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Article

Comparative Analysis of Deep Learning Models on Depression Prediction

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Abstract: Major depressive disorder (MDD) is a severe psychiatric condition characterized by persistent emotional, cognitive, and functional impairments. Traditional diagnostic approaches heavily rely on subjective self-report scales and clinical observations, which are inherently vulnerable to recall biases and social desirability effects. While recent advancements in artificial intelligence (AI) offer promising paradigms for enhancing predictive accuracy and enabling personalized mental healthcare, implementing these models effectively across heterogeneous clinical environments remains highly challenging. This study conducts a horizontal comparison of DNNs, RNNs, and CNNs in MDD prediction, focusing on the correspondence among model architecture, training data type, and predictive accuracy. The findings indicate that DNNs are more suitable for structured clinical and questionnaire variables, RNNs for longitudinal and time-series data, and CNNs for image-based and spatial-representation data. However, model accuracy is highly dependent on the characteristics of the processed data and the sources of training samples, which broadly constrain existing findings. Future research should further develop multimodal transformer-based modeling to improve the capacity of AI models to process multimodal data.

Keywords: MDD prediction; DNNs; RNNs; CNNs; transformer

1. Introduction

Major depressive disorder (MDD) is a clinical psychiatric disorder that severely compromises health and profoundly disrupts daily life. Patients experience a persistent inability to perceive pleasure, accompanied by a marked reduction in interest or hedonic experience. This disorder can lead to systematic abnormalities across cognitive, behavioral, and neural functional domains. Its clinical manifestations include persistent depressed mood, impaired cognitive function, reduced energy, disturbances in sleep and appetite, psychomotor changes, and suicidal ideation [1]. In addition, patients' functioning in social, occupational, and other domains of life should be severely impaired [2].

The prediction and assessment of MDD have traditionally relied on self-report scales, clinical data, and observable behavioral indicators [3]. Research shows that although these methods can capture patients' subjective symptom expression, the evaluative process is susceptible to recall bias and social desirability effects, thereby limiting the precision and reliability of assessment [4].

Recently, AI models have increasingly been recognized as capable of enabling more accurate and personalized diagnosis of patients with depression within the field of mental disorders, while also supporting the

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development of tailored treatment strategies. The review by Li et al. demonstrated that deep learning machine approaches and AI models have been widely adopted to study depression-related patterns, enabling further learning of the disorder features, and enhancing the representational capacity of complex clinical signals, hence significantly improving the overall stability and predictive accuracy of depression prediction tasks [5]. However, AI-driven healthcare models still face several barriers to implementation, requiring greater attention to sources of uncertainty and the incorporation of more diverse data sources for model training [6].

Although multimodal models are constructed through the fusion of single-model architectures, their predictive accuracy still depends on whether each type of data is processed by an appropriate model structure. While complex multimodal models integrate and process diverse forms of raw data, their accuracy must be enhanced through well-matched single-model architectures. Therefore, it is essential to conduct a horizontal comparison of the training data sources and structural characteristics of single models, as well as the types of data they are suited to process, their feature-learning mechanisms, and their predictive accuracy in depression prediction.

2. Comparative Analysis of AI Models for Depression Prediction

This study analyzes these models from three mainly dimensions: the training data sources associated with model structures, different feature-learning methods, and their performance in depression prediction tasks. The analysis will focus on comparing the applicability of different deep learning model structures in processing clinical variables, time-series signals, and spatial representation data. Thereby, based on this conceptual framework, we will further appraise the advantages and limitations in predictive accuracy of these single deep learning modals.

2.1. DNNs

DNNs are primarily used to learn complex nonlinear relationships among input features and represent one of the most fundamental deep learning models. Structurally, DNNs rely on multiple layers of neural units to progressively integrate shallow and deeper feature representations. Through nonlinear transformations across layers, the model continuously reorganizes input information, enabling raw features or initially extracted features to be progressively transformed into class-discriminative representations [7]. Research indicates that the methodological advantage of DNNs lies not merely in performing classification or prediction, but in enhancing the model's capacity to fit complex mapping relationships through deep architectures, thereby allowing it to capture subtle latent associations among input variables [8].

Previous studies have already tested the accuracy of DNNs on depression prediction. Pandit et al. used data from the U. S. COVID-19 Impact Survey, which covered physical health, economic status, social and psychological health, behavioral factors, and COVID-19-related symptoms, while also incorporating demographic variables such as gender, income, and educational attainment [9]. This study used multiple deep learning models to predict depression in this experiment. The model comparison showed that the DNNs achieved an accuracy of 0.96 in depression prediction. This high predictive performance was primarily attributable to the capacity of DNNs to learn complex nonlinear relationships among structured mental health-related variables.

Moreover, in the study by Rafiei et al., the MDD detection was formulated as an EEG time-series classification task, in which a DNN was used to directly process raw EEG signals. However, the results showed that when the complete 19-channel EEG dataset was used, the DNNs achieved an accuracy of 91.67% in detecting MDD [10]. Although previous studies have demonstrated that DNNs can be applied to EEG signal analysis, their capacity to learn neural representations embedded in raw EEG time series remains less effective than their performance on structured and readily classifiable text-based data.

2.2. RNNs

The core structure of RNNs lies in their recurrent connections and in the feedforward computational structure of an RNN, the state from the preceding time point is incorporated during forward propagation at each time step, enabling the model to continuously integrate historical information along the temporal dimension and generate dynamic sequential representations. This mechanism enables the model to retain historical information within continuous inputs and capture temporal dependencies. Research found that the most basic Elman cell implements short-term memory through the hidden state. Therefore, the primary predictive function of RNNs is not merely to perform sequence classification or prediction, but to capture dynamic changes, long-term dependencies, and nonlinear patterns in data [11]. In the context of depression prediction, this structural property makes RNNs more suitable for processing temporally continuous dynamic data, such as EEG signals, speech signals, and longitudinal behavioral records.

Jiang et al. conducted their study using a four-year longitudinal dataset of 1,500 Chinese college students and developed RNN-based predictive models based on demographic, behavioral, and psychological questionnaire variables to capture the temporal dynamics of depression risk across different stages of university life [12]. The results showed that all four RNN models demonstrated strong predictive performance, with accuracy ranging from 0.920 to 0.964 and AUC ranging from 0.921 to 0.952. Among them, Model 4, which was based on the four-year follow-up dataset, achieved the highest AUC of 0.952, with a sensitivity of 0.714, outperforming traditional models such as LR. These findings suggest that the advantage of RNNs does not lie simply in processing static variables, but rather in leveraging temporal dependencies within longitudinal data to continuously integrate dynamic risk factors, including students’ psychological status, sleep quality, family relationships, and prior adverse experiences, thereby improving the prediction of depressive symptom trajectories.

Kour and Gupta used Twitter textual data as the input source and classified users as depressive or non-depressive based on their textual content [13]. In their experiment, the RNN machine achieved an accuracy of 90.66%, which was lower than the CNN model and the final CNN-biLSTM hybrid model, which reached the highest accuracy of 94.28%. What’s more, Mahayossanunt et al. employed facial-expression features extracted from interview videos for depression detection, and the baseline Bi-LSTM model achieved an accuracy of only 68.75% [14]. These findings suggest that, for depression-related textual data, RNNs show higher prediction accuracy while applied to temporally structured EEG signals.

2.3. CNNs

CNN is a typical convolutional feedforward architecture, generally composed of convolutional layers, pooling layers, and fully connected layers. Yamashita et al. demonstrated that the model extracts local spatial features through convolutional layers, compresses redundant information while enhancing feature stability, and ultimately maps hierarchical spatial representations onto classification outputs [15].

In MDD prediction, Ma et al. constructed brain functional connectivity graphs from multi-site REST-meta-MDD resting-state fMRI data and applied an APO-GCN model for MDD classification, achieving an accuracy of 91.8–93.8% [16]. This study indicates that CNN-family models can achieve high predictive performance when processing spatially organized brain network representations derived from rs-fMRI; however, this advantage is not based on raw image-pixel classification, but rather on the spatial-topological information encoded in functional connectivity graphs.

Amanat et al. used depressed and non-depressed tweets as textual data sources for depression detection, where the TF-IDF + CNN model achieved an accuracy of 91% [17]. Moreover, Latha et al. used EEG signals for depression detection and reported that the standalone CNN model achieved only 85% accuracy, which was lower than the CNN-LSTM model incorporating temporal learning, which reached 92% [18]. These findings suggest that CNNs exhibit relatively limited predictive accuracy when applied to time-series neural signals and text-based data that primarily depend on semantic information.

2.4. Cross-Model Accuracy Comparison

The results across studies indicate that predictive performance depends not only on the algorithm itself, but also on the fit between model architecture and input data type. As shown in Table 1, DNNs perform better on structured questionnaire or clinical-variable data, RNNs show advantages in longitudinal and time-series data, and CNNs are more suitable for image-based and spatial-representation data. Therefore, cross-model accuracy comparison should not focus on numerical ranking alone but should clarify the applicability boundaries and data dependence of different deep learning models in depression prediction.

Table 1. Comparison of Depression Prediction Accuracy Across Heterogeneous Data Types Among Different Deep Learning Models.

Deep Learning Machine	Structured Tabular Data	Time-Series Data	Image-Based Data
DNNs	96.00%	91.67%	72.8%
RNNs	90.66%	96.40%	94.28%
CNNs	91.00%	85.00%	93.80

Although research on predictive accuracy in MDD prediction is already extensive, accuracy results primarily reflect model performance under specific datasets and experimental conditions and cannot be directly generalized as universal conclusions for MDD prediction. Because the training samples used by different models are derived from different sources, the representativeness and generalizability of their results may be affected by dataset-specific bias. Meanwhile, hospitals rarely make MDD-related clinical data openly available; therefore, MDD prediction results cannot fully reflect clinical manifestations.

3. Discussion

The limitations above mainly arise from heterogeneity in data sources, insufficient sample representativeness, inconsistent control of demographic variables, and restricted feature representation within single modalities. Future research should standardize diagnostic criteria and variable control in larger multi-center samples and evaluate model generalizability through external validation. On this basis, multimodal modeling may serve as a further optimization strategy to reduce single-source data bias and improve the stability of MDD prediction.

In recent years, MDD prediction research has increasingly adopted multimodal feature-fusion strategies, as different modalities reflect distinct dimensions of symptoms. Nguyen et al. reviewed that multimodal models are generally composed of modality-specific feature extraction modules and a multimodal fusion module [19]. During the feature extraction stage, representations are learned separately from textual, auditory, and visual data, while additional physiological signals may further be incorporated to enhance the expressiveness of the feature space. What's more, research indicates that the multimodal deep learning machine can significantly improve predictive accuracy, highlighting the heterogeneity and multidimensionality of MDD-related data [20].

Jia et al. demonstrated that multimodal transformer-based modeling can assign differential weights to different modalities and key features through an attention mechanism, thereby addressing the susceptibility of single-modal models to data noise and their limited capacity to handle data heterogeneity [21].

4. Conclusions

In conclusion, the cross-model comparison of DNNs, RNNs, and CNNs for MDD prediction indicates no absolute superiority among these architectures. Predictive performance primarily depends on the fit between model structure and input data type. DNNs are more suitable for structured clinical and questionnaire variables, RNNs for longitudinal and time-series data, and CNNs for image-based and spatial-representation data. However, existing accuracy results remain limited in generalizability due to training-sample sources, demographic-variable control, single-modality bias, and insufficient external validation. Future research should further develop multimodal transformer-based modeling to enhance the integration of heterogeneous data and improve the clinical applicability of depression prediction.

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