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REVIEW ARTICLE

Classification of Mental Disorders Using Deep Generative Models: A Review of Techniques and Comparative Analyses

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ABSTRACT

In this case, the diagnostic and statistical manual for mental disorders has experienced increased advancements in deep generative models (DGMs) that incorporate deep learning in analyzing neuroimaging information. The following review looks at different approaches that have been used in the classification of mental disorders and the specific performance of DGMs like GANs and VAEs. In classifying psychiatric symptoms, it remains challenging to represent the inherent intricacy of data by conventional methods. Thus, techniques that are more accurate are needed to identify complex patterns in extensive data. The newer studies also suggest that DGMs yield higher accuracy than traditional machine learning approaches because the most important features can be identified without requiring significant feature engineering. For example, using GANs to distinguish between major depressive disorder and healthy controls surpasses traditional classifier accuracy by remarkable margins. Moreover, this review contrasts the DGM architectures and their implementations in various psychiatric disorders that can improve diagnostic accuracy and pathophysiological features of diseases. Altogether, the results of the present study emphasize the possibilities of DGMs' contribution to the field of psychiatry and open possibilities for further studies to deliver more precise diagnostic classifications and enhance the efficacy of treatment by employing the perspective of personalized medicine.

Keywords: Deep Generative Models ▪ Neuroimaging ▪ Mental Health Diagnostics ▪ Data Augmentation ▪ Personalized Medicine

1. INTRODUCTION

Mental disorders have always been grouped in a way throughout the history of psychiatry, primarily because of aspects of symptoms that touch individuals. Historically, diagnosing psychiatric disorders has mainly relied on manual examination and diagnostic references that depend on clinical interviews and questionnaires. These methods, however, continue to predispose the practitioners to missing diagnosis or even an inadequate understanding of the disease course in various mental health disorders. Over the years, psychiatry has advanced, and with advancement, there are new ways of categorizing mental health disorders with better precision and more precise diagnostic means. Deep generative models (DGMs) are machine-learning methodologies, among which it is possible to affirm that they have brought quite promising results in their attempts to solve questions related to high-dimensional information.

The advance of deep learning as one of the essential tools of artificial intelligence in recent years has significantly transformed the conventional method of medical diagnosis, especially in psychiatry. Some generative models that are widely used, like GANs and VAEs, are highly accurate in analyzing the data sets, including the neuroimaging data. These models are great at fitting patterns into data, making them an essential resource for mental health professionals seeking to improve their decision-making processes. In contrast to the conventional approach, in which diagnosis often depends on engineered features, DGMs can learn reasonable representation of data, minimizing the workload of the feature engineer and improving overall classification [1].

Another advantage of enhancing the ability to analyze neuroimaging data is peculiar to psychiatric disorders' diagnosis. Modern techniques in imaging like functional magnetic resonance imaging (fMRI) and structural MRI give massive datasets that cannot be easily handled using existing conventional paradigms. DGMs, however, are built to accommodate and extract particular features from this big data and are, therefore, suitable for complex neuroimaging research. For instance, studies have revealed that GANs outperform classifiers in accurately classifying major depressive disorder patients from controls. It is crucial in clinical decisions as it helps evaluate proper treatment procedures for patients.

Despite the observed promise of DGMs, their use in and the development of models focused on psychiatry is still in its infancy. Most of the conducted studies are disease-oriented, with a focus on depression, schizophrenia, and bipolar effects. Nonetheless, there are still great opportunities for further research concerning the diagnostic potential of DGMs in various other mental health disorders. By utilizing deep learning's strengths, researchers enhance diagnostic accuracy and reveal novel information on these conditions' etiology and pathophysiology processes. Identifying these patterns could help develop targeted interventions that could help improve patient outcomes worldwide [2].

Other DGMs also have the flexibility of learning the contribution of the essential features from scratch from the raw data without specifying these features in advance. Classical machine learning classifiers are sensitive to features chosen prior to the execution of the method and are deemed necessary for the problem in question. Unlike usual classifiers, DGMs can detect patterns within the data and make more precise and stable classification. This characteristic makes them useful in the taxonomy of mental disorders, where signs and sources may be partly obscure or understated.

The second advantage derived from using DGMs is their capacity to process big data sets, a factor increasingly characteristic of data available in psychiatry. Regarding the amount and variety of the data, today's researchers are equipped with far broader stimuli due to such new possibilities as neuroimaging data or electronic health records. Conventional analysis methods can be inconvenient when handling such massive data sets, which would take much time. DGMs, in contrast, are intended for application in big data, where much information is processed at one time. This capability enables the formulation of enhanced models to note patient differences even when they exhibit similar symptoms.

For similar reasons, the use of DGMs in psychiatry also has bright prospects in enhancing the pathophysiologic understanding of mental disorders. The patterns that can be discerned in the data regarding neuroimaging point to the biological factors behind signs and symptoms or different subtypes of a given disorder. This understanding could help in the discovery of other biomarkers for diagnosing mental disorders, a potential breakthrough that could revolutionize psychiatric diagnosis and treatment. DGMs could also be used to chart the trajectory through which mental health concerns manifest, possibly providing an essential mechanism for closely assessing the progress of such conditions and patient response to treatment plans and making corrections if necessary [3].

As helpful as DGMs can be, several problems can arise from their use in psychiatry. One of the biggest hurdles is the requirement to acquire high-quality big data focusing on the variety and identification of mental health issues. These sorts of datasets are scant, and it is not easy for researchers to obtain data that is both inclusive and fair. Further, DGMs are valuable tools that have drawbacks including overfitting, lack of model interpretability, and the impossibility of running the models using average computing power in clinical consultations.

However, the prospects for the further use of DGMs in the field of psychiatry seem bright. These models will only become more integrated into the diagnostic process as research continues and new technologies emerge. With the improvement of the deep learning technique, psychiatrists can diagnose their patients accurately and recommend more patient-friendly treatments. Furthermore, this increased understanding of the patterns underlying mental health data will enable biometrics to understand better the respective biosignatures, which will be the key to developing new treatment paradigms and optimal patient outcomes.

More specifically, this review paper aims to achieve three objectives: to assess existing research on the efficacy of various deep generative models to classify mental disorders, to compare their techniques and outcomes, and to identify novel research directions and potential applications for such models. Subsequent sections detail the classifications available of DGMs, such as GANs and VAEs, and look closer at their utility in treating or analyzing several major psychiatric disorders.

2. LITERATURE REVIEW

Incorporating deep generative models into various fields has opened new possibilities for solving problems and analyzing data with high-dimensional and imbalanced forms. In psychiatry and healthcare, these models support classification, prediction, synthetic data generation, and representation learning. This section summarizes studies included in the review and emphasizes their techniques, comparative strengths, and reported limitations.

Gao et al. [4] proposed a GAN and CNN-based EEG imbalanced classification model for seizure detection. The method uses GAN augmentation to balance EEG data and then applies a one-dimensional convolutional neural network for classification. Evaluations on three public EEG databases showed improvements over several competing methods, demonstrating the value of synthetic sample generation in medical classification tasks where labeled data are limited.

Yao and Lu [5] addressed functional connectivity augmentation for mental disease classification using GANs. Their method introduces Wasserstein distance and double-class distance constraints to improve the generated functional connectivity samples. The approach was evaluated on attention-deficit/hyperactivity disorder and autism spectrum disorder classification tasks and achieved improved classification accuracy compared with baseline approaches.

Ko et al. [6] proposed a deep generative-discriminative learning framework for multimodal representation in imaging genetics. The model jointly learns neuroimaging and genetic representations and distinguishes itself by enabling the learning of nonlinear relationships between imaging phenotypes and genotypes without requiring prior neuroscientific knowledge. Experimental results based on publicly available datasets support the framework's potential to advance deep-learning-based imaging genetics studies, particularly for Alzheimer's disease and mild cognitive impairment.

The limited availability of psychologists highlights the need for efficient identification of individuals in urgent need of mental healthcare. Harne et al. [7] explored Natural Language Processing pipelines to analyze text data from online mental health forums, aiming to flag users who may require immediate professional attention. Their work introduces CASE-BERT, an advanced model that identifies potential mental health disorders based on forum text. CASE-BERT outperforms existing methods, achieving an F1 score of 0.91 for depression and 0.88 for anxiety.

Wang et al. [8] proposed an audio-based depression recognition method that integrates convolutional neural networks with generative adversarial networks. The approach begins by preprocessing audio, removing extended periods of silence, and splicing the remaining audio segments. Key speech features, including MFCCs, short-term energy, and spectral entropy, are extracted using an audio difference normalization algorithm. Experimental results on AViD-Corpus and DAIC-WOZ datasets show that the proposed method significantly reduces depression recognition errors, with RMSE and MAE values exceeding existing methods by more than 5%.

Karimi et al. [9] presented a deep generative model for drug combination design, integrating graph-structured domain knowledge with a reinforcement-learning-based chemical graph-set designer. Hierarchical variational graph auto-encoders jointly embed gene–gene, gene–disease, and disease–disease networks using attentional pooling. Results show that the proposed approach outperforms existing graph embedding methods in learning generalizable disease representations, while generated drug combinations were low in toxicity and aligned with FDA-approved combinations.

Kahng et al. [10] introduced GAN Lab, an interactive visualization tool for non-experts to learn and experiment with GANs. The tool allows users to interactively train generative models and observe intermediate results from the dynamic training process. GAN Lab integrates a model overview graph and layered distributions view to help interpret the interplay between submodels. Built using TensorFlow.js, it is accessible via modern web browsers without installation or specialized hardware.

Li et al. [11] addressed the limitation of DGMs in discriminative ability by introducing max-margin deep generative models and class-conditional variants. These models integrate max-margin learning to improve predictive performance in supervised and semi-supervised learning while maintaining generative capabilities. Empirical results show that max-margin learning significantly enhances predictive performance and yields competitive classification accuracy.

Fernando et al. [12] presented a framework for predicting shot location and type in tennis, incorporating neural memory modules to represent a player's episodic and semantic memory. A semi-supervised GAN architecture combines memory models with deep neural feature learning and is evaluated using tennis tracking data from the 2012 Australian Open, effectively predicting player behaviors and adaptation to match context.

Table 1 summarizes the literature reviewed in this study on using deep learning approaches across different medical fields. The table summarizes the research objectives, methods, and outcomes for each study, and distinguishes which deep learning models and data types are used. From the reviewed studies, deep learning promises to transform medical diagnosis, treatment, and patient management; nevertheless, issues like data quality, model interpretability, and ethical usage require more research for this technology to reach its rightful potential in healthcare applications.

Bahrami et al. [13] introduced a single-cell GAN designed to extract meaningful patterns from raw single-cell RNA-sequencing data while minimizing confounding effects from technical artifacts or inherent factors. Experiments on three public datasets demonstrate that SCGAN outperforms state-of-the-art methods in clustering known cell types and identifying psychiatric genes linked to major depressive disorder.

Sun and Wu [14] proposed a deep learning-based model for preliminary diagnosis of mental health conditions and screening of individuals at risk. The model analyzes semantic and syntactic structures of daily public comments and posts, capturing mental health status indicators embedded in online communication. This approach seeks to provide a scalable and accessible solution to mental health assessment in the digital age.

Ive et al. [15] proposed an approach to generate artificial clinical documents to address restricted access to mental health clinical text. The study includes intrinsic evaluation of text preservation, memorization, and clinical validity, together with extrinsic evaluation on downstream classification. Results show that artificial data can yield classification results comparable to those obtained with original data while reducing privacy risks.

Zhu et al. [16] proposed BILSTM-CNN GAN, which integrates bidirectional long short-term memory and convolutional neural networks to generate synthetic ECG data. Using ECG data from the MIT-BIH database, the study compared BILSTM-CNN GAN with recurrent neural network autoencoder and variational autoencoder models. Results demonstrated fast convergence and high morphological similarity to actual recordings.

Saha et al. [17] explored social media as a passive sensor for assessing college students' mental health. Researchers combined consultation records from a large U.S. public university with 66,000 Reddit posts. SARIMA models incorporating social media data achieved prediction accuracy of $r = 0.86$ and SMAPE of 13.30, outperforming models without social media data by 41%.

Table 1. Summary of Literature Review

Study	Key Contribution	Methodology	Evaluation
[4]	Improved seizure detection using GAN-augmented data and 1DCNN	GAN data augmentation, 1DCNN	Evaluated on three public EEG databases, outperforming other methods
[5]	Enhanced fMRI data analysis using improved GAN	Wasserstein distance and double-class distance constraints for GAN	Improved classification accuracy for ADHD and ASD
[6]	Deep learning framework for imaging genetics	Joint representation of neuroimaging and genetic data	State-of-the-art performance in Alzheimer's disease and mild cognitive impairment diagnosis
[7]	NLP for mental health identification in online forums	Pre-training NLP pipelines with mental health curricular texts	CASE-BERT model for identifying depression and anxiety
[8]	Audio-based depression recognition using CNN and GAN	Feature extraction (MFCCs, energy, entropy), DR AudioNet model	Improved depression recognition accuracy on AViD-Corpus and DAIC-WOZ datasets
[9]	Deep generative model for drug combination design	Graph-structured domain knowledge, reinforcement learning	Outperforms graph embedding methods in disease representation learning
[10]	GAN Lab: interactive visualization tool for GANs	Interactive training and visualization	Addresses the need for accessible GAN learning and experimentation
[11]	Max-margin deep generative models	Max-margin learning principle for improved discriminative ability	Enhanced predictive performance in supervised and semi-supervised learning
[12]	Neural memory-based framework for tennis shot prediction	Neural memory modules and semi-supervised GAN	Effective prediction of player behaviors and adaptation to match context
[13]	Single-cell GAN for batch effect reduction in scRNA-seq	SCGAN for extracting meaningful patterns from raw scRNA-seq data	Outperforms state-of-the-art methods in clustering and identifying psychiatric genes
[14]	Deep learning for mental health diagnosis from social media	Analyzing semantic and syntactic structures of online communication	Preliminary diagnosis and risk screening of mental health conditions
[15]	Generating artificial clinical documents for NLP	Generating synthetic clinical documents to address privacy and scarcity	Improved text classification performance with artificial data
[16]	GAN-based ECG data generation for heart disease diagnosis	BILSTM-CNN GAN for generating synthetic ECG data	Improved accuracy and efficiency in heart disease diagnosis
[17]	Social media as a passive sensor for college student mental health	Analyzing social media posts to predict mental health consultation	Improved prediction accuracy using SARIMA models with social media data
[18]	Multimodal psychological computing for mental health	Long-term interpretable model for emotion detection and prediction	State-of-the-art accuracy in emotion detection and continuous symptom identification
[19]	Generative model for social interaction stimuli	Parametrically controlled generation of social interaction videos	Facilitates behavioral and neuroimaging studies of social interaction perception
[20]	scNODE: predicting single-cell gene expression at unobserved time points	Deep learning model for continuous gene expression modeling	Improved cell trajectory inference and in silico perturbation analysis
[21]	Deep belief networks with complementary priors	Efficient learning of deep directed belief networks	Improved generative modeling and digit classification performance
[22]	GS-VDAE: data augmentation for MRI data analysis	Combining VAE and GSDAE for generating realistic MRI data	Enhanced biomarker identification in high-dimensional small-sample-size scenarios

Sun et al. [18] proposed a multimodal psychological computing technology for emotion and mental health prediction. They established a mental health database based on a naturalistic paradigm and introduced a long-term interpretable psychological computing model using prior knowledge and multimodal information fusion. The model achieved state-of-the-art accuracy in emotion detection and identification of continuous emotional symptoms.

Salatiello et al. [19] proposed a dynamical generative model of social interactions for parametrically controlled generation of social interaction videos. The approach facilitates behavioral and neuroimaging studies of social interaction perception by providing structured stimuli that can be controlled across experimental dimensions.

Zhang et al. [20] presented scNODE, a generative model for temporal single-cell transcriptomic data prediction. The model supports continuous gene expression modeling and improves cell trajectory inference and in silico perturbation analysis for unobserved time points.

Hinton et al. [21] introduced a fast learning algorithm for deep belief nets with complementary priors. This foundational work enables efficient learning of deep directed belief networks and improved generative modeling and digit classification performance.

Huang et al. [22] addressed high-dimensional data with small sample size by combining VAE and graph-regularized sparse deep autoencoder, termed GS-VDAE. Unlike standard approaches that use final GSDAE outputs, GS-VDAE embeds the generation process into GSDAE to ensure augmented samples retain significant original features. Generated samples achieved classification accuracy of 0.84, outperforming 0.74 accuracy obtained with VAE-generated samples.

3. CONCLUSION

The numerous studies analyzed show that deep generative models hold significant promise across the domains studied to classify and analyze complex data sets. Through GANs and VAEs, for instance, researchers have recorded outstanding achievements in areas like diagnosing mental health and neuro and genetic studies. These models stand out in overcoming shortcomings of the conventional approaches that involve feature selection and operating within high dimensions. In addition, their effectiveness in identifying subtle cycles in vast, unsorted data proves their applicability to solving current scientific and clinical problems.

One main advantage of DGMs is that the concept is versatile for many operations. Starting from identifying seizures within EEG signals, moving up to increasing the accuracy of the diagnoses of mental health issues such as depression and schizophrenia, DGMs have it all. In addition, the reviewed studies show their ability to enrich data, deal with the lack of balanced datasets, and help find new biomarkers and drug regimes. These enhancements refine diagnostic and therapeutic results and expand known pathophysiological processes, creating further research and treatment opportunities.

However, some problems still need to be solved before DGMs can be applied in real-world and clinical applications. The constraints regarding the availability of large, clean datasets, computational power, and model explicability impede their broader adoption. One crucial aspect that needs to be addressed is the demographic balance of datasets. Ensuring diversity in data is essential for model creation and will require cross-disciplinary work and effective training paradigms.

The development of automated DGMs will be more integrated into clinical and scientific applications shortly. As computation and algorithms get more sophisticated and datasets grow and become more significant and of higher quality, DGMs offer the potential to define and empower breakthroughs in areas such as personalized medicine and predictive analytics. These models can close the gap between data density and value and become helpful instruments in improving results in various spheres of decision-making. DGMs will continue to be highly valued and needed as more research advances to confront some of the most significant issues in science and medicine.

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