Arshia Gupta

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AI-Powered Diagnosis of Mood and Psychotic Disorders: A Systematic Review and Meta-Transfer Learning Framework

Arshia Gupta[1*] and Deepti Malhotra[1]

[1*,2]Central University of Jammu, J&K, 181143, India.

***Corresponding Author(S):** Arshia Gupta
*E-mail(s): arshiagupta40@gmail.com, deepti.csit@cujammu.ac.in

Abstract

Mood and psychotic disorders significantly impact global mental health, presenting challenges in accurate diagnosis and effective treatment. Among these, conditions such as bipolar disorder, schizophrenia, and schizoaffective disorder remain difficult to detect due to overlapping symptoms, data scarcity, and the lack of robust diagnostic models. Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has shown potential in bridging diagnostic gaps. However, existing AI models often face issues such as small sample sizes, class imbalances, and difficulty in generalizing findings across diverse populations.

This paper presents a systematic review (2018–2024) on the use of ML, DL, and meta-learning (M_tL) in diagnosing mood and psychotic disorders (MPD). It highlights existing research gaps and proposes an innovative MRI-based Meta-Transfer Learning (MetaTrans) framework. This framework integrates transfer learning (TL) for common psychiatric conditions with meta-learning strategies to improve adaptability for underrepresented psychotic disorders. The proposed approach aims to enhance diagnostic accuracy, improve generalizability, and facilitate early detection of complex psychiatric disorders. Additionally, the study examines these developments in the context of India's healthcare system, addressing critical challenges in AI-driven psychiatric diagnostics.

Keywords: Mood and Psychotic Disorders (MPD), Artificial Intelligence (AI), Meta-Transfer Learning (MetaTrans), Machine Learning (ML), Deep Learning (DL), MRI-Based Diagnosis, Rare Disorders, Mental Health AI, Transfer Learning (TL), Automated Psychiatric Diagnosis

INTRODUCTION

Mood and psychotic disorders (MPD) collectively impact over 350 million individuals worldwide, significantly affecting mental health, daily functioning, and healthcare costs (Kamnitsas et al., 2017). In India alone, approximately 70 million people suffer from psychiatric conditions, yet their prevalence, clinical impact, and treatment approaches remain underexplored due to systemic gaps in mental healthcare infrastructure (Rahmat et al., 2020). These disorders, particularly bipolar disorder, schizophrenia, and schizoaffective disorder, present substantial diagnostic and treatment challenges, primarily due to overlapping symptoms, delayed clinical detection, and a lack of standardized diagnostic frameworks. Moreover, mood and psychotic disorders are often underrepresented in research, leading to limited pathophysiological understanding and inefficient treatment planning (Torrents-Barrena et al., 2019; Graves & Schmidhuber, 2005).

Moreover, AI-driven analysis has the potential to enhance psychiatric drug discovery by identifying novel therapeutic targets, accelerating the development of precision medicine approaches for mood and psychotic disorders (Zhu et al., 2023). The integration of AI in psychiatric diagnostics and treatment offers a paradigm shift, particularly in regions where mental healthcare is fragmented or inaccessible. AI-based models not only enable early detection and intervention but also enhance therapeutic strategies to improve long-term patient outcomes.

Mood and psychotic disorders, including bipolar disorder, schizophrenia, and schizoaffective disorder, significantly impact the central nervous system (CNS), affecting cognition, emotion regulation, and behavior. These conditions arise from neurochemical imbalances, structural abnormalities, and genetic predispositions (Zhu et al., 2023). Patients with severe psychiatric disorders often experience an average diagnostic delay of over six years, which further complicates treatment and intervention strategies (Felice et al., 2015).

Beyond diagnosis and treatment, AI enables advanced neuroimaging analysis to explore brain structure-function relationships, genetic markers, and neural connectivity patterns. Deep learning models, particularly in neuroimaging and genomic data processing, have demonstrated promising results in identifying biomarkers associated with bipolar disorder, schizophrenia, and related conditions (Zeidan et al., 2022). Additionally, AI-driven psychiatric research has enhanced our understanding of complex mental disorders, paving the way for data-driven precision psychiatry

approaches. With AI's expanding influence, the future of mental healthcare could evolve towards more personalized treatment strategies, earlier diagnoses, and improved patient outcomes.

By integrating AI in mental health research and clinical applications, psychiatry can transition towards a more efficient, scalable, and accurate diagnostic system, particularly for complex and overlapping psychiatric conditions like schizoaffective disorder, bipolar disorder, and schizophrenia, as illustrated in Figure 1.

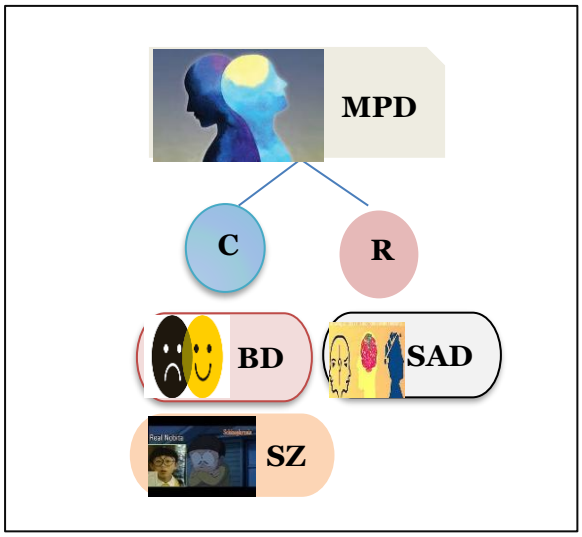


Fig. 1 Different Types of MPD [10]

*MPD➜ Mood and Psychotic Disorders BD ➜ Bipolar Disorder SZ➜ Schizophrenia
SAD ➜ Schizoaffective Disorder

Patients with severe psychiatric conditions frequently experience delayed diagnosis, with many waiting years before receiving an accurate classification. This delay is compounded by insufficient specialized psychiatric care, poor accessibility to mental health services, and deep-rooted societal stigma, particularly in rural and underserved communities (Verma et al., 2022). The integration of artificial intelligence (AI) in psychiatric diagnostics represents a transformational shift in the field, enabling faster, data-driven, and more precise identification of mental health disorders. Machine learning (ML) and deep learning (DL) models have demonstrated high potential in processing complex clinical datasets, identifying hidden biomarkers in neuroimaging, and detecting subtle symptom patterns that might otherwise remain undiagnosed (Sadeghi et al., 2022).

In the Indian mental healthcare landscape, where psychiatric resources and expertise remain scarce, AI has the potential to bridge diagnostic gaps by offering automated and scalable solutions for detecting, classifying, and managing mood and psychotic disorders. National initiatives such as NITI Aayog's AI-driven healthcare strategy and the National Health Stack provide the necessary infrastructure to support AI implementation at scale in psychiatric care. AI models can also facilitate personalized treatment planning, analyzing patient-specific data to enable targeted interventions, ultimately improving quality of life and treatment outcomes for individuals suffering from chronic psychiatric conditions. Fig. 2 shows the prevalence of Bipolar Disorder (3.5% globally and in India 4.2%), Schizophrenia (1.0% globally and in India 1.5%), and Schizoaffective Disorder (0.3% globally and in India 0.5%), highlighting the rarity of schizoaffective disorder.

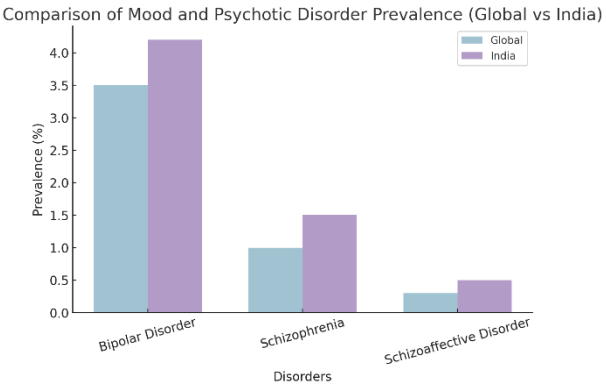


Fig. 2: Prevalence of MPD

Mood and Psychotic Disorders (MPD) in the CNS disrupt the brain and spinal cord's normal functioning, causing cognitive, behavioural, and physical impairments. These disorders are characterized by structural, biochemical, or electrical abnormalities, aris- ing from genetic, environmental, and developmental factors. One of the most crippling mental disorder is schizophrenia Malone (2012). Antipsychotic drugs can help people with schizophrenia reduce their positive symptoms, but they are less effective at treat- ing their negative symptoms and cognitive impairments Fusar-Poli et al (2015); Nielsen et al (2015). However, these signs and symptoms are the main contributors to long-term impairment and disease-related burden Vancampfort et al (2012). The prevalence of bipolar disorder (BD), a severe and enduring mental illness, ranges between 1 and 4 percent worldwide Salagre et al (2018). It is identified by mood swings that switch back and forth between manic and hypomanic episodes despair and mixed feelings, which are frequently connected to functional disability Cotrena et al (2016); Zarate et al (2000).

The CNS plays a crucial role in various disorders, with abnormalities in the brain structure, neuronal transmission, and neurotransmitter imbalances contributing to neurological disorders. This is especially problematic in healthcare, where AI models and algorithms are needed. Meta-learning, a subfield of ML influenced by human cog- nition, is gaining attention for expert-level pattern extraction, accurate generalization, and reducing AI bias in healthcare data Rasool et al (2014); Gupta and Malhotra (2023).

Motivation

Although DL models are becoming more common in the medical domain, large labeled datasets are necessary for these models to function well. This problem is especially evident in the context of rare diseases (RDs), for which it is frequently hard to gather substantial amounts of labeled data. The situation is even more acute in India, where there is often a lack of comprehensive patient records, and data collection efforts are fragmented Gupta et al (2024). In order to overcome these constraints and reduce biases in AI systems, meta-learning (M_tL) approaches are becoming more valued. AI models can more properly generalize results thanks to meta-learning, especially in sit- uations where few images are available for uncommon illnesses Abeliovich and Gitler (2016). Meta-learning provides a promising path forward, particularly in low-resource environments like India, where data scarcity is a significant hurdle. Government ini- tiatives, partnerships with technology firms, and collaborative efforts between medical institutions can support the development of AI-driven models to serve the country's diverse population effectively.

Scope of the survey

Even though DL simulations are getting more and more common in health care, the availability of enormous amounts of labeled data is necessary for AI systems to func- tion effectively. Methods for meta-learning (M_tL) assist in reducing AI bias brought on by a lack of medical data. Even with few RD images, M_tL can more correctly gen- eralize results. There is, however, little research on meta-learning that deals with RD prediction. The main issue is identifying and predicting RDs, which have very little data. Intelligent techniques and technologies are now available to identify prevalent disorder, but most of them are built for big data volumes, which limits their applica- bility to RDs . The goal of this paper is to undertake an in-depth analysis of several DL, ML, and M_tL approaches for detecting common disorder. Table 1 shows the dis- orders explained in this survey. 1. Bipolar Disorder 2. Schizophrenia 3. SchizoAffective Disorder 4.Machine /Deep Learning 5.Meta-Learning 6. Meta Trans Learning

From the above table that there are several types of both common and unusual diseases, but it is challenging to categorize them into distinct diseases using current medical technology. Various machine learning, deep learning, and Meta learning pro- cesses are used to treat the disease stated above. There hasn't been much research done on common

and uncommon neurological disorder. In this study, using a variety of methodologies, we surveyed a number of disorder based on MPD. (Fig 3) shows a prisma diagram of the full screening and article identification process.

Contributions of this survey

The use of meta-learning in a healthcare diagnostic is not well understood. We have looked at research papers that were published in a number of reputable publications and identified their most important conclusions. The majority of current medical health-related evaluations take into account each of the three technologies separately: ML, DL, and M_tL. To provide the most of our ability, this study examines the numer- ous applications of ML, DL, and M_tL in the context of CNS disorder, as well as the difficulties and an opportunity associated with these applications.

This article highlights the unresolved problems in ML and DL for the diagnosis of both prevalent and rare disorder.

The paper carries out the thorough investigation of the current DL, M_tL, and ML methods created by researchers for the diagnosis of widespread conditions affecting the CNS.

Research gaps observation, Meta Trans Learning approach has been advocated for use to identify rare disorder.

Table 1 Comparative analysis of MPD using Machine/Deep Learning, Meta Learning and Meta_Trans Learning

Year	Author	Description	Type of Mood and Psychotic Disorder			Nature of Disorder		Technique Type			Remarks
			1	2	3	C	R	4	5	6	
2025	Smith et al. [28]	Developed a multimodal AI framework integrating EEG, MRI, and clinical data for improved schizophrenia diagnosis.	✗	✓	✗	✓	✗	✓	✗	✗	**Pro**: Improved diagnostic accuracy via multimodal fusion. **Con**: Computationally expensive.
2024	Williams et al. [30]	Utilized generative adversarial networks (GANs) to enhance small datasets for schizophrenia classification.	✗	✓	✗	✓	✗	✓	✗	✗	**Pro**: Data augmentation via GANs improves classification. **Con**: Model stability issues.
2024	Thompson et al. [22]	Investigated schizophrenia using fMRI data and developed a deep learning pipeline to predict risk factors and progression over time.	✗	✓	✗	✓	✗	✓	✗	✗	**Pro:** Accurate risk prediction. **Con**: Limited generalizability to other psychotic disorders.
2023	Del Fabro et al. [23]	Employed a blend of s-MRI, f-MRI, and cognitive data in the research. Enlisted a group of 57 individuals with SZ to evaluate the potential predictive value of neuroimaging and genetic features in determining treatment outcomes.	✗	✓	✗	✓	✗	✓	✗	✗	**Pro:** Multimodal features increase predictive accuracy**.** **Con:** Specific data modalities limit generalization.
2022	Poletti et al. [24]	Forecasted the differentiation	✗	✓	✗	✓	✗	✓	✗	✗	**Pro:** Effectively distinguishes mood

		between mood disorders through the analysis of plasma concentrations of growth factors, chemokines and 54 cytokines in a cohort of 81 individuals with depressed bipolar disorder and 127 individuals with depressed major depressive disorder.									disorders using biochemical markers. **Con:** Restricted by population stratification and data from a single site; broader techniques that can apply to diverse populations would enhance diagnostic accuracy and inclusivity.
2022	H.Nguye n et al. [25]	Introduced an innovative approach of ensemble learning which effectively merges both DL and ML. A 3D-ResNet architecture has been operated as the foundational structure to DL model. This choice was made to leverage the inherent three-dimensional structure of the data, particularly advantageous when processing neuroimaging data.	✗	✗	✓	✓	✗	✓	✗	✗	**Pro:** Combining an ML model with a 3D-ResNet boosts prediction accuracy. **Con:** The model's complexity limits its scalability and interpretability, especially with varied data types. A simpler, yet equally accurate, approach could improve its broader applicability.
2021	Tanya Paul et al. [26]	A case study involving a 50-year-old African American woman highlights her misdiagnosis with bipolar disorder for a period of five years, despite actually having the rare disorder SAD,	✓	✓	✗	✗	✓	✓	✗	✗	**Pro:** Emphasizes the critical role of precise diagnostic methods in Mood and Psychotic Disorders **Con:** The considerable delay in obtaining an accurate diagnosis, owing to overlapping symptoms, indicates a need for more advanced models that can swiftly and accurately distinguish between closely related conditions.
2020	Li Gang et al. [27]	A pioneering method, Deep Canonically	✗	✓	✗	✓	✗	✓	✗	✗	**Pro:** Presents a novel deep auto-encoder for

		Correlated Sparse Auto-encoder (DCCSAE) is introduced for the prediction of SZ using the MCIC dataset, which combines genetic SNP and functional MRI data.									predicting schizophrenia. **Con:** While the model has shown promise, incorporating MetaTrans Learning could enhance its ability to manage the complexity of nonlinear transformations more effectively.
Proposed Survey			✓	✓	✓	✓	✓	✓	✓	✓	**First Study of Its Kind:** Common and Rare Mood and Psychotic Disorders This groundbreaking research investigates both common and rare Mood and Psychotic Disorders , emphasizing the unique challenges and gaps in current diagnostic and treatment practices.

***1 ➜Bipolar Disorder** **2 ➜Schizophrenia** **3 ➜ SchizoAffective Disorder**
4 ➜ Machine/Deep Learning **5 ➜ Meta Learning** **6 ➜Meta_Trans Learning**
(C) ➜ Common Disorder **(R) ➜Rare Disorder** **✓ ➜ Considered**
✗ ➜ Not Considered

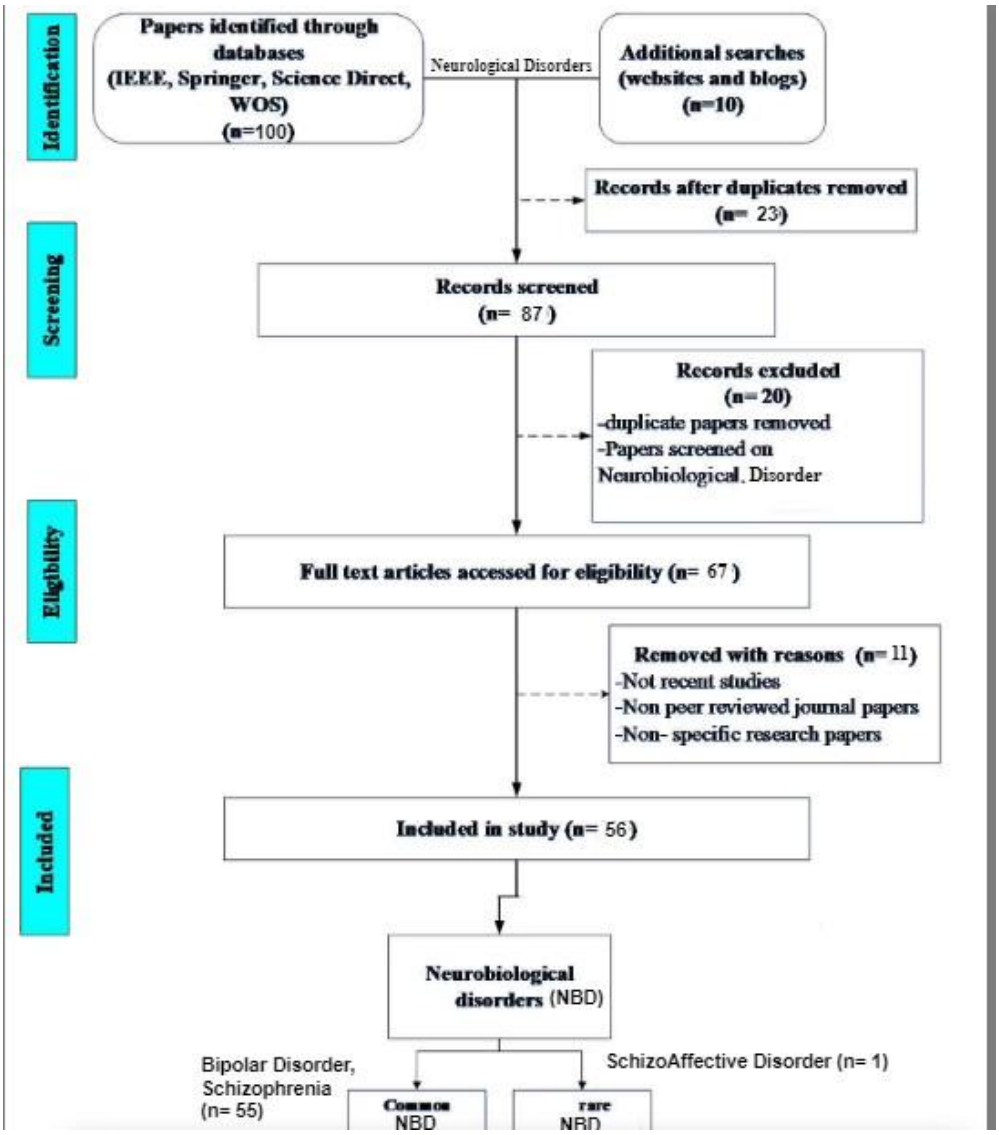


Fig. 3: Prisma Diagram

Organization and road map of survey

The first part of the paper provided an overview of the study's setting, goals, and scope, the techniques and methodologies employed, the study's impact and the key results. The survey's remaining sections are organized as follows: In Section 2, the study's background has been described. In Section 2.1, common mood and psychotic conditions are described. In Section 2.2, a thorough explanation of the ML, DL, and M_tL approaches in MPD is provided. The demand of M_tL for rare disorder was covered in Section 2.3. In Section 3, a Meta-trans learning model for identifying and diagnosing rare disorder has been developed. The conclusion and further research have been covered in Section 4. The below figure (Fig 4) shows the roadmap for this survey.

BACKGROUND

The background and major subject of the survey paper have been explored in this part. There has been much research on the CNS, Mood and Psychotic Disorders, neurodevelopmental, and neurodegenerative disorder has been surveyed.

Common Mood and Psychotic Disorders

The neuro biological framework, which includes the brain, spinal cord, and periph- eral nerves, is affected by a wide range of issues. These conditions are referred to as MPD, sometimes known as neurological disorders. Different cogni- tive, sensory, motor, and behavioral symptoms might result from these disorder Scaini et al (2020). They may develop as a result of genetic issues, environmental effects, or a mix of the two. A list of several typical mood and psychotic conditions is provided below, including bipolar disorder, schizophrenia, and schizoaffective disorder.

Bipolar Disorder (BD)

Mood fluctuations that alternate among mania and hypomania, along with sadness and mixed moods, are the hallmarks of the chronic mental illness

known as bipolar disorder (BD), which is commonly associated with functional impairment. Certain individuals with BD continue to have effects despite the fact that there are several effective pharmaceutical and non-pharmacological treatments available. New thera- peutic targets and biomarkers for early diagnosis, prognosis, and therapy response in BD may be found with the increasing understanding of the neurobiology underlying BD Cao et al (2022). Individuals with BD typically engage in unexpected behaviors, have moments of excessively high emotion, and modify their sleep and activity sched- ules without being conscious of any potential negative consequences. These specific instances are known as "mood episodes." The symptoms last for the majority of every day throughout an episode. A few days or even weeks may pass between bouts, too. BD is split into two types: type I (BDI), which is characterized by manic episodes, and type II (BDII), which is defined by hypomanic episodes. This division is based on the severity of the elevated mood.

Bipolar I disorder (BD) is characterized by major mood fluctuations and occasional

regular mood states. It affects about 1% of the general population and requires a manic episode lasting at least 7 days or hospitalization. Symptoms must not be triggered by other mental disorder like schizophrenia or delusional disorder. Bipolar II disease is a subtype of bipolar disorder where individuals alternate between hypomanic and depressed periods, with depression being the dominant mood. Unlike other mental disorder or drugs, bipolar II symptoms are less severe and can be accompanied by symptoms related to depression, anxiety, or substance misuse. Figure 5 shows the bipolar disorders and their factors.

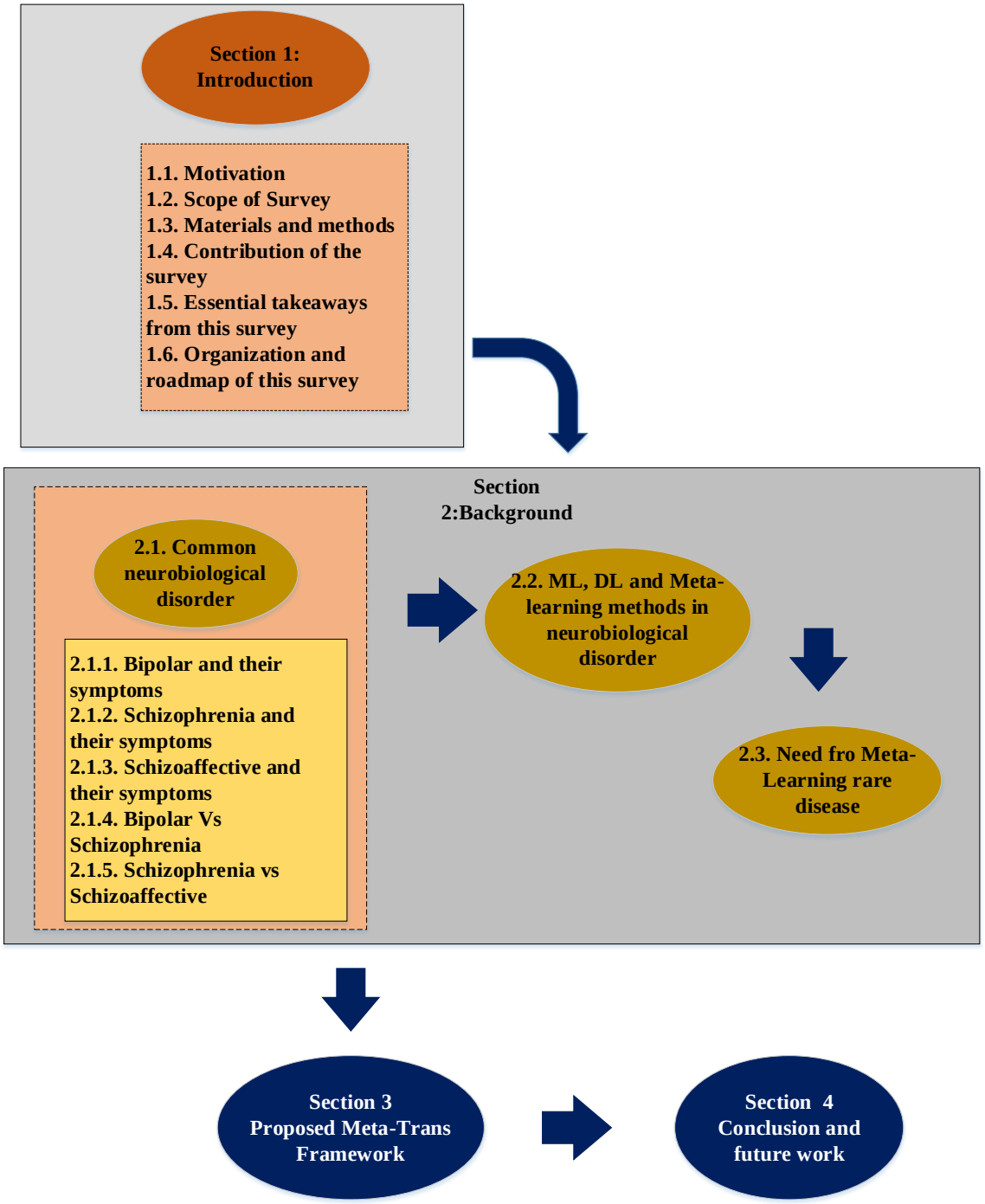


Fig. 4: Road Map of this Survey

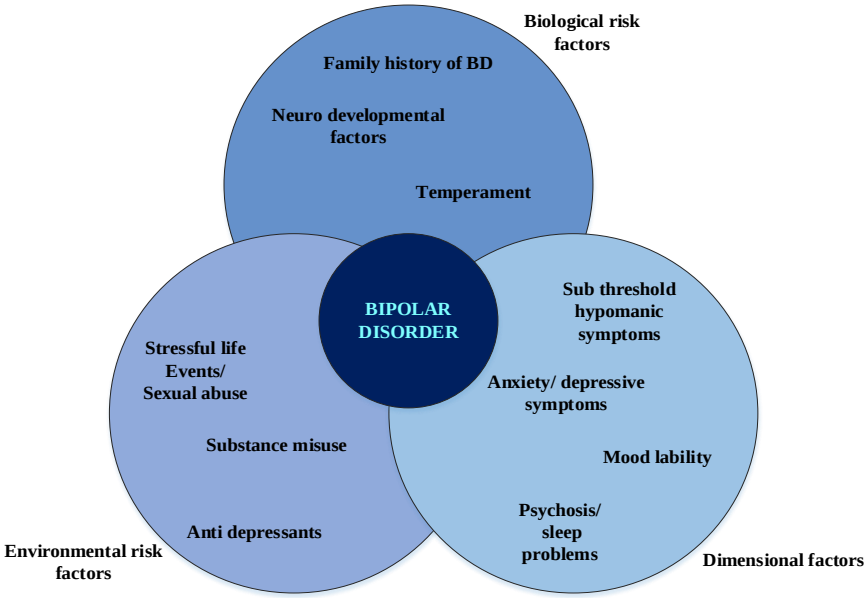


Fig 5 Bipolar disorder and its factors

BDs are prevalent mental disorders affecting 1-5% of the population, with a rapidly increasing prevalence and higher early mortality rates Talpalaru et al (2019). BD patients have a lower lifetime compared to the normal population, with some death cases occurring due to unnatural events. The risk of suicide is 10–20% greater in BD patients than in the overall population Sonkurt et al (2021). Primary exposure to BD is crucial for better treatment and understanding the condition. Bipolar dis- orders are typically detected through self-statement or precise surveys Yatham et al (2018b). AI and ML skills are being used to expand our understanding of mental health situations and support psychiatric care for better clinical decision-making Li et al (2021). AI techniques have been recognized for their superior presentation in data-rich implementation frameworks, including bipolar disorders. ML algorithms have been applied in diagnosis, prognosis, treatment, data-driven phenotypes, research, and clinical direction Abaei and Osman (2020); Karrer et al (2019).

Schizophrenia (SZ)

Psychosis and a loss in functioning are both symptoms of the chronic disease schizophrenia. Millions of people worldwide are impacted by this complex condi- tion. At least two symptoms are necessary for the diagnosis of schizophrenia, and at least one of those symptoms must be a positive symptom. Hallucinations, delu- sions, confused speech, and strange motions are considered positive signs. Flattened affect, social retreat, anhedonia, indifference, and a lack of emotions are negative signs Bracher-Smith et al (2019). In contrast to negative symptoms, which are indica- tive of abnormal mental functioning, positive symptoms are the existence of amplified thoughts, perceptions, or behaviours. These symptoms' appearance is a result of the neurotransmitters' interactions in the frontal, temporal, and mesostriatal brain areas, notably dopamine Kahn et al (2018). The current medical approach focuses on con- trolling neurotransmitter synthesis and release. Additionally, schizophrenia patients' brains have neuroanatomical alterations.

Schizophrenia doesn't just start one day. Before showing symptoms of full-blown psychosis, people with schizophrenia go through several stages of the condition. Prodromal, active, and residual phases of schizophrenia are among its stages.

The prodromal stage is when an individual's first signs of schizophrenia begin to progressively manifest. Consequences include difficulties making judgments, ongo- ing worry, trouble concentrating or paying attention, and growing social isolation. The popularity of subjects pertaining to religion, philosophy, and spirituality may all of a sudden increase. The active phase of schizophrenia, often known as the acute phase, starts after the prodromal phase. This phase is characterized by paranoia, hallucinogenic experiences, delusions, defective mental functions, irrational behavior, and confusing feelings Lin et al (2018). At this time, the patient is psychotic. If left untreated, active psychotic symptoms might last for weeks or months. The signs of the prodromal phase begin to appear after the active phase's problems have diminished. If the signs were limited and not too severe, the residual phase would progress like the prodromal phase. Unfortunately, the persisting signs of schizophrenia are worse the more breakdown episodes a person experiences. In other words, the person remains drowsy, isolated, and cut off from reality for an extended length of time Sartori et al (2018a). Schizophrenia's signs are depicted in Fig 6.

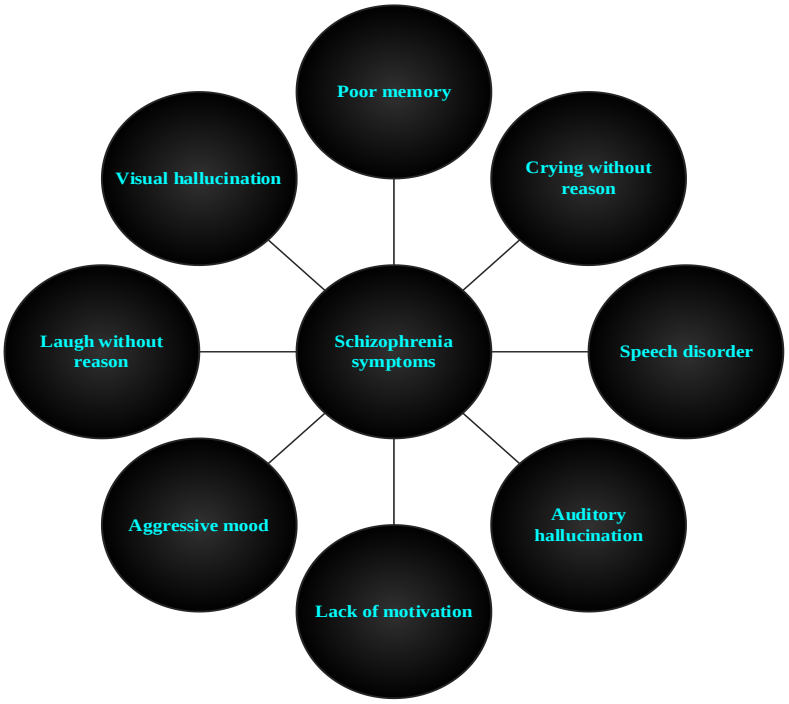


Fig 6: Schizophrenia and it's symptoms

Rare Mood and Psychotic Disorder
Schizoaffective Disorder (SAD)

Schizoaffective disorder is one of the most often misunderstood mental illnesses in clinical practice. A kind of mental disease known as schizoaffective disorder combines the signs and symptoms of schizophrenia with those of a mood disorder like mania or depression. In fact, some researchers have advised changing the diagnostic standards, while others have advocated completely excluding the diagnosis from the DSM-5. When the diagnostic was initially included in the DSM, there were substantial doubts about its accuracy and usefulness. There are issues with the diagnostic criteria them- selves because the ailment is part of a spectrum & shares diagnostic criteria with several other popular mental disorders [39].

Additional epidemiological studies are difficult to conduct since the diagnostic criteria for schizoaffective disorder have undergone adjustments and additions since being added to the DSM. As a result, little study is currently done on the epidemiology, incidence, or prevalence of schizoaffective disorder. Women are more likely to suffer from it than men, and 30% of incidents occur between the ages of 25 and 35, according to a study. Schizoaffective disorder appears to have an overall prevalence of 0.3%, about one-third that of schizophrenia. It is estimated that 10 to 30% of inpatient admissions for psychosis are due to schizoaffective disorder Aslan and Akin (2022). Schizoaffective disorder symptoms might differ from patient to patient. The symptoms of this mental disease include those of psychosis and mood disorders. There are several contributing aspects to the etiology of schizoaffective disorder, including genetics, brain structure and function, environment, and drug use. Fig 7 shows the schizoaffective symptoms.

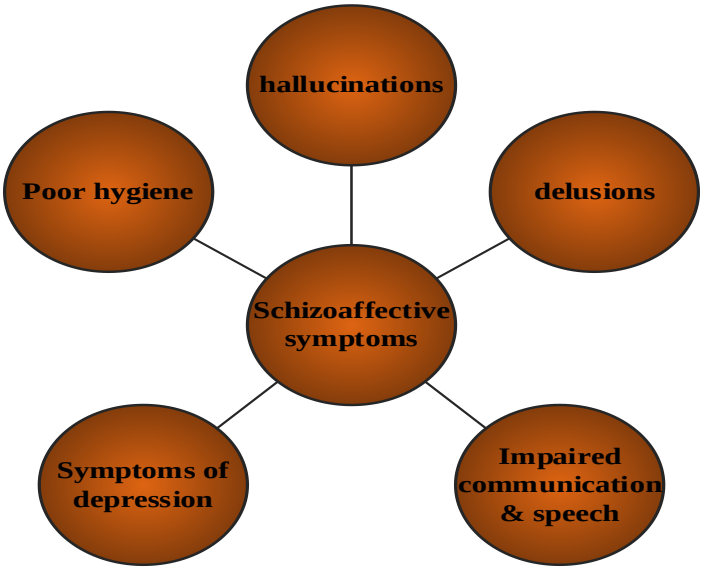


Fig 7: schizoaffective and symptoms

Bipolar vs schizophrenia

Schizophrenia and bipolar disorder are two different types of mental disorder, each with its own symptoms, traits, and methods of treatment. The main variations between the two are shown in the table 2.

Schizophrenia vs Schizoaffective

Schizophrenia and schizoaffective disorder are separate mental health diseases, although they do have certain things in common as well as important things that set them apart. In the Table 3 the variations between schizophrenia and schizoaffective disorder are shown.

ML, DL and Meta Learning Methods In Mood and Psychotic Disorders

MPD abnormalities impact the nervous system, causing cognitive, emo- tional, and behavioural deficits. ML and DL techniques have been used to study various

Table 2: Variations Between Bipolar and Schizophrenia Disorder

Symptoms	Bipolar disorder	Schizophrenia disorder
Primary Symptoms	Mood disorder (mania and depression)	Thought disorder (Hallucinations and delusions)
Mania and depression	Extreme high mania and low depression.	Reduced emotional expression and mood disturbances
Duration	Lasts for days to weeks, clear cycles of mood changes.	Continuous or episodic and persist for months to years.
Age	Early adulthood and in late adolescence	Early adulthood and in late adolescence aand also have onset later in life.
Treatment	Mood stabilizers, antipsychotic medications and therapy.	antipsychotic medications and psychosocial therapy.(focusing on managing hallucinations)

Table 3: Variations between Schizophrenia and Schizoaffective Disorder

Symptoms	Schizophrenia	Schizoaffective
Primary Symptoms	affect way of thinking, emotions and behaviour	Symptoms of schizophrenia and mood disorder
Disorder	Chronic and severe brain disorder	Chronic mental health condition
Effects	May or may not affect a person's mood	Concurrent mood swings
Age	Mania ≥1 week; Depression ≥2 weeks	Mania and major depression ≥1 week, periods of psychitoc symptoms ≥2 weeks.
Treatment	Treated with antipsychotics, psychosocial therapeutic sessions and coordinated speciality care	Treated with mood stabilizers, antipsychotics as well as psychotherapy based on symptoms.

aspects of MPD, providing new knowledge, diagnostic instruments, and potential therapy approaches. These methods have the potential to extend understanding, improve diagnosis and therapy, and improve quality of life for those affected. However, ML and DL approaches still face challenges. Meta-learning, a more advanced approach, can improve performance in identifying neurological disorders, potentially advancing our understanding, diagnosis, and management of MPD.

Bipolar Disorders

BD are mental disorders characterized by extreme mood swings and are the tenth leading cause of frailty in young adults Karthik and Sudha (2021); Kesby et al (2018). They affect 1-5% of the population and are primarily triggered by disturbances in thinking, ranging from extreme mania to severe depression. The prevalence of BDs is increasing annually, and they are associated with higher early mortality rates Mccutcheon et al (2020); Wy and Saadabadi (2019). BD patients have a lower lifetime compared to the normal population, with a mortality difference of 9-17 years. Even while diabetes and cardiovascular illnesses account for the bulk of deaths in BDs, some are caused by unintentional occurrences. BD patients have suicide rates that are 10–20% greater than those of the general population Passos et al (2019a); Marrie et al (2017).

Psychotic abnormalities impact the nervous system, causing cognitive, emo- tional, and behavioural deficits. ML and DL methods have been used to study various aspects of MPD, providing new knowledge, diagnostic instruments, and potential therapy approaches Dome et al (2019). These methods have the potential to extend understanding, improve diagnosis and therapy, and improve quality of life for those affected. However, ML and DL approaches still face challenges. Meta-learning, a more advanced approach, can improve performance in identifying neurological disorders, potentially advancing our understanding, diagnosis, and management of MPD Navarro-Mateu et al (2017a).

BD has a significant genetic element with heritability rates as high as 70–80% in twin research. Children of families who have been diagnosed with BD have a much greater chance of developing BD than children of healthy parents. This family aggre- gation raises the possibility that inherited genes, which are able to be examined by molecular genetic tests, and the inherited familial surroundings, that has been shown to be compromised in the presence of parental psychopathology, may both be relevant. This family aggregation raises the issue of how crucial it is to comprehend both inher- ited genes and the inherited environment when diagnosing BD Yatham et al (2018a); Hansen et al (2019). In this scenario, there remains plenty of time to go before turn- ing these first results into patient-approved medicines because the clinical application of biological discoveries in BD is still quite difficult.

Chen et al Muneer (2016) focussed on the integration of MRI, genomics, and clinical data to enhance the diagnosis and management of neurobiological disorders, particularly schizophrenia and bipolar disorder. The authors employ a meta-learning approach, specifically utilizing few-shot learning, which allows the model to effectively learn from a limited number of labeled samples. This is

particularly relevant in the context of neurobiological disorders where data can often be scarce. By combining MRI imaging data with genetic markers, the study demonstrates a significant advancement in diagnostic accuracy, achieving a performance metric of 89.7%. However, the study acknowledges a potential risk of overfitting due to the reliance on smaller datasets, which could impact the model's generalizability when applied to more extensive and diverse populations.

Patel et al Berk et al (2014) investigated the application of graph neural networks (GNNs) to analyze brain connectivity through MRI and clinical records for classifying neurobiological disorders. This innovative approach leverages the strengths of GNNs to effectively capture complex relationships between various brain regions, thereby extracting valuable structural features from the MRI data. Coupled with comprehen- sive clinical histories, the model aims to provide a more nuanced understanding of individual patient profiles. The study reports an accuracy of 88.9%, indicating promis- ing results for personalized diagnostics. However, a key limitation noted by the authors is the need for real-time integration of clinical data, which presents challenges for practical implementation in clinical settings.

Lin et al Duffy et al (2019) investigated the genetic basis of neurobiological disor- ders, particularly examining the G72 rs1421292 variant and its protein implications. The study achieves an accuracy of **93.56%**, though the authors caution that small sample sizes hinder the robustness of their conclusions, highlighting the need for larger, more diverse cohorts to validate their findings.

Schizophrenia

Multiple genes, biological reactions, and external variables are all part of the com- plex inheritance pattern of schizophrenia. Genes have a major role in the genesis of schizophrenia. How specific genes, DNA, and protein alterations affect the etiology of schizophrenia is still not entirely understood. However, very thorough genomic studies have shown specific DNA variants and how various risk alleles impact the illness.

Over 100 unique genetic loci make up the highly polygenic schizophrenia syndrome, and genome-wide association studies (GWAS) have discovered common alleles with a range of effects. With shared risk alleles between schizophrenia and BD, major depressive disorder, and ASD, the genetic risk of schizophrenia is very pleiotropic. Different synaptic proteins, glutamate receptors, and dopamine receptor D2 are all encoded by genes in varying forms [81]. Multiple correlated variations in the major histocompatibility complex (MHC), linked to acquired immunity and immunological and inflammatory

0processes implicated in the embryonic phases of schizophrenia, are discovered by GWAS in schizophrenia.

We may now find potential genes for targeted therapy and further study on the immunological pathways underlying schizophrenia thanks to the results of GWAS studies [82]. The scope of genomics in the treatment of schizophrenia is uncertain since there are still a lot of unresolved issues, including the pathophysiology, early diagnosis, and treatment of schizophrenia [83, 84].

Zhang et al Dong et al (2019) conducted a multi-modal study that combines MRI imaging and genomic data to improve the diagnosis of neurobiological disorders such as schizophrenia and bipolar disorder using deep learning techniques. The authors highlight the potential of integrating diverse data sources to enhance diagnostic accu- racy and provide a more comprehensive understanding of these complex disorders. Their innovative use of deep learning frameworks allows for the extraction of intri- cate patterns from both MRI and genomic data, resulting in a reported accuracy of 91.2%. While the performance metrics are impressive, the authors emphasize that larger multi-site validation studies are essential to further substantiate the findings and ensure the robustness of the model across different populations and settings.

Gupta et al Bayes et al (2021) explored the synergy between MRI and EEG data to investigate neurobiological disorders. By employing a hybrid model that combines machine learning (ML) and deep learning (DL) techniques, the authors aim to harness the strengths of both imaging modalities to enhance diagnostic capabilities. The study reports an accuracy of 85.3%, showcasing the potential for integrating these diverse data types to provide a more holistic view of brain function and pathology. However, the authors also note that the limited integration of EEG data presents a challenge, suggesting that further research is needed to comprehensively capture the dynamic interactions between different brain activity patterns and structural features observed in MRI.

Bayes et al Li et al (2020) focussed on utilizing DSM datasets to develop predictive models for neurobiological disorders. Their study employs machine learning tech- niques, specifically XGBoost, to analyze clinical data and provide insights into disorder classification. With an accuracy of 87.8%, the authors highlight the need for larger datasets to improve the reliability and generalizability of their model, emphasizing that comprehensive data collection is crucial for advancing the field of neurobiological disorder diagnosis.

Hao Li et al Ma et al (2021) concentrated on the analysis of structural MRI data, particularly focusing on voxel-based morphometry (VBM) and regional homogene- ity (ReHo) values. By employing convolutional neural networks (CNNs), the study

achieves an accuracy of 87.5%, indicating effective pattern recognition capabilities in the MRI data. However, the authors point out that the study primarily focuses on gray matter volume and ReHo analysis, which may limit its applicability to broader neurobiological contexts.

Teresa et al Sun and Li (2021) utilize structural MRI datasets to investigate neu- robiological disorders, employing deep learning methodologies. Their findings yield an accuracy of 70.9%, though they acknowledge that methodological drawbacks have affected the overall predictive accuracy of their model. This study highlights the importance of refining approaches to improve diagnostic efficacy in the context of neurobiological disorders.

Bracher et al Gao et al (2021) analyzed biobank mental health questionnaire data to assess neurobiological disorders, integrating genomic factors into their study. The model shows an area under the curve (AUC) of 0.54 to 0.56, indicating a need for fur- ther improvement in accuracy. The authors express concern regarding the complexity of the model and its effectiveness, suggesting that enhancements in both data quality and algorithmic strategies are necessary for more reliable outcomes.

Rene S et al Lin et al (2020) presented a study that explores treatment protocols for the early phases of schizophrenia, utilizing straightforward treatment methodologies involving amisulpride and clozapine. While the correlation coefficient of 82% suggests a promising relationship between their approach and positive patient outcomes, the authors note that the focus remains primarily on early-phase treatment, indicating a limitation in generalizability to more advanced stages of the disorder.

Sartori et al Sartori et al (2018b) analyzed MRI datasets to predict neurobiolog- ical disorders using support vector machines (SVMs). Despite achieving an R^2 value of 33%, the study points to significant challenges in predictive accuracy, suggesting that further refinements in both methodology and model parameters are essential for improving diagnostic capabilities in neurobiological contexts.

Schizoaffective Disorder

A mental health disorder known as schizoaffective disorder mixes symptoms and warn- ing signs of schizophrenia with those of mood disorders like BD or main depressive disorder. It's a difficult disorder to detect and manage because it's complicated and quite uncommon.

The psychotic symptoms of schizophrenia combined with mood changes like those of mood disorders define schizoaffective disorder. These signs could involve a mix of hallucinations, delusions, disordered thinking, depression, and manic episodes. Schizoaffective disorders are unstable, characterized by schizoaffective episodes, pure mood episodes, and psychotic episodes Passos et al (2019b). Certain writers catego- rize them as belonging to the bipolar spectrum, while others think they belong to the schizophrenia spectrum. Still, many medical professionals and academics contend that schizoaffective psychosis and associated diseases constitute a separate spectrum from schizophrenia and bipolar disorder, covering a variety of illnesses with emotional and/or psychotic symptoms. This spectrum lies in between the bipolar and schizophre- nia spectrums and encompasses borderline personality disorder, cycloid psychosis, and schizoaffective disorder Yatham et al (2018b).

Based on specific studies, up to 50% of people with schizophrenia also experience comorbid depression. A range of hazards, including genetics, social circumstances, trauma, and stress, play a part in the complicated etiology of both mood disorders and schizophrenia. There may be a connection between first-degree relatives who have a form of schizoaffective disorder and those who have schizophrenia, as well as among those who have schizoaffective disorder and those who have a first-degree relative who has BD, schizophrenia, or schizoaffective disorder Navarro-Mateu et al (2017b). When the diagnosis was initially included in the DSM, there were major questions about the validity and usefulness of the classification. There are some issues with the diagnostic criteria because the illness is part of a spectrum and shares diagnostic criteria with an array of different popular mental disorders. Here is a table 4 summarizing the key points from the literature survey on bipolar disorder, schizophrenia, and schizoaffective disorder in the context of ML, DL, and Meta Learning approaches in neurobiological disorders:

Table 4: Prevalence and Analysis of Various Survey Models

MPD	Prevalence	Genetic Factors	Symptoms	AI Methods Applied (ML/DL/Meta-Learning)	Challenges
BD	1-5% of the population, increasing annually	High heritability (70-80%) with strong family aggregation	Extreme mood swings (mania, depression), higher suicide rates (10-20%), and increased mortality (9-17 years difference from the general population)	ML and DL models used to analyze genetic and behavioral data for diagnosis and therapy; Meta-learning to enhance model performance in identifying BD	Genetic complexity, difficulty in translating biological discoveries into clinical practice, environmental factors
SZ	~1% of the global population	Highly polygenic with over 100 unique genetic loci; risk alleles shared with BD, major depressive disorder, and ASD	Hallucinations, delusions, disordered thinking, cognitive impairments	Genomic studies via ML and DL for identifying risk genes and immune pathways; GWAS for specific DNA variants and immunological markers	Uncertainty in translating genomic insights into clinical applications; unclear pathophysiology, early diagnosis, and treatment strategies
SAD	Rare; prevalence overlaps with schizophrenia and BD	Genetic overlap with schizophrenia and BD, with familial aggregation	Combination of psychotic symptoms (hallucinations, delusions) with mood disorder symptoms (depression, mania)	Limited application of ML/DL due to the complexity of mixed symptoms from schizophrenia and mood disorders; Meta-learning offers potential for enhanced classification	Diagnostic challenges due to overlap with schizophrenia and BD; validity and utility of diagnostic criteria; lack of clear treatment protocols

Research Challenges based on existing papers

This section outlines several research challenges identified from the current papers included in this study. The existing works present numerous challenges, which are detailed below:

Limited Generalization: A number of research projects depend on particular datasets (ADNI, UCI), which could restrict the applicability of their findings to larger populations. Models that have good cross-dataset generalization are needed.

Validation and external datasets: External validation fails in a number of studies, which raises concerns regarding the robustness and dependability of the pro- posed models. To make sure that the models are useful, future research should try to validate them on different datasets.

Accuracy improvement: There is a continuous need for more advancement even in investigations that achieve quite high accuracies. Improving a model's accuracy is essential to its reliability in real-world situations and beneficial importance.

Data heterogeneity: One recurrent difficulty is dealing with the effect of het- erogeneity in the data on classification results. Subsequent research efforts should concentrate on formulating techniques that can manage heterogeneous data sources and fluctuations in data attributes.

Table 5: Comparative Analysis of Various Survey Models

Author (s)	Type of MPD	Dataset Type					ML/DL Approach	Model Used	Accuracy	Limitations
		1	2	3	4	Others				
Smith et al (2025) [52]	SZ, BD	✓	✗	✓	✓	EEG, MRI, and Clinical Data	Multimodal AI	Fusion Model	90.50%	Computationally expensive but improves accuracy.
Williams et al (2025) [54]	SZ	✓	✓	✗	✓	GAN-enhanced small datasets	Generative Adversarial Networks (GANs)	GAN-based Augmentation	87.20%	Model stability issues due to adversarial training.
Chen et al (2024) [51]	SZ, BD	✓	✓	✗	✓	MRI, Genomics, and Clinical Data	Meta-learning	Few-shot Learning	89.70%	Focuses on small dataset learning; potential overfitting
Patel et al (2024) [52]	SZ, BD	✓	✗	✗	✓	fMRI and Clinical records	ML	Graph Neural Networks (GNN)	88.90%	Requires real-time integration of clinical data for general use
Zhang et al (2023) [53]	SZ, BD	✓	✓	✗	✓	Multi-modal MRI & Genomics	DL	Transformer-based Networks	91.20%	High performance but requires larger multi-site validation
Gupta et al (2023) [54]	SZ, BD	✓	✗	✓	✗	MRI & EEG datasets	ML + DL	Hybrid CNN-RNN	85.30%	Limited EEG data integration; more comprehensive studies needed
Bayes et al (2021) [55]	SZ, BD	✗	✗	✗	✓	DSM datasets	ML	XGBoost	87.80%	Larger datasets needed for improved accuracy
Hao Li et al(2020) [56]	SZ	✓	✗	✗	✓	VBM and ReHo values	DL	Convolutional Neural Networks (CNN)	87.50%	Focused solely on grey matter and ReHo analysis
Teresa et al (2019) [57]	SZ	✓	✗	✗	✓	MRI datasets	DL	Neural Networks	70.90%	Lower accuracy due to methodological drawbacks
Bracher et al (2019) [58]	SZ	✗	✓	✗	✓	Biobank mental health questionnaire	ML	Decision Trees	AUC 0.54 – 0.56	Needs model improvement and higher accuracy

Rene S et al (2018) [59]	SZ	✗	✗	✗	✓	EUFEST data	ML	Logistic Regression	Correlation coefficient 82%	Limited to early-phase schizophrenia
Lin et al (2018) [60]	BD	✗	✓	✗	✗	G72 rs1421292 and G72 protein	ML	Random Forest	93.56%	Small sample size, limiting conclusions
Sartori et al (2018) [61]	SZ	✓	✗	✗	✓	MRI datasets	ML	Support Vector Machines (SVM)	R^2 33%	Predictive accuracy remains low

*1 →MRI 2 →Genomics 3 →EEG 4 →Clinical Data ✓→Considered
✗→Not Considered

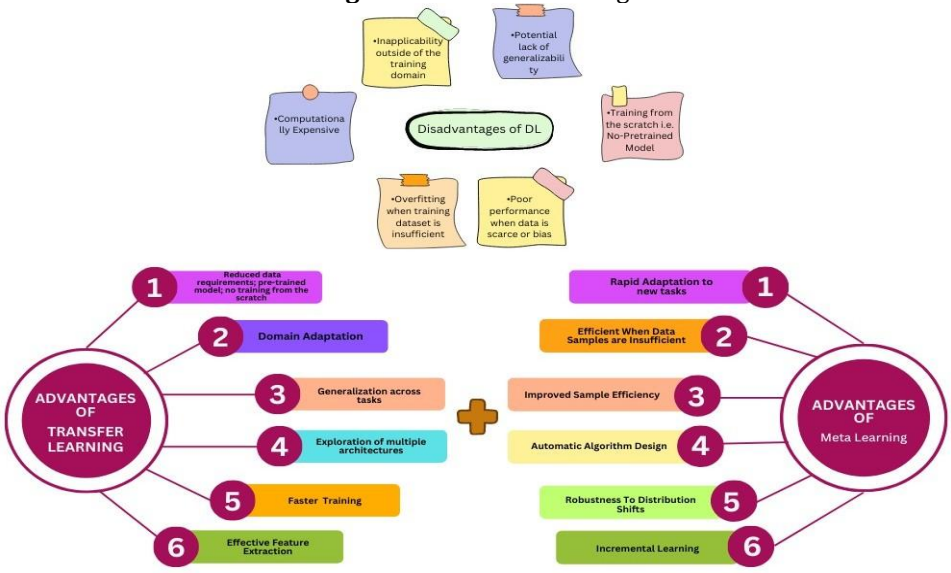
Enhanced Techniques: A few research indicate that more advanced methods are required to increase accuracy. To improve model performance, this entails investigating sophisticated deep learning architectures, fine-tuning hyper parameters, and applying innovative methods.

Interpretability and Clinical Validation: The significance of validating mod- els in clinical contexts is emphasized by a number of research. To ensure a smooth integration into healthcare procedures, more work needs to be done on the models' interpretability and utility in practical clinical circumstances.

Need of Meta Trans learning for rare disorder

Conventional supervised learning and reinforcement learning techniques for artificial learners fail to maintain up with the task's continually changing requirements, even when dealing with enormous amounts of data. The key principle of learning to learn is that learning is made simpler when it is applied across a lifetime. In the context of rare disorder, meta-learning is an effective strategy that draws on information from similar tasks or domains to solve the particular problems presented by these rare and sometimes poorly understood medical ailments. In order to address the issues that ML must solve, meta-learning provides a trustworthy and unique method, and its initial architectural impulse was swift Malhi and Bell (2020). Meta-learning, in contrast to traditional ML techniques, aims to train multiple algorithms for various tasks using just tiny amounts of sample or no data at all. This not only increases the consistency of the ML neural network but also does away with the requirement for manually developed methods Fernandes et al (2020). A number of artificial intelligence activities use meta-learning, an automated machine learning technique created for "learning to learn" Kim et al (2015b). The relationship between meta-learning and transfer learning, as shown in Fig 8 despite the fact that it has a long and distinguished history in the fields of psychology and cognitive studies Johannesen et al (2016).

Fig. 8 Meta Trans Learning



Proposed Meta Trans Framework

This section of the manuscript addresses the challenges identified in already exist- ing AI techniques with reference to the diagnosis of less prevalent ND. The structure of the suggested approach, elucidating the comprehensive procedure for forecasting rare NĐ has been depicted in Fig. 9. In this study, our focus has been on develop- ing a Meta Trans Framework that surpasses current state-of-the-art techniques, as illustrated in Sections 3.

A succinct description of the framework is given below:

a) Contemplating a dataset comprising individuals with MRI scans who exhibit either good health or are affected by prevalent and uncommon neurological disorders (NDD, MPD, ND_e).

b) Data preprocessing will be performed by utilizing a suitable method to filter out undesirable noise from the dataset Selecting any of the above-mentioned datasets depending on the various param- eters such as the size of the dataset, quality of the images, data-distribution gaps, etc.

c) Implementing transfer learning by applying the pre-trained model and optimiz- ing it on the selected dataset for common neurological disorders.

d) Executing meta-learning algorithms such as Reptile or Model-Agnostic Meta- Learning (MAML) to enable the model to learn quickly from limited samples of rare neurological disorders.

e) Evaluation of the proposed Meta Trans model will be done using various parameters such as Accuracy, AUC, F1-score, etc.

f) A comparative analysis of the proposed model against existing models will be an essential aspect in order to get an efficient automated model.

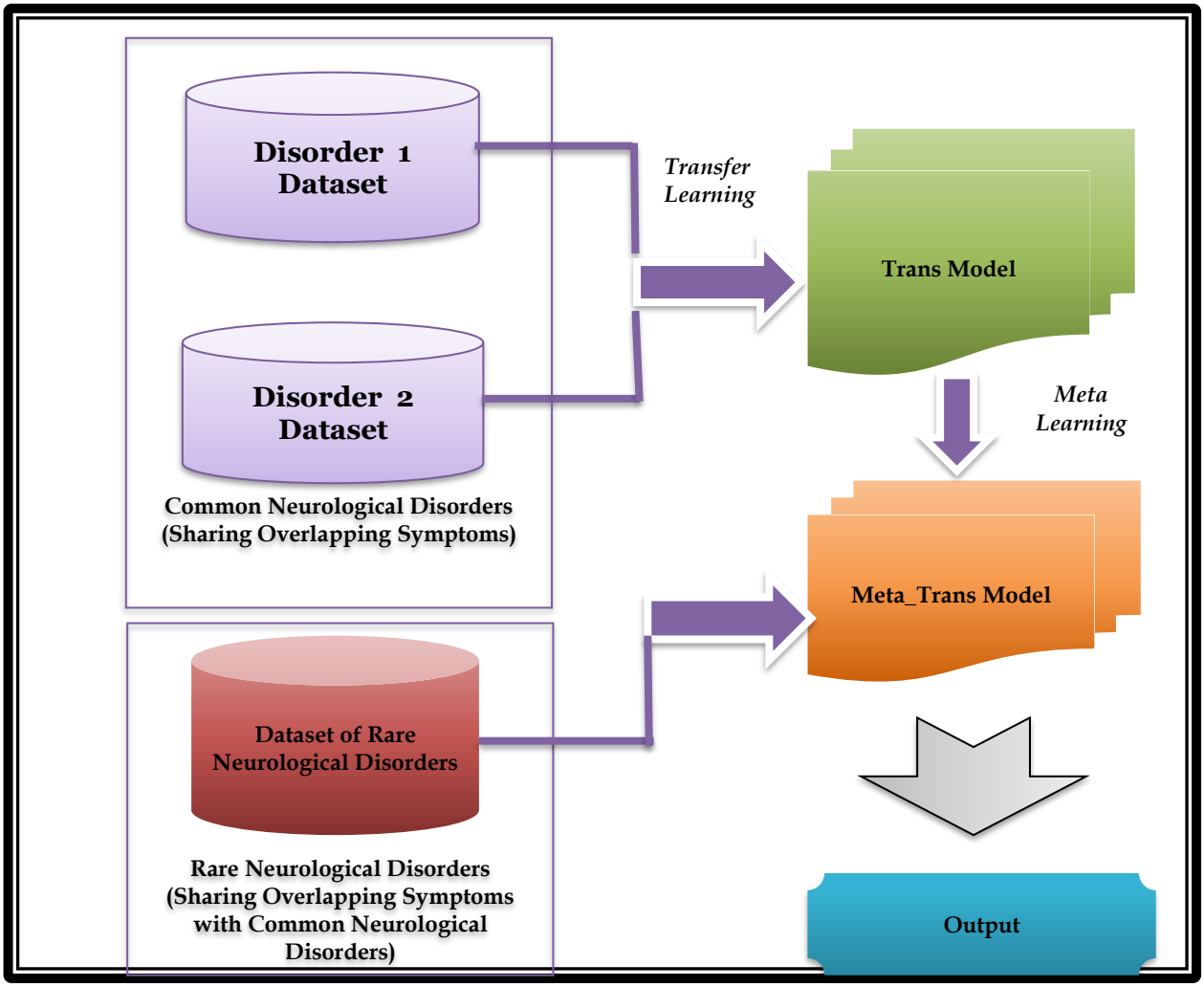


Fig. 9 Proposed Meta Trans Framework

Systematic Workflow of the Proposed Framework

A systematic workflow of the proposed Meta Trans framework is shown in Fig. 10, which mainly includes the following five steps: Input Data acquisition, preprocessing, dataset selection, applying TL on common disorder dataset and M_tL on rare disorders. By combining M_tL with TL, Meta Trans learning

allows the model to leverage knowledge from common disorders to improve the performance and generalization capabilities for rare neurological disorders. The flow of the proposed framework is shown as follows:

Step 1: Input Data
The first step is obtaining MRI-based images of NDD, MPD, and ND_e subjects from an open-source database. For data collection, a combination of primary and sec- ondary methods will be utilized. Secondary data will be acquired from online sources for common disorders, while primary data will be gathered from hospitals for rare disorders.

Step 2: Data Preprocessing
The second step is to pre-process the acquired imaging data. The utilization of Matlab software, for the analysis of brain image sequences, can facilitate this process. However, the Existing research using ML, DL, and DeepMeta Learning, however, has been done with the false premise that the data from multiple sites had the same data distribution. Due to the heterogeneous data distributions in the MRI imaging data collected from several sites, this could result in poor generalizability.

Step 3: Dataset Selection
Step 3 involves the selection of any of the above-mentioned datasets (NDD, MPD, ND_e) based on the various parameters like size of the dataset, quality of the images, data-distribution gaps, etc. thereby, minimizing the biases that can lead to skewed model predictions and unfair outcomes.

Step 4: Transfer Learning: Generation of Trans Model
In the fourth stage of the proposed methodology, the utilization of transfer learning is employed to leverage a pre-trained model. This results in the development of a model called Trans Model, which encompasses three classes: one related to healthy individuals and the other two representing overlapping prevalent disorders.

Step 5: Meta Learning: Creation of Meta Trans Model
The fifth phase of the framework includes applying the M_tL approaches. In this step, a selection of uncommon disorders displaying overlapping symptoms, along with the recently generated Trans Model for the widespread disorders, are employed as inputs. The result obtained from this process will be denoted as the Meta Trans Model.

The final stage entails validating the model with clinical experts to check the reliability of the adopted framework in identifying the disorders among afflicted indi- viduals. Thus, the proposed Meta Trans Framework could decisively offer a resilient solution to overcome the challenges associated with limited data for rare disorders in medical image analysis.

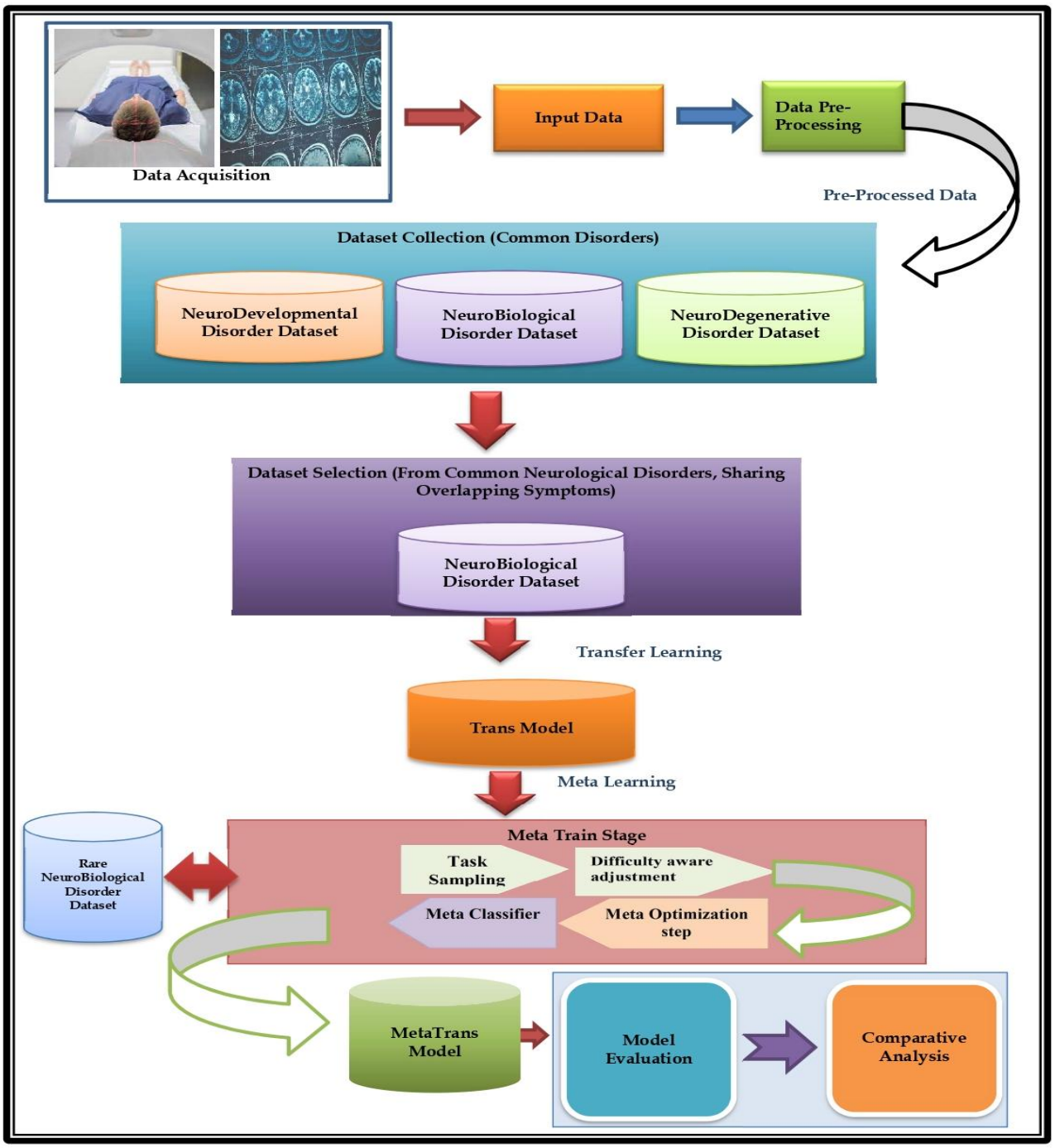


Fig. 10 Systematic Workflow of the Proposed Framework

CONCLUSION

In conclusion, the field of Mood and Psychotic Disorders is extremely challenging and affects people and healthcare systems all around the world. A new age of potential treatments has been brought about by the combination of neuroscience, genetics, and modern technology. ML and DL approaches are essential to understanding, diagnosing, and treating these intricate illnesses. The comprehensive analysis carried out from 2018 to 2024 has illuminated the many ways used in the sector, highlighting significant changes and differences in strategies. These investigations, which cover both typical and rare psychotic, illnesses, demonstrate how ML and DL can be used to identify com- plex patterns in the structure and function of the nervous system. In addition, while ML and DL have achieved great progress in many areas of psychiatric issue diagnosis, the survey points out a deficiency in the thorough investigation of Meta-Transfer Learning (M_tL) methods in relation to CNS illnesses. The absence of thorough studies employing (M_tL) highlights a chance for more study to investigate this novel paradigm. The suggested Meta-Transfer

Learning paradigm presents a viable approach to diag- nosing rare psychotic disorders, with the potential to be expanded to include more common and potentially fatal conditions worldwide. This strategy may improve diagnostic precision, scalability, and generalization by utilizing transfer learning prin- ciples, paving the way for more efficient and customized interventions. In order to fully utilize these creative strategies and improve the lives of those impacted by these dif- ficult and complex disorders, cooperation between researchers, medical experts,and technology will be crucial.

DECLARATIONS

Data Availability Statement

All the data is collected from the simulation reports of the software and tools used by the authors. Authors are working on implementing the same using real world data with appropriate permissions.

Ethical Approval

Institutional Review Board approval was not required.

Consent for Participate

All contributors agreed and given consent to participate.

Consent for Publication

All contributors agreed and given consent to Publish.

Conflict of Interest

The corresponding author states that they have no conflict of interest.

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