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Deep And Machine Learning in Psychology- A Survey of Depression Detection, Diagnosis, and Treatment Progress

T. Srajan Kumar[1], Dr. M. Narayanan[2], and Dr. Harikrishna Kamatham[3]

[1]Research Scholar, Department of CSE, Malla Reddy University, Hyderabad, India.
[2] Professor, Supervisor, Department of CSE, Malla Reddy University, Hyderabad, India
[3] Associate Dean, Co-Supervisor, Department of CSE, Malla Reddy University, Hyderabad, India

Correspondence should be addressed to T. Srajan Kumar; 2232CS010020@mallareddyuniversity.ac.in

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ABSTRACT- Recent research focuses on mental health and brain informatics. Emerging technologies like AI, deep learning, and machine learning drove the advancements. Customizing, diagnosing, and treating depression with data-driven approaches could improve mental health care. A growing field, precision psychiatry uses cutting-edge computer tools to provide tailored mental health care. AI in precision psychiatry is examined in this paper. Complex formulations aid therapy. These tools can identify and treat mental health patients. They can customize therapies for most patients. Unsupervised learning algorithms have shown considerable sadness-related sickness disparities. These methods separate diagnostic categories. Artificial intelligence could help us suggest drugs based on facts, not group averages. Our findings show that data-driven paradigms in healthcare face several challenges. Surprisingly, none of the survey studies reveal how current procedures improve patient outcomes. Standardizing field terminology, forming diverse research teams, evaluating models, identifying flaws, and making datasets accessible are crucial. Randomized controlled trials must show that computer algorithms improve patient outcomes to make models more feasible.

KEYWORDS: Psychiatry, Artificial intelligence, Depression, Deep learning, Neural networks, Treatment response prediction

I. INTRODUCTION

Mental illness affects Australian healthcare. Government financing for inpatient mental health treatment seems inadequate. Coronavirus psychological effects may increase mental health service demand. Modern data-driven algorithms can diagnose mental health illnesses early to satisfy therapy demands. Deep, AI, and machine learning may improve mental health. These innovations improve precision medicine. Precision medicine values patients over demographics. New precision medicine offers customized mental health services. Customization usually requires "precision psychiatry". AI, machine learning, and big data are treating mental illness quickly. Brunn et al. [6] found 250% more psychiatric and AI Pub Med papers in 2015–2019.Future mental health care will use AI. Many psychiatrists agree. A global survey by Dorai Swamy et al. [7] found that many psychiatrists feel AI will impact their field. Practitioners disagree on AI's medical impact. Many psychiatrists believe AI can't treat patients. A minority believes AI can diagnose and forecast better than psychiatrists. While medical professionals vary on AI's disruptive potential, most say mental health doctors won't be replaced by AI. Data-driven informatics may enhance depression diagnosis, detection, and therapy. We must realize this: Mentalists' customized and sympathetic care may never be replaced by AI.Machine learning and deep learning recognize patterns. The above strategies may reveal mental health trends. Carrillo et al. [10] found that a Gaussian Naive Bayes classifier could distinguish healthy controls from depressed patients with an F1-score of 0.82. The procedure examined transcription. Due to its challenges, depression diagnostic systems may help psychiatrists detect mental illness. Medical disorders have symptoms, but not mental sickness. Psychopathology is challenging to diagnose without markers. Current diagnostic procedures are evaluated since patients with the same ailment may have diverse symptoms. Depression subgroups and diagnoses are found unsupervised. Drysdale et al. [11] used hierarchical clustering, an unsupervised learning method, to investigate functional connectivity among depressed patients to examine depression variation. Supervised approaches dominate this discipline, while unsupervised methods can find new relationships. Using fMRI, Drysdale et al.[11] discovered four depression biotypes. Research reveals biotypes respond differentially to rTMS. Therapeutic responses may distinguish each category as an illness. This study suggests AI can create diagnostic taxonomies.Personalize mental health diagnosis and therapy with modern technologies. Trial and error helps doctors pick the best antidepressant. The groundbreaking Chang et al. [16] study shows doctors can predict antidepressant side effects before prescribing. They found that ARPNet can anticipate side effects before treatment. Technology may improve patient-specific care. AI simulated human functions.This early research advanced symbolic AI. The symbolic AI study used language-like representations for logic. The bulk of AI researchers have abandoned symbolic AI. Artificial neural networks dominate pattern recognition. Most contemporary neural network research uses Rosenblatt's perceptron. Technology has expanded these networks for deep learning. The number of hidden layers in an artificial neural network is "depth" in "deep learning". Definitions of "deep" neural networks differ. Sheu says deep neural networks comprise input, hidden, and output layers. Contemporary researchers must identify numerous buried layers before calling a network deep neural.This essay calls machine learning, neural networks, and deep learning AI. Machine learning uses all non-neural network methods, regardless of complexity. Linear regression, nearest neighbor, and logistic follow. Artificial neural networks and deep learning will be interchangeable owing to uncertainty. Figure 1's concept map aids comprehension. This picture summarizes depression detection, diagnosis, and therapy prediction.

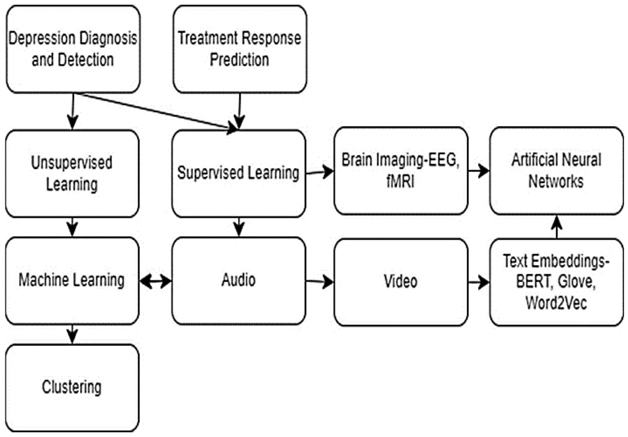

Figure-1: Depression detection, diagnosis, and therapy prediction.

This essay explains how machine learning and deep learning can help with mental health diagnosis, treatment, and identification. Therefore, this article helps:

- This study examines the data types and methodologies used by scientists to detect, diagnose, and predict mental health therapy outcomes.
- This research examines current computational approaches to mental health diagnosis, identification, and treatment prediction. Include feature-development-friendly software repositories.
- This study covers the methodological and technical problems associated with precision psychiatric research.
- Reflection on field issues and potential solutions to inform future research.

II. INFORMATICS PARADIGMS FOR DEPRESSION DIAGNOSIS AND DETECTION

Psychiatry research has prioritized statistical inference. Inferential statistics emphasizes distributions. Inference "creates a mathematical model of the data generation process" to formalize understanding or verify a system's behavior. Statistical inference uses a few variables to explain group differences. Predictions about a target variable work best with larger datasets. Pattern recognition and prediction are machine learning-related. Common patterns must be identified to make an individual mental health disorder prediction. Increased computer processing power has made deep learning models more popular.

A. Machine learning for depression diagnosis

Social media's massive text corpus helps machine learning identify depression quickly. Detecting depression from social media posts requires supervised learning. Studies that use self-report or psychometric testing to confirm depression in patients are reviewed. Variable preprocessing is needed for depression detector model input. NLP preps text for machine learning. NLP converts speech to numbers. Processing techniques include LIWC, Affective Norms for English Words, LabMT, LDA, n-grams, and bag-of-words. Quantify text with n-grams and bag-of-words. Simple text bag-of-words counts word frequency. These simple methods have worked many times. Audio-visual systems use processed audio aspects in recent developments. Most depression detection methods are text-based. De Choudhury et al. [21] pioneered Twitter depression prediction. Twitter posts labeled sad persons like depression was validated by crowd sourced volunteers and psychological diagnostic assessments. Each group completed the self-report Center for Epidemiological Studies Depression Study. Diagnostic results identified depressed and non-depressed ground truth. Some instances confirmed depression using surveys, others self-reported. Early depression diagnosis methods were developed by De Choudhury et al. [21] The shortcomings of self-report questionnaires inspired De Choudhury et al. [21] to create an objective depression measure. Text analysis tools for early depression and word usage was dictionary-based. Systems used psychometrically ordered hard-coded word dictionaries. Doctors mostly utilized this to compare depressed and non-depressed language use. Early text analyzers included Language Inquiry and Word Count. Human raters' text analysis before LIWC was worthless, expensive, and emotionally taxing for judges. The same writing rarely has different ratings. Thus, computational solutions are faster and more reliable.Depression researchers used the LIWC to compare depressed and healthy language. [21] found that an SVM classifier could predict a depressive episode 12 months ahead using LIWC and Twitter behavioral data. Similar to how Tsugawa et al.[22] diagnosed Japanese depression using Twitter data and language factors. Tweet themes predict mood and depression, say Tsugawa et al. [22]. Identified text passage subjects using sentiment, twitter, and LDA and obtained an F1-score of 0.46. Depression was found in both surveys. A text corpus from self-reported depression was created by Hassan et al. [17] SVM and linguistic characteristics gave depression system an F-score of 0.81. Class sentiment analysis fits LabMT and ANEW. One machine learning classifier can employ valences of every word in these dictionaries. LabMT lists 5,000 popular Twitter phrases. Comparison: ANEW lists term valences. These research tools are configurable. Shen et al. [39] built VAD with ANEW. The VAD method by Shen et al. [39] revealed textual emotions.Reece et al. [23] etected Twitter depression signals using random forest classifiers. A psychiatric questionnaire confirmed depression. 0.644 F1 Reece et al. [23] reported supporting computerized depression diagnosis. According to Islam et al., [24] NNs can detect depression using all LIWC factors. Table 1 shows this survey's classifications. Based on participant health reports, some detection algorithms label ground truth. All Pirina-Ultekin research Islam co-authors Shen and Tadesse [22] claim depression. Pattern matching determined "I have depression," in these trials. Label depression posts for supervised learning. Psychologists and surveys never assess depression with these datasets. Expect some mistagged samples in the collection. Researchers find depression detection and diagnosis techniques in big datasets.Established link between speech and mental health. Audio features assess sound, while text features focus on speech. Before applying depression detection system auditory characteristics in classification models, signal processing is needed. Open-source speech processing repositories like COVAREP and openSMILE extract features. FAUs analyze visual data similarly.The FAUs "objectively describe facial muscle activations." Table 1 clearly shows depression diagnosis validation technique performance differences. These data raise doubt on self-reporting. Present methods neglect self-reported data uncertainty. Mental health data is subjective, making ground truth classifications difficult. Future studies should account for data uncertainty with Bayesian Neural Networks (BNN).

Table 1 Detection systems and their features

Researcher	Method	Features	Dataset	F1-score
McGinnis et al [25]	Logistic regression and linear SVM	Zero crossing rate, Mel frequency cepstral coefficients and the Z-score of the power spectral density	DASS-42	-
Tadesse et al. [22]	SVM	LIWC, LDA and Bigram	Pirina and Çöltekin	0.91
Islam et al.[24]	Coarse KNN	LIWC	DSM-5	0.71
Reece et al.[23]	Random Forest	LIWC, LabMT, ANEW and Unigram	Twitter	0.61
Hassan et al. [17]	SVM	N-gram, POS tagger, Sentiment Analyser and Negation	LabMT	0.81
Shen et al [39].	Multimodal dictionary learning	LIWC, VAD, LDA, word2vec and Twitter behaviour data	NHI Database	0.85
Deshpande and Rao [40]	Multinominal Naive Bayes	Bag-of-words	Twitter Data set	0.83
Tsugawa et al. [22]	SVM	Bag-of-words, LDA, sentiment analysis + user specific information	Twitter Data set	0.46
De Choudhury et al. [21]	SVM	ANEW,LIWC and Twitter behaviour data	Twitter	0.68

B. Hand-Crafted Features, Text Embeddings, And More: Artificial Neural Networks And Deep Learning

The above technologies have worked well for depression detection systems. Feature selection is crucial to machine learning model building. It takes time and effort to create these features. Thus, subsequent methods aim to automate selection. Deep learning algorithms can learn feature representations without complex feature selection. More recently, deep learning has identified depression using text, audio, and visual cues. Similar to machine learning, deep learning uses labelled samples to identify patterns between depressed and non-depressed people. Unlike traditional machine learning, deep learning algorithms rarely require handcrafted features. Advanced deep learning algorithms that use textual data need word embeddings to understand text. Embeddings represent text vector-wise. These vector representations help deep learning algorithms extract data features Neural word embeddings like Word2Vec, Global Vectors for Word Representation, and transformer-based architectures like Google's Bidirectional Encoder Representation from Transformers are increasingly used in depression research to numerically represent text for deep learning models.Deep learning has not been widely used to assess psychopathology. Several factors may have delayed the adoption of these strategies. Concerns include deep learning model prediction's lack of openness.

These issues have led some to oppose deep learning models for critical health decisions. preferring conventional methods for clearer predictions. Despite model transparency issues, deep learning models outperform conventional machine learning methods in depression detection. The Cong et al. [42] system used XGBoost and an Attentional Bidirectional LSTM (BiLSTM). They assessed their work using the Reddit Self-Reported Depression Dataset (RSDD;) The authors found an F1-score of 0.60 compared to many systems on the same dataset, including a LIWC-featured SVM. As mentioned, self-report data is effective but has major drawbacks. Even with an effective system design, a dataset trained on a self-reported sample may not be suitable for clinical use. Rosa et al. [43] developed a deep learning method to identify anxious or depressed users. Their study used 27,308 tagged Facebook messages. The scientists found that their CNN BiLSTM-RNN with SoftMax performed best at identifying depressed users. They outperformed Random Forest and Naive Bayes in sad user identification with an F1-score of 0.92 and a precision of 0.9. However, their publication does not explain response labeling or participant selection. As mentioned earlier, study participant recruitment methods greatly affect model performance.Thus, textual data are often used to identify mental health issues. Multimodal data is being used to diagnose depression, building on text-based algorithms. 621 interviews were collected for the Distress Analysis Interview Corpus (DAIC;), automated agent, teleconference, and in-person interviews. The dataset includes text, voice recordings, physiological data (ECG), and psychological questionnaire scores. Alhanai et al. [44] mixed audio and transcripts to categorize depression using a neural network. They trained two independent LSTM models on text and audio features. Each model was trained with different weights and hyper parameters. The outputs from these two models were then combined and sent to an additional LSTM layer. Alhanai et al [44] .found that the best model used text and audio to achieve an F1score of 0.77. demonstrating how integrating different data types improves model performance.

Chen et al. [26]. automated prenatal depression diagnosis using deep learning. They used popular social media platform WeChat in the system's architecture. Researchers selected participants using the Edinburgh Postnatal Depression Scale from a physician pool. They built their work using LSTM neural networks [57]. This paper claims their findings are consistent with the EDPS's in their sample, but they provide little data.

Table 2 Deep learning and neural network

Researcher	Deep learning architecture	Feature types	Dataset	F1-score
Kabir et al. [24]	BERT, DistilBERT	BERT	DEEPTWEET	
Ansari et al. [41]	LSTM with Attention	GLoVE, SenticNet	Reddit, CLPsych 2015, eRisk Dataset	0.77
Wani et al. [48]	CNN, LSTM	Word2Vec, TF-IDF	COVID-19 Data Set.	0.99
Nemesure et al. [49]	Stacked ensemble	Electronic health records; demographic and medical	MDD Data Set	
Wan et al. [48]	Hybrid EEGNet	Resting state EEG	RCTs	0.95
Ray et al. [50]	BiLSTM	Audio, text and visual	DIAC	
Rosa et al. [43]	CNN, BiLSTM and RNN with SoftMax		MEDLINE and PsycINFO	0.92
Tadesse et al. [22]	MLP	LIWC, LDA and Bigram	Pirina and Çöltekin	0.91
Alhanai et al. [44]	LSTM	Audio and text	DIAC	0.77
Cong et al. [42]	XGBoost and attentional-BiLSTM		RSDD	0.6
Chen et al. [26]	LSTM		PSD	
Yang et al. [27]	Deep CNN and DNN	Audio and video	AVEC '17	

Table 2 summarizes the surveyed deep learning model-based depression detection systems. This table relies heavily on text. According to, the literature has progressed from handcrafted features to complex neural word embedding models. In data science, powerful text embedding models are becoming the standard. Future research should involve interdisciplinary teams that use cutting-edge data science methods. There are few deep learning systems that simulate depression treatments, but their use in diagnosing depression is increasing. Although advanced deep learning networks are increasingly being used in research, their lack of transparency has several practical implications. Deep learning systems can detect, but they cannot explain or justify their classification of research participants. Because "black box" models cannot be interpreted by humans, argue that they should not be used in high-risk industries such as healthcare.

C. Data-driven informatics and unsupervised learning discover new diagnostic categories:

In contrast to objective disorder measurements, psychiatry employs research-based diagnostic labels. The majority of literature acknowledges the difficulties associated with diagnosing mental health disorders. The subjective nature of mental health diagnoses is a weakness. Categorial psychopathology descriptions disregard within-group variation for specific conditions. Fried and Nesse identified 1030 distinct symptom profiles among 3703 clinical depression patients in the Sequenced Treatment Alternatives to Relieve Depression (STAR⋆ D) trial. According to Fried and Nesse, "Acknowledging that major depressive disorder is not one coherent condition with a single cause might reduce dissatisfaction with the diagnostic criteria of major depressive disorder,"Categorical diagnostic systems treat conditions as binary. Disease entities are classified as either present or absent. Neuroimaging has been used to distinguish healthy and depressed patients. Yang et al. [27] discovered that the left dorsolateral prefrontal cortex was less active than the prefrontal cortex when resting. Recent advances in AI pattern recognition enable the identification of disease subgroups. Pattern recognition is an example of unsupervised learning. In contrast to supervised tasks, unsupervised algorithms "identify inherent groupings within the unlabeled data". Unsupervised algorithms can identify groupings that go beyond diagnostic labels. Drysdale et al. [11] used hierarchical clustering, an unsupervised learning method, to identify four depression subtypes and propose new diagnostic criteria. Their method classified patients based on fMRI connectivity. Additional research revealed that these subtypes could predict rTMS treatment efficacy, whereas symptom-only models failed to predict treatment response as well as the machine learning classifier. These findings suggest that depression could be a combination of conditions rather than a single disease. Kuai et al. [45] recently investigated how brain computing can construct and test prediction models based on different brain states. According to Kuai et al [45], hypothesis testing validates causal findings, making brain mapping superior to other mental health approaches. Future brain computing research may confirm brain structure differences among people with the same diagnosis.This section discussed the possibility of depression subtypes and other underlying conditions. Patients should be aware that these depressions respond differently to treatment. As a result, data-driven mental health treatment decisions have been thoroughly investigated. Personalized medicine and psychiatric treatment customization research have grown concurrently. The use of machine learning algorithms to predict patient treatment response prior to intervention is a growing field.

III. PREDICTING DEPRESSION TREATMENT RESPONSE WITH LEARNING SYSTEMS

Treatment outcomes for mental health disorders are rarely consistent. Conventional research focuses on successful group-level interventions. As previously stated, current studies demonstrate significant symptom heterogeneity among people with the same diagnosis. Thus, a diagnosis alone cannot direct treatment. Categorical diagnostic systems are heterogeneous, so patients with the same condition react differently to treatment. Major depressive disorder highlights treatment challenges as well as response and remission rates. Initial antidepressant treatment is expected to result in 25-33% remission. This does not imply that patients will never recover. Approximately 67% of patients who try multiple antidepressants experience remission. As a result, assigning treatments to maximize success is optimal. There is no standard method for prescribing medications, so doctors must experiment to find the most effective one.A more effective approach is to identify intervention responders prior to treatment. This method targets treatments to the patients who will benefit the most. Precision psychiatry aims for this. AI-powered precision psychiatry would enable doctors to go beyond diagnostic classifications and provide patient-specific car. Treating each patient individually has numerous advantages. If a patient's response to treatment can be predicted before it starts. Thus, less time will be spent on ineffective treatments. Saving time reduces financial and mental stress for both patients and healthcare providers.

A. rTMS response prediction

According to research, repetitive transcranial magnetic stimulation (rTMS) can help treat depression. rTMS is clinically beneficial when compared to a control, but it is not effective for all patients. Berlim et al. [46] discovered a 19% remission rate and 30% response rate to rTMS in their meta-analysis. Fitzgerald et al. [28] discovered a 46% response rate and a 30% remission rate in their pooled sample analysis. According to Koutsouleris et al. [31] rTMS's variability is a significant barrier to its widespread use. This section describes data science methods for identifying rTMS treatment responders and non-responders. concentrating on individual patient treatment response prediction systems. These treatment response prediction systems rely on supervised learning, genetics, phenomenology, neuroimaging (MRI, EEG, fMRI), and multiple variable combinations.Fitzgerald et al. [28] observed a bimodal response to rTMS. This pattern distinguishes rTMS responders and nonresponders. Conventional inferential statistical methods revealed that no single variable distinguished respondents from nonresponders. This statistical flaw works in favor of artificial intelligence and machine learning. Advanced methods can consider a variety of factors and recommend a course of action. In cases where a single variable cannot distinguish between responders and non-responders, combinations of variables can. These advanced methods allow you to combine data from various sources. Researchers have recently used advanced machine learning to identify rTMS responders. Table 3 summarizes the EEG and fMRI studies. Table 4 summarizes the common EEG features used in this survey's models.Bailey et al. [29] .investigated the predictive power of working memory-related EEG measurements after discovering a link between working memory and depression. Models were developed based on MADRS scores, working memory test results, reaction times, and EEG data. Theta gamma coupling, power, and connectivity were measured using EEG. We computed connectivity using the weighted Phase Lag Index (wPLI;).Chen et al. [26] used MRI connectivity features to investigate connectivity and rTMS responses. Chen et al. [26] utilize functional connectivity maps as SVM regression features. Hopman et al. [47] trained a linear SVM on fMRI connectivity features from the subgenual anterior cingulate cortex, frontal pole, superior parietal lobule, lateral occipital cortex, and central opercular cortex. Fivefold cross-validation yields a training accuracy of 97%, but model performance on a held out test set averages 87%, with a 95% confidence interval of 100%-70. An SVM model with 30 features from has an F1-score of 0.93 and a balanced accuracy of 91%. These measures were based on an average of 200,000 fivefold cross-validation iterations, with strong internal validity. To build on these preliminary findings, used a linear SVM and resting EEG features before and after one week of rTMS treatment to predict depression response. Using 54 features and 5000 iterations of fivefold cross-validation, the study achieved 86.6% balanced prediction accuracy. The 54 features consisted of quantitative EEG signals Alpha Power, Theta Power, Alpha Connectivity, Theta Cordance, Individualized Alpha Peak frequency, and MADRS questionnaire measures.

Table 3 rTMS treatment response prediction

Author	Condition	Features	Algorithm
Chen et al. [26]	Depression	Resting state MRI	SVM regression
Hopman et al. [47]	Depression	Resting state fMRI	Linear SVM
Bailey et al. [29]	Depression	EEG and MADRS	Linear SVM
Hasanzadeh et al. [14]	Depression	EEG	K-NN
Zandvakili et al. [30]	Depression and post-traumatic stress disorder	EEG	Lasso regression and SVM
Bailey et al. [29]	Depression	EEG	Linear SVM
Koutsouleris et al. [31]	Schizophrenia	–	Linear SVM
Drysdale et al. [11]	Depression	fMRI	Hierarchical clustering and SVM
Rostami et al. [14]	Unipolar and bipolar depression	Clinical and demographic	Binary logistic regression

Table 4: EEG feature summary

Feature	Description
Cordance	The sum of z-transformed absolute and relative power for a frequency band
Coherence	Coherence is a measure of correlation between signals. Contextualised, coherence is operation-alised as a measure of functional connectivity between brain regions.
Power	A measure of the activity in a frequency band
Theta gamma coupling	Research has shown a relationship between theta gamma coupling and deficits in working memory
Weighted Lag Phase Index (wPLI;	A measure of functional connectivity

PTSD and depression patients can predict their rTMS response using machine learning. Zandvakili et al. [30] odeled treatment prediction using lasso regression, unlike Bailey et al. [29] Alpha EEG coherence was used to create the lasso prediction model. Coherence measures signal correlation. Coherence contextualizes brain region functional connectivity. The model predicts a percentage decrease in the Inventory of Depressive Symptomatology-Self-Report (IDS-SR; and Post-Traumatic Stress Disorder Checklist-5 (PCL-5;). This is done with a regression model. Minimum 50% reductions are clinical responses. From continuous questionnaire score reduction predictions, classifications are made. A model can accurately predict a 60% IDS-SR reduction for 65%. Zandvakili et al. [30] predicted IDS-SR response and classified PCL-5 response using alpha coherence with AUC values of 0.83 and 0.69. Due to their low specificity (approximately 50%) and high sensitivity (approximately 100%), these results may produce many false positives.Pretreatment EEG characteristics predicted rTMS response. A 50% reduction on the Beck Depression Inventory (BDI;) or Hamilton Rating Scale for Depression (HRSD;) was the response. A balanced 46-patient sample responded and remained silent. K-NN was applied to EEG features and Power of Beta to find the best single feature model. This model achieved 91.3% classification accuracy using leave-one-out cross-validation. Best multifeature model maintained power measurement accuracy across all four bands (Delta, Theta, Alpha, and Beta) as Beta-only model. In contrast, the model with every power feature was sensitive and specific. Hasanzadeh et al [14] their EEG-only pretreatment system is better than multi-measurement.Only one deep learning algorithm predicts rTMS responders. Erguzel et al.[33] xamined quantitative EEG for treatment response using an artificial neural network. The primary predictive model used QEEG cordance. This partially supports Bailey et al.'s [29] claim that cordance can be an input feature. The correlation between treatment responders and nonresponders is supported by more evidence. Most EEG papers use handcrafted signal processing. Recent studies show that an innovative deep learning CNN can directly process EEG data. Future researchers can optimize the data pipeline by directly entering EEG data into networks.Some depressed people may benefit from rTMS, research shows. Further research suggests rTMS may treat schizophrenia. Koutsouleris et al. [31] predicted schizophrenia rTMS response using linear SVM. Twenty-five principal components were identified by structural magnetic resonance imaging and principal component analysis. Koutsouleris et al. [31] used the positive and negative syndrome scale to define response. Unlike depression, schizophrenia causes delusions, hallucinations, and positive symptoms. Schizophrenia treatments work if the positive or negative symptoms subscales (PANSS-NS or PANSS-PS) improve by 20%. Thus, positive or negative symptoms determine treatment response. In active treatment, cross-validated models identified responders and non-responders with 85% accuracy. Leave-one-site-out validation reduced balanced accuracy to 71%, as predicted by Koutsouleris et al. [31] l.demonstrate machine learning algorithms' universality. Large amounts of data may allow advanced computing to treat psychiatric disorders.The research community is interested in patient-level responder prediction. EEG is still the most common neuroimaging characteristi, but fMRI and MRI are rising. Power, cordance, and connectivity (wPLI) are important EEG measurements. MADRS depression rating scales are also included. These findings support Lee et al, who used machine learning algorithms to predict depression and bipolar disorder treatment outcomes. The present study used SVM most often to distinguish rTMS treatment responders from non-responders. Many studies report excellent predictive performance, but most use cross-validation. One group was excluded from pseudo-external validation. To validate the model across multiple sites, one site was omitted from training. Strangely, this model performed poorly on a non-training website. Streamlining fMRI, MRI, and EEG data preparation for deep learning models is possible. Future preprocessing automation may eliminate the need for manually developed features.

IV. DISCUSSION: CHALLENGES AND OPPORTUNITIES

Precision psychiatry is gradually adopting NLP, machine learning, and deep learning. This paper advises psychiatrists and data scientists on unresolved issues and current methods that need more research.AI enables precision psychiatry by predicting treatment response. Intervention efficacy is supported by treatment response prediction. Antidepressants are chosen by trial and error. Treatment response prediction moves from trial and error to evidence-based treatment. The literature review examines pharmaceutical interventions and rTMS-predicted single patient responses. These systems use any demographic, clinical, or neuroimaging characteristi. Jaworska et al [34] found neuroimaging characteristics outperformed clinical and demographic characteristics. "Clinical symptoms alone were not strong predictors of rTMS treatment responsiveness at the individual level," Drysdale et al. [11] This matches their findings. Neuroimaging systems consistently identified rTMS and drug-based treatment responders. Certain concerns must be addressed before clinical implementation of these systems.

A. Challenges and limitations

Our survey found several literature themes that researchers should consider. The reviewed research shows excellent treatment response, detection, and diagnosis prognosis. Despite the positive findings, none of the studies showed improved patient treatment outcomes. Over the past decade, surveys have examined customized psychiatry. Data scientists and mental health professionals must work together more to ensure patient outcomes from this research. Existing systems are flawed and impractical.

B. Model validation: the need for external validation

Many of the survey studies discussed above outperform current practice-based standards in predicting treatment response. However, clinical implementation of these research systems is difficult. Model validation is the main implementation barrier, according to the papers.Two studies use multiple sites, while two others evaluate models using independent data. Machine learning systems need strict validation for industrial use. Internal validation or k-fold cross-validation is used by most cited papers. The widely cited work of Harrell. [37] presents a hierarchy of validation methods to predict model performance on novel data. The best method in this hierarchy is independent research team validation of new data. Reporting only the best model iteration. Harrell Jr. says k-fold cross-validation repeated iterations is best for internal validation. Transitioning to predictive models requires model validation. According to Frohlich et al. [38], predictive artificial intelligence models need robust internal validation, external validation on independent data, and empirical validation in clinical trials.Browning et al. [36] ecommend randomized control trials to validate model performance before clinical adoption. Few surveyed papers have included randomized control trials of their systems, and none have evaluated their models using independent data. External depression model validation is difficult without public data. OPEN datasets let scientists test their models across samples with one dataset. This is done with ADNI datasets, which provide a solid Alzheimer's research pipeline. External validation researchers receive data.

C. Small sample sizes and greater data access

Data access and sample sizes summarize each evaluation aspect. Depression detection data is more accessible than treatment response prediction data. AVEC, DIAC, and social media text are accessible. Data lets computer scientists and researchers compare systems using identical datasets. Access to data and small sample sizes hinder patient treatment response prediction research. Chen et al. [26] propose a cloud-based mental health data repository, but it would require a lot of infrastructure.Neuro imaging is increasingly used to predict treatment response. Due to small sample sizes, the surveyed articles have few labeled treatment response prediction examples. This paper's sample sizes are listed in Table 3. Except for, most studies have sample sizes under 150, supporting Arbabshirani et al. [35] According to Arbabshirani et al. [35] small sample results are difficult to generalize to the entire patient population. Small samples can overestimate a system's predictive power. Small sample sizes reduce statistical power, Due to publication bias, only the published literature can determine the theoretical maximum effectiveness of AI systems in precision psychiatry. Small sample sizes increase the likelihood of over fitting, causing researchers to overestimate model efficacy.

Expanding personalized psychiatry research requires larger datasets. Few depression datasets are public. Open data helped the Alzheimer's Disease Neuro imaging Initiative succeed. Birkenbihl et al. [36] found over 1300 articles citing the ADNI dataset. No similar depression data exists. While Chen et al. [26] proposed promising large-scale cloud-based solutions, more research is needed.

D. Future trends and opportunities

Over the past decade, mental health care technology has advanced due to research. Depression detection and diagnosis are shifting from machine learning algorithms to complex deep learning architectures. Transformer-based embeddings like BERT are replacing n-grams and bag-of-words in text classification. Deep learning architecture for treatment response prediction changes less. This field uses SVM despite using quantitative data like MRI, fMRI, and EEG. Few methods feed deep learning algorithms raw neuroimaging data like EEG. Deep learning accelerates data preparation and learns treatment response prediction feature representations.

E. Causal artificial intelligence

Recent survey trends suggest a shift from hypothesis testing to AI pattern recognition. Randomized controlled trials and hypotheses prove causality, but predictive methods don't. Some people mistake pattern recognition for causation, but warn that "exclusively relying on predictive models of AI in fields as diverse as health care, justice, and agriculture risks catastrophic consequences when correlations are misconstrued as causation."Artificial intelligence-based causality determination would revolutionize precision psychiatry and depression research. Some medical fields are using deep learning to prove causality. Wang et al.'s [42] [45] Deep Causality model identified 20 drug-induced liver disease causes using electronic health records. Kuai et al. [45] showed that brain mapping could help scientists link brain activity to depression severity.

F. New technologies and automating data pipelines

Practitioners increasingly use BERT, GloVe, and Word2Vec to generate depression detection text. Transformer-based word embeddings boost data pipeline efficiency. Wan et al. [42] and other data scientists have more opportunities to develop neuroimaging data processing methods. CNNs excel at sequence data, and features could allow networks to process neuroimaging data without preprocessing.Most mental health disorders are diagnosed by clinician questionnaires or self-report. Psychopathology has no objective biomarkers .Due to this challenge, text, audio, and visual depression detection have been extensively studied. Speech content, not visual or auditory cues, predicts mental health disorders best. Depression diagnosis algorithms range from basic to advanced machine learning. Most of this survey focused on dementia detection. Large text collections and public datasets like AVEC and DIAC have accelerated this progress.

G. Uncertainty quantification

Additional research is needed to fully account for model construction uncertainty before clinically applying the AI systems under review. This includes aleatoric (data) and epistemic (model) uncertainty. Ground truth labelling methods affect depression detection systems, demonstrating aleatoric uncertainty. Self-reported ground truth labels decreased performance. Current methods ignore self-reported uncertainty. These models need a confidence level for their predictions to be widely used to inform treatment decisions. Data uncertainty and prediction confidence are supported by new Bayesian neural networks. Complex models require more effort to understand their internal mechanisms. The lack of transparency in deep learning model prediction is concerning. Some oppose deep learning models for critical health decisions due to these concerns. Scientists want precise, interpretable predictive models.

V. CONCLUSION

I'm excited about machine learning and AI changing psychiatry. This article describes how scientists diagnose and treat depression. Although we tried to include all relevant literature in this survey paper, data science is advancing rapidly. This article evaluates current AI applications in psychiatry.Over the past decade, mental health care technology has advanced due to research. Depression detection and diagnosis are shifting from machine learning algorithms to complex deep learning architectures. Transformer-based embeddings like BERT are replacing n-grams and bag-of-words in text classification. Deep learning architecture for treatment response prediction changes less. This field uses SVM despite using quantitative data like MRI, fMRI, and EEG. Few methods directly feed deep learning algorithms EEG or other neuroimaging data. Deep learning accelerates treatment response prediction by acquiring feature representations.Treatment response systems have small sample sizes and model validation deficiencies. Due to small sample sizes, Section 3's treatment response prediction systems are difficult to extrapolate. This problem could be solved by using larger, more accessible datasets like Alzheimer's disease data pipelines insufficient sample sizes can cause model overfitting [4]. Model validation challenges prevent widespread adoption of such systems. A clinical trial for predicative AI models should include strong external, internal, and empirical validation, according to Frohlich et al. [38] Internal validation is the main focus of this review, which is much less than implementation. Future studies should use larger datasets and randomised control trials to advance personalized psychiatry into clinical practice. Healthcare professionals and artificial intelligence researchers should collaborate to accelerate innovation and improve patient outcomes.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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