results in a better diagnostic performance for depression. In contrast, both 1D-CNN and C3D recognise the original EEG images by CNN, but the original EEG images have unclear contours and cannot represent the potential features between the EEG data more accurately and comprehensively, which leads to their extracted features not being optimal as well as the loss of important feature information for subsequent classification. GANE uses the generator of GAN to complete the feature extraction of EEG, but its feature extraction is not sufficient compared to that of CNN. GO-INC does not properly consider the spatial information of EEG and the amount of samples is insufficient, which results in incomplete feature information extracted by the model.

5.2. **Stability Analysis.** Due to the existence of experimental errors, there may be a certain degree of chance in each experiment. In order to verify the stability of GAN-CNN, a 5-fold cross-validation is used to comprehensively estimate the model, and the evaluation indexes are selected as the mean accuracy (MA), mean precision (MP), mean F1-score (MF1), mean kappa coefficient (MK) [28], and ROC curve. The experimental outcome is implied in Table 1.

The MF1 of GAN-CNN is 91.37%, which is 15.28%, 7.92%, 4.11%, and 7.1% higher compared to 1D-CNN, C3D, GO-INC, and GANE, respectively. The MK coefficient is a multivariate discrete measure of classification accuracy and error; the larger the MK coefficient, the higher the classification accuracy. The MK of 1D-CNN, C3D, GO-INC, GANE and GAN-CNN are 72.06%, 77.22%, 83.35%, 80.11% and 87.41%, respectively, and the MK coefficient of GAN-CNN is the highest, which not only generates high-quality EEG images by using improved GAN, but also extracts and enhances the multi-channel

Table 1. 5-fold cross-validation results

Model	MA (%)	MP (%)	MF1 (%)	MK (%)
1D-CNN	76.14	77.81	76.09	72.06
C3D	82.06	79.22	83.45	77.22
GO-INC	86.52	84.15	87.26	83.35
GANE	84.42	83.38	84.27	80.11
GAN-CNN	91.28	90.64	93.37	87.41

expansive convolutional and attentional mechanisms through the deeper features of EEG, thus the classification has the highest accuracy and the best stability.

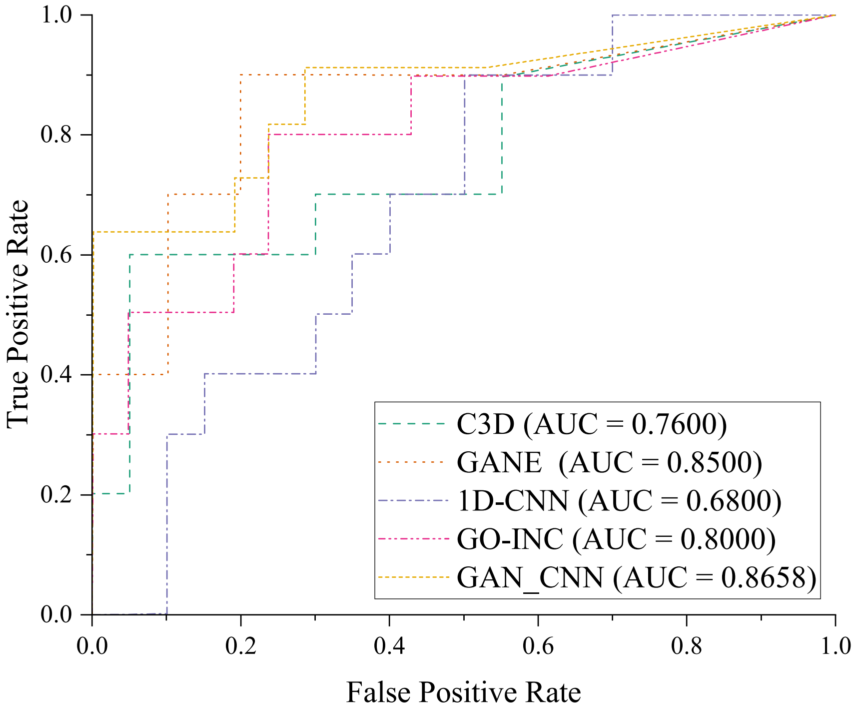


Figure 5. ROC curves for different depression diagnostic methods.

Figure 5 shows the comparison of the ROC curves of different methods with 5-fold cross validation, the AUC value is the size of the area below the ROC curve, the larger the AUC value, the better the classification efficiency. The average AUC values of 1D-CNN, C3D, GO-INC, GANE, and GAN-CNN are 0.68, 0.76, 0.80, 0.85, and 0.8658, respectively, and the ROC curve values of 1D-CNN, C3D, GO-INC, and GANE are greater than 0.5, which are above the invalid ROC curves, indicating that the individual models are valid. In addition, the average AUC value of GAN-CNN is greater than 0.85, which is higher than other models, verifying the superiority of GAN-CNN.

6. **Conclusion.** Depression both disrupts the lives of patients and has a huge impact on economic development and social stability. Therefore, depression diagnosis has received more and more attention from all walks of life. This article designs an intelligent diagnosis approach for depression based on GAN and CNN to address the problems of blurred image details and insufficient feature extraction in existing research, which lead to poor classification results. Firstly, to address the problem of distortion in EEG images, a variational self-encoder is introduced into the generator of the GAN, which obtains the

hidden spatial information of the original EEG after encoding, and generates a new EEG image through the decoder. And the discriminator is used to discriminate between the real EEG and the generated EEG, so that the generator outputs a more realistic image. Then the deep feature extraction of EEG is performed by combining multi-channel CNN and dilated convolution, and the extracted features are mapped to hybrid attention for feature enhancement, and the classification and diagnosis results are outputted by Softmax classifier. The designed method further improves the classification performance of depression diagnosis on the publicly available MODMA dataset. However, the method is only validated on the MODMA dataset, and its stability and generative performance need to be further investigated on other datasets.

REFERENCES

[1] K. M. Smith, P. F. Renshaw, and J. Bilello, "The diagnosis of depression: current and emerging methods," *Comprehensive Psychiatry*, vol. 54, no. 1, pp. 1–6, 2013.

[2] S. Aleem, N. u. Huda, R. Amin, S. Khalid, S. S. Alshamrani, and A. Alshehri, "Machine learning algorithms for depression: diagnosis, insights, and research directions," *Electronics*, vol. 11, no. 7, 1111, 2022.

[3] A. Yadollahpour, and H. Nasrollahi, "Quantitative electroencephalography for objective and differential diagnosis of depression: a comprehensive review," *Global Journal of Health Science*, vol. 8, no. 11, pp. 249–256, 2016.

[4] W. Mumtaz, L. Xia, S. S. A. Ali, M. A. M. Yasin, M. Hussain, and A. S. Malik, "Electroencephalogram (EEG)-based computer-aided technique to diagnose major depressive disorder (MDD)," *Biomedical Signal Processing and Control*, vol. 31, pp. 108–115, 2017.

[5] F. S. de Aguiar Neto, and J. L. G. Rosa, "Depression biomarkers using non-invasive EEG: A review," *Neuroscience & Biobehavioral Reviews*, vol. 105, pp. 83–93, 2019.

[6] S. Jayawardena, J. Epps, and E. Ambikairajah, "Ordinal logistic regression with partial proportional odds for depression prediction," *IEEE Transactions on Affective Computing*, vol. 14, no. 1, pp. 563–577, 2020.

[7] K. Srinivasan, N. Mahendran, D. R. Vincent, C.-Y. Chang, and S. Syed-Abdul, "Realizing an integrated multistage support vector machine model for augmented recognition of unipolar depression," *Electronics*, vol. 9, no. 4, 647, 2020.

[8] P. Chikersal, A. Doryab, M. Tumminia, D. K. Villalba, J. M. Dutcher, X. Liu, S. Cohen, K. G. Creswell, J. Mankoff, and J. D. Creswell, "Detecting depression and predicting its onset using longitudinal symptoms captured by passive sensing: a machine learning approach with robust feature selection," *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 28, no. 1, pp. 1–41, 2021.

[9] W. Mumtaz, and A. Qayyum, "A deep learning framework for automatic diagnosis of unipolar depression," *International Journal of Medical Informatics*, vol. 132, 103983, 2019.

[10] A. Safayari, and H. Bolhasani, "Depression diagnosis by deep learning using EEG signals: A systematic review," *Medicine in Novel Technology and Devices*, vol. 12, 100102, 2021.

[11] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, H. Adeli, and D. P. Subha, "Automated EEG-based screening of depression using deep convolutional neural network," *Computer Methods and Programs in Biomedicine*, vol. 161, pp. 103–113, 2018.

[12] L. Lin, X. Chen, Y. Shen, and L. Zhang, "Towards automatic depression detection: A BiLSTM/1D CNN-based model," *Applied Sciences*, vol. 10, no. 23, 8701, 2020.

[13] W. C. De Melo, E. Granger, and A. Hadid, "A deep multiscale spatiotemporal network for assessing depression from facial dynamics," *IEEE Transactions on Affective Computing*, vol. 13, no. 3, pp. 1581–1592, 2020.

[14] H. Kour, and M. K. Gupta, "An hybrid deep learning approach for depression prediction from user tweets using feature-rich CNN and bi-directional LSTM," *Multimedia Tools and Applications*, vol. 81, no. 17, pp. 23649–23685, 2022.

[15] C. Uyulan, T. T. Ergüzel, H. Unubol, M. Cebi, G. H. Sayar, M. Nezhad Asad, and N. Tarhan, "Major depressive disorder classification based on different convolutional neural network models: deep learning approach," *Clinical EEG and Neuroscience*, vol. 52, no. 1, pp. 38–51, 2021.

[16] R. U. Khan, X. Zhang, and R. Kumar, "Analysis of ResNet and GoogleNet models for malware detection," *Journal of Computer Virology and Hacking Techniques*, vol. 15, pp. 29–37, 2019.

[17] J. Li, Z. L. Yu, Z. Gu, H. Liu, and Y. Li, "Dilated-inception net: multi-scale feature aggregation for cardiac right ventricle segmentation," *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 12, pp. 3499–3508, 2019.

[18] J. Zhao, J. Huang, D. Zhi, W. Yan, X. Ma, X. Yang, X. Li, Q. Ke, T. Jiang, and V. D. Calhoun, "Functional network connectivity (FNC)-based generative adversarial network (GAN) and its applications in classification of mental disorders," *Journal of Neuroscience Methods*, vol. 341, 108756, 2020.

[19] R. Fu, Y.-F. Chen, Y. Huang, S. Chen, F. Duan, J. Li, J. Wu, D. Jiang, J. Gao, and J. Gu, "Symmetric convolutional and adversarial neural network enables improved mental stress classification from EEG," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 1384–1400, 2022.

[20] F. Ye, Y. Su, H. Xiao, X. Zhao, and W. Min, "Remote sensing image registration using convolutional neural network features," *IEEE Geoscience and Remote Sensing Letters*, vol. 15, no. 2, pp. 232–236, 2018.

[21] P. Li, R. Jing, and X. Shi, "Apple disease recognition based on convolutional neural networks with modified softmax," *Frontiers in Plant Science*, vol. 13, 820146, 2022.

[22] A. Aggarwal, M. Mittal, and G. Battineni, "Generative adversarial network: An overview of theory and applications," *International Journal of Information Management Data Insights*, vol. 1, no. 1, 100004, 2021.

[23] L. Wu, R. Hong, Y. Wang, and M. Wang, "Cross-entropy adversarial view adaptation for person re-identification," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 30, no. 7, pp. 2081–2092, 2019.

[24] B. Tu, N. Li, L. Fang, D. He, and P. Ghamisi, "Hyperspectral image classification with multi-scale feature extraction," *Remote Sensing*, vol. 11, no. 5, 534, 2019.

[25] T.-Y. Wu, H. Li, S. Kumari, and C.-M. Chen, "A Spectral Convolutional Neural Network Model Based on Adaptive Fick's Law for Hyperspectral Image Classification," *Computers, Materials & Continua*, vol. 79, no. 1, pp. 19–46, 2024.

[26] F. Zhang, T.-Y. Wu, J.-S. Pan, G. Ding, and Z. Li, "Human motion recognition based on SVM in VR art media interaction environment," *Human-centric Computing and Information Sciences*, vol. 9, 40, 2019.

[27] R. F. Brenes, A. Johannssen, and N. Chukhrova, "An intelligent bankruptcy prediction model using a multilayer perceptron," *Intelligent Systems with Applications*, vol. 16, 200136, 2022.

[28] J. M. Miller, F. Zanderigo, P. D. Purushothaman, C. DeLorenzo, H. Rubin-Falcone, R. T. Ogden, J. Keilp, M. A. Oquendo, N. Nabulsi, and Y. H. Huang, "Kappa opioid receptor binding in major depression: a pilot study," *Synapse*, vol. 72, no. 9, e22042, 2018.