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Clinical Utility of Psychiatric Neuroimaging: Exploring Psychoradiology and Use of Machine Learning in Psychoradiology

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Abstract: ***Psychoradiology, an emerging discipline, applies advanced radiological imaging technologies to psychiatric disorders. Over the past thirty years, progress in brain imaging has significantly enhanced our understanding of psychiatric illnesses and treatment outcomes [1]. Radiologists have shown growing interest in utilising these advancements for accurate diagnosis and personalised patient care in common psychiatric conditions. This shift from research to clinical application marks the initial phase of psychoradiology's evolution [1]. This review outlines recent developments in the field, focusing on its clinical roles. The review also offers practical guidelines for implementing psychoradiology in clinical settings and suggests areas for future research to validate its broader clinical applications. Given the prevalence of psychiatric disorders and the increasing involvement of radiologists in this area, this guide aims to assist radiologists in contributing effectively to this rapidly advancing field.***

Keywords: Psychoradiology; emerging discipline; advanced radiological imaging; psychiatric disorders; brain imaging; psychiatric illnesses; psychiatry; radiology; radio - diagnosis

1. Introduction

Psychiatric disorders are significant contributors to global disability, accounting for 4.9% of disability - adjusted life years in 2019. Nearly 14.6% of global years lived with disability that year were due to these disorders, marking a 48.1% increase in cases between 1990 and 2019. Both genetic and environmental factors play roles in the development of psychiatric disorders, with adverse life events and genetic predispositions impacting gene regulation and, subsequently, brain function and behaviour.

Currently, diagnosing psychiatric disorders relies on symptom self - reporting, behavioural observations, and cognitive assessments [2]. However, this process is time - consuming and relies heavily on the expertise of experienced psychiatrists. Challenges persist in determining effective treatments and prognoses. Consequently, there is a critical need for identifying objective abnormalities, understanding underlying pathophysiological mechanisms, and developing precise treatments for psychiatric disorders.

In recent years, neuroimaging technologies have emerged as invaluable tools for investigating the potential mechanisms underlying psychiatric disorders. Psychoradiology, a nascent field at the crossroads of psychiatry and radiology, leverages medical imaging techniques to explore brain structure and function abnormalities in psychiatric patients. This interdisciplinary approach not only offers insights into these abnormalities but also holds promise for clinical applications.

Addressing the diverse biological aspects of psychiatric disorders and unraveling their underlying mechanisms pose considerable challenges. Psychoradiology stands poised to make significant contributions in this regard. Various medical imaging technologies, including magnetic resonance imaging (MRI), positron emission tomography, and electroencephalography, can serve as valuable tools for identifying biomarkers of psychiatric disorders and enhancing clinical practice. Among these, MRI techniques, such as blood oxygenation level - dependent (BOLD) functional MRI, diffusion tensor imaging (DTI), and three - dimensional structural MRI, enable the detection of subtle structural and functional alterations in patients with psychiatric disorders [3]. These advancements shed light on how brain abnormalities correlate with the diverse clinical presentations observed in patients.

Clinical implications of Psychoradiology

Diagnostic practices in psychiatry have long been criticised for their subjective nature, often relying on ill - defined and overlapping clinical syndromes. Attempts to subtype these syndromes based on clinical symptoms have not successfully reduced their heterogeneity. Current syndromal diagnoses serve as general descriptions until neurobiologically discrete subgroups can be established, unlike most medical disciplines that define diseases based on biological measures and pathophysiological models.

To address these challenges, researchers have proposed new strategies and nosologies guiding diagnosis and syndrome subtyping based on objective biomarkers [1]. Techniques such as pattern recognition and machine learning, especially using neuroimaging data, show promise in detecting biomarkers from psychiatric disorders. Subtyping patients using statistical cluster analysis based on shared brain abnormalities is a common focus, aiming to identify biologically homogeneous groups within and across current diagnoses. This approach holds potential for identifying shared biological abnormalities, allowing for targeted treatments [2].

Recent advancements in neuroimaging, particularly in the field of psychoradiology, have allowed the identification of distinct neurophysiological subtypes in patients with depression, providing promising avenues for personalised treatment approaches. Similar approaches have been applied to disorders like attention - deficit/hyperactivity disorder (ADHD), illustrating the potential utility of psychoradiology in clinical psychiatry [4].

Predicting and monitoring psychiatric disorders, such as psychosis onset or relapse, has been a challenging task. Advances in image acquisition and analysis techniques, like structural MRI and functional connectivity (FC) analysis, enable the development of predictive models. For example, connectome analysis in high - risk individuals has shown promising results in predicting transitions to psychosis. Combining imaging markers with clinical profiles in prediction models enhances accuracy, paving the way for tailored interventions and improved social functioning [5].

Psychoradiological biomarkers have also shown utility in predicting treatment response and relapse in depression. Studies utilising machine learning techniques, such as measuring hippocampal subfield volumes, have offered valuable insights into early response to antidepressant treatment [6]. These predictive models are crucial, especially considering the slow onset of action of psychiatric medications. Moreover, psychoradiology has potential in guiding treatment selection. Cluster analysis based on pre - treatment data allows for identifying heterogeneity in complex syndromes, aiding in the evaluation of treatment outcomes in specific subgroups [7, 8].

In summary, clinical psychoradiology, particularly through advanced imaging techniques and machine learning, holds immense promise in predicting and monitoring psychiatric disorders, tailoring interventions, and improving treatment outcomes. These advancements represent a significant leap forward in diagnostic and treatment planning practices within clinical psychiatry.

Practical Recommendations for Implementing Psychoradiology in Clinical Settings

"Recent studies have offered substantial evidence supporting the potential clinical utility of psychoradiology in diagnosing, predicting, and evaluating treatments for patients with psychiatric disorders [9, 11]. Considering this, it becomes essential to formulate appropriate clinical guidelines for this emerging field, which bridges radiology and psychiatry. Notably, the MR group within the Chinese Society of Radiology has released the inaugural expert consensus report on clinical psychoradiological MR examinations for patients with schizophrenia in China. According to this consensus paper, individuals suspected of having schizophrenia should undergo MR examinations, including high spatial resolution structural imaging with a minimum thickness of 1 mm, in addition to traditional clinical MR scans with higher slice thickness [10]. The consensus emphasises the importance of quantitative analysis of GMV and cortical thickness to identify specific patterns of regional grey matter changes [11]. Apart from defining scanning sequences and data analysis methods, the consensus also outlines additional safety requirements for patients and special environmental considerations before and during MR examinations, particularly crucial for psychiatric patients. "

2. Challenges

In the past two decades, there has been rapid evolution in radiological imaging methods and image analysis techniques, providing precise tools for studying the human brain. These sophisticated methods have enabled the identification of subtle structural and functional brain changes associated with psychiatric disorders. Despite ongoing efforts to address methodological issues, progress might not have been substantial enough to warrant enthusiasm or the initiation of large multisite validation studies to establish the clinical utility of MRI in psychiatry. Several practical challenges must be overcome to develop MRI measures as diagnostic and predictive biomarkers in psychiatry.

Firstly, since neuroimaging findings were rarely replicated in identical settings within psychiatric samples in the past, determining the optimal acquisition parameters and analytical methods to extract clinically useful information for individual patient care planning is essential. Additionally, with the availability of numerous complementary imaging methods, defining approaches for combining and utilising multimodal information provided by MRI examinations is crucial.

Moreover, recent scientific advancements and methodological developments necessitate a reexamination of previous observations. For instance, most prior resting fMRI studies focused on the traditional low - frequency band (0.01–0.1 Hz) [12]. However, recent research has revealed resting state FC patterns at frequency bands higher than 0.1 Hz [13]. Studies investigating amplitude fluctuations within discrete frequency bands higher than 0.1 Hz in patients with psychosis have been conducted. Furthermore, exploring dynamic as well as static FC and examining the clinical significance of connectivity in specific frequency bands may offer additional clinically useful information [14].

Secondly, discrepancies across studies are common in any field. Some differences may arise due to variances in patient recruitment strategies, demographic considerations, or MR protocols, while others might reflect true inconsistencies within disorders. To address this issue, conducting larger - scale consortia multisite studies is essential. These studies should collect sufficiently large samples to leverage within - disorder heterogeneity, identifying more biologically homogeneous subgroups of patients than those included in the original syndromal diagnosis. Ideally, these advancements will pinpoint groups with distinct optimal treatments, enabling MRI data to guide personalised care for patient subgroups meeting criteria for a particular syndrome but presenting with non - significant psychiatric differences. These data collections could be further improved using statistical methods to harmonise data gathered across multiple sites.

Utilising Machine Learning in Psychoradiology: Applications and Constraints

Machine learning, a subset of AI, refines its parameters autonomously to perform specific tasks with increasing precision. Within machine learning, two key approaches are employed: supervised learning and unsupervised learning. Supervised learning algorithms analyse labeled data to form predictive models, enabling the classification of new data [15]. For instance, utilising the support vector machine (SVM) method and functional MRI data from over 1000 patients with schizophrenia, researchers successfully identified functional striatal abnormalities, distinguishing individuals with schizophrenia from controls with 80% accuracy. Combining multiple modalities, such as functional MRI, diffusion tensor imaging, and structural MRI data, with SVM has facilitated accurate differentiation of schizophrenia patients from healthy controls, achieving a remarkable accuracy of 91.75% [16]. Current psychoradiological research emphasises predicting long - term clinical outcomes and patient responses to various therapies. For example, Cao et al [17] demonstrated that using SVM to analyse functional connections between the superior temporal cortex and other cortical regions led to individual - level diagnosis accuracy of 78.6% and treatment prediction accuracy of 82.5% in schizophrenia. In patients with OCD, functional connectivity (FC) within specific brain networks predicted post - treatment scores and treatment response with 70% accuracy [18].

Unsupervised learning explores patterns within datasets to identify discrete heterogeneity or subgroups within large patient samples. For instance, researchers have employed agglomerative hierarchical clustering analysis to identify different patterns of white matter abnormalities in early - phase schizophrenia [19]. Additionally, the Bipolar - Schizophrenia Network for Intermediate Phenotypes consortium employed multivariate taxometric analyses to identify three patient biotypes based on brain function biomarkers, later validated using structural imaging biomarkers and clinical features. Another study used spectral clustering to delineate subgroups in first - episode drug - naive schizophrenia patients, revealing distinct functional connectivity patterns and cognitive deficits [20]. While these studies highlight the potential of biomarker - based approaches in understanding schizophrenia's heterogeneity, further research and replication studies are necessary to confirm these findings and establish the clinical applicability of MRI - based subgroup classifications.

However, there are notable limitations in psychoradiological studies utilising machine learning. Data quality is a significant concern, as magnetic non - uniformity can distort brain images, leading to signal loss [21]. To address this issue, generative adversarial networks (GAN) have been introduced, generating high - quality synthesised images. Although studies employing GAN for psychoradiological analyses are limited, they offer promising solutions to enhance image quality [22]. Another challenge is model overfitting, often arising from small sample sizes and high - dimensional imaging features. Feature selection, particularly within cross - validation loops, can introduce selection bias, potentially inflating the estimated model performance. To mitigate this bias, it is recommended to conduct feature selection within nested cross - validation loops.

Deep learning and GNN

Deep learning, a subset of machine learning methods, excels in extracting intricate patterns from data to address complex problems with remarkable accuracy, setting benchmark records in speech recognition, image recognition, and natural language processing. It stands as one of the most prominent domains in machine learning. Unlike conventional machine learning, deep learning autonomously identifies optimal feature representations from raw data, eliminating the subjectivity associated with feature extraction and selection. This quality proves invaluable in psychoradiology, where the affected brain regions are unknown, and understanding the neural mechanisms of psychiatric disorders is uncertain [23]. Deep learning employs multilayer neural networks, inspired by how the human brain processes information, to tackle challenging tasks [24]. Its capacity for higher levels of complexity and abstraction makes it particularly suitable for exploring complex relationships between brain structure and function in human brain imaging data compared to traditional shallow machine learning models [23].

In recent years, deep learning has found success across various domains. However, while deep learning adeptly handles Euclidean data, a significant portion of data exists in graph form. Constructing features from graph data often involves manual intervention, potentially leading to information bias and graph loss. To mitigate these challenges, the concept of graph neural networks (GNN) was introduced by Scarselli and colleagues [25]. GNN extends neural networks to process data represented in graph domains, addressing limitations posed by conventional convolutional neural networks (CNN), which work only on Euclidean data like images and texts.

In the realm of psychoradiology, Yang and colleagues developed an interpretable edge - weighted graph attention network (EGAT) framework [26]. This model combines anatomical features and functional connectivity measures to classify patients with bipolar disorder and healthy controls, achieving an impressive accuracy of 82%, outperforming other models such as random forest and SVM. Using an attention mechanism, this model revealed intricate interactive patterns among default mode, fronto - parietal, and cingulo - opercular networks underlying bipolar disorder. Additionally, Ma and colleagues introduced a novel GNN with a multi - resolution representation of the graph to identify disease - specific variations in brain functional connectivity networks associated with ADHD and structural connectivity networks of patients with AD [27]. Their multi - resolution framework surpassed conventional graph methods in classification and in identifying disease - specific brain connectivity patterns linked to ADHD or AD.

While GNN has shown substantial success, it does have limitations. Traditional GNN struggles with iterative updates of node hidden states for a fixed point, uses uniform parameters across layers, lacks a hierarchical feature extraction process, and inadequately represents informative edge features [28]. Future research in GNNs should focus on designing genuinely deep GNNs for more intricate tasks, creating specialised models to handle graph heterogeneity and diversity, and developing optimal representation methods balancing graph integrity and algorithm efficiency.

3. Conclusion

In summary, high - field MRI (specifically, 3.0 Tesla and higher field MRI) has facilitated the identification of structural and functional correlates related to various psychiatric disorders, marking a significant advancement toward the translational use of psychiatric imaging for diagnosis, treatment response prediction, and therapeutic intervention monitoring. To ensure the success of this field, interdisciplinary collaboration involving radiologists, psychiatrists, psychologists, physicists, biochemists, mathematicians, and engineers with computer science skills is essential. These teams are crucial for developing optimal measurements tailored for examining psychiatric patients.

Radiologists must play an active role in conducting clinical trials to establish and validate the utility of imaging markers and quantitative imaging measures that can be easily applied in clinical settings. They should also familiarise themselves with the quantitative procedures necessary to detect the subtle brain changes typically associated with neuropsychiatric disorders and understand the functional brain system conceptualisations of psychiatric disorders. It is hoped that more clinically oriented validation studies will be carried out in the near future to achieve this end, given the urgent need for improving clinical outcomes of psychiatric patients.

While artificial intelligence (AI) methods have been employed in various neuropsychiatric disorders within the development of psychoradiology, most applications still operate at the level of simple case - control dichotomous classification. In the complex landscape of mental illness clinical practice, physicians often encounter intricate situations such as comorbidity, differential diagnosis, and treatment selection. Moreover, there are fundamental questions about the neurobiological validity of presently defined psychiatric syndromes and diagnostic nosology. Therefore, instead of rigidly classifying psychiatric disorders into traditional discrete categories, integrating multiple neurobiological dimensions of illness to define categories based on neurobiological features could be a more promising long - term approach for understanding enigmatic psychiatric disorders. Despite the numerous challenges, psychoradiology holds great promise for addressing clinical complexities in psychiatry. By establishing comprehensive databases from multiple centers using standardized acquisition protocols and leveraging sophisticated algorithms and computer hardware, psychoradiology, combined with AI, has the potential to evolve into a clinical examination method in psychiatric disorders. This integration has the capacity to gradually enhance the efficiency, accuracy, and utility of diagnostic evaluations and treatment planning for psychiatric patients.

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