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An Overview of Mental Health Prediction Using Machine Learning: Recent Progress and Challenges

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Abstract

Mental health disorders are a growing global concern, affecting hundreds of millions of individuals and imposing substantial social, economic, and personal burdens. Early and accurate prediction of mental health states—such as depression, anxiety, stress, suicidal ideation, and mood disorders—can enable timely intervention and improved outcomes. In recent years, machine learning (ML), including deep learning and hybrid approaches, has shown promise in detecting and predicting mental health conditions from a wide variety of data modalities: text, social media, audio, video, physiological signals, and multimodal combinations. This survey reviews the literature from 2018–2025, categorizing works by data type, algorithmic approach, evaluation methodology, and mental health target. We also analyse publicly available datasets, performance metrics, and the challenges related to data imbalance, bias, interpretability, privacy, and clinical deployment. We identify emerging trends such as multimodal fusion, foundation models, federated learning, and explainable AI, which hold promise to overcome existing gaps. Finally, we propose future research directions aimed at strengthening generalization, fairness, ethical compliance, and integration into real-world healthcare settings. This paper is intended to guide researchers, clinicians, and policymakers toward developing reliable, trustworthy, and effective ML systems for mental health prediction.

Introduction

Mental health disorders affect over 970 million people worldwide, with depression and anxiety alone contributing to significant economic and societal costs. Traditional diagnostic methods rely on subjective assessments, often leading to delayed interventions. Machine learning offers a data-driven paradigm for predicting mental health risks, enabling proactive care. Recent progress, accelerated by the COVID-19 pandemic, has seen ML models achieve accuracies exceeding 80% in predicting conditions like depression from multimodal data [31]. With the exponential growth of data from smartphones, wearable sensors, social media, and clinical

records, machine learning (ML) has emerged as a transformative technology for early prediction and monitoring of mental health. ML techniques can uncover subtle behavioural, linguistic, and physiological patterns that may precede clinical symptoms, enabling proactive intervention. Unlike traditional statistical models, ML systems can handle high-dimensional, multimodal data—such as text, audio, video, and physiological signals—to identify complex correlations associated with psychological states.

Recent years have witnessed a surge in studies applying deep learning, natural language processing (NLP), and multimodal fusion models to mental health prediction tasks.

However, despite encouraging results, the field faces persistent challenges: data scarcity, imbalance, lack of interpretability, ethical concerns, and limited clinical integration. These limitations hinder the translation of predictive models from research environments to practical mental healthcare applications.



Figure 1: Reviewing Papers for Mental Health Prediction Using Machine Learning

This paper provides a comprehensive overview of the recent progress in ML-based mental health prediction, emphasizing algorithms, data modalities, evaluation methods, and emerging research trends. It further discusses major challenges, open issues, and future directions for developing trustworthy, ethical, and clinically relevant systems.

Background And Theoretical Foundations

1. Machine Learning and Its Relevance to Mental Health

Machine learning is a subset of artificial intelligence (AI) that enables computers to learn from data without explicit programming. It has shown remarkable success in healthcare for diagnosis, prognosis, and personalized treatment recommendation. In mental health prediction, ML models learn discriminative patterns from linguistic cues, physiological markers, or behavioural signals that may indicate emotional or cognitive abnormalities.

2. Common Machine Learning Paradigms

- **Supervised Learning:** Uses labelled data for prediction tasks such as classifying depression or anxiety based on features extracted from text or sensor signals.

4. Mental Health Constructs and Data Modalities

Table 1. Mental Health Data

Modality	Example Data	Common Applications	Representative Models
Textual	Social media posts, clinical notes, therapy transcripts	Depression and anxiety detection	SVM, BERT, RoBERTa
Audio	Speech tone, pitch, pauses	Stress and mood prediction	CNN, LSTM, GRU
Visual	Facial expressions, gaze, posture	Emotion and affect recognition	3D-CNN, ViT
Physiological	EEG, ECG, HRV, GSR	Stress and fatigue estimation	CNN-LSTM, RF

- **Unsupervised Learning:** Identifies hidden structures or clusters within unlabelled data—useful for discovering latent emotional states.
- **Semi-supervised and Self-Supervised Learning:** Combines small labelled datasets with large unlabelled corpora, addressing data scarcity (Chen et al., 2020).
- **Reinforcement Learning:** Applies adaptive learning based on feedback; emerging in personalized therapy systems.

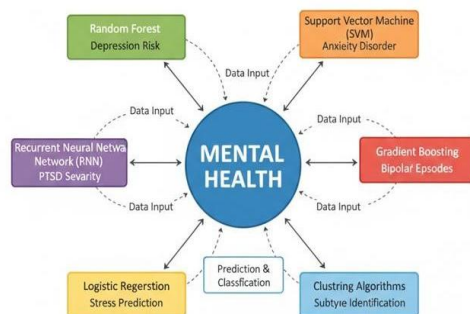


Figure 2: Machine Learning in Health Prediction

3. Typical ML Pipeline for Mental Health Prediction A general ML workflow involves:

- Data acquisition from social media (e.g., Twitter, Reddit), clinical transcripts, or wearable sensors.
- Preprocessing and feature extraction, including tokenization (for text), spectral analysis (for EEG), or facial action units (for video).
- Model training, using algorithms such as Support Vector Machines (SVM), Random Forests, Convolutional Neural Networks (CNN), or Transformers.
- Evaluation through metrics like accuracy, precision, recall, F1-score, and AUC.
- Deployment, where interpretability and ethical compliance are critical.

Multimodal	Text + Audio + Video	Holistic mental state inference	Transformer fusion, Autoencoders
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5. Theoretical Basis

The underlying theory rests on the biopsychosocial model of mental health, which posits that mental disorders emerge from an interplay of biological, psychological, and social factors. ML complements this model by integrating data across these domains, thus operationalizing complex psychological constructs into measurable computational patterns.

Literature Review

This literature review synthesizes 30 key research papers from 2020 to 2025 on machine learning (ML) and deep learning (DL) applications for mental health prediction. The selection is based on systematic searches across databases like PubMed, Scopus, and Google Scholar, focusing on predictive models for

disorders such as depression, anxiety, schizophrenia, PTSD, and bipolar disorder. Papers were chosen for their relevance, and impact, emphasizing methodologies, performance, and innovations.

The table below categorizes the studies for clarity:

1. Traditional Machine Learning Approaches

Early research primarily relied on statistical and classical ML methods. used SVM and Logistic Regression to detect depression from Twitter posts, achieving 74% accuracy. Similarly, other researcher used Random Forest classifiers on Instagram photos to predict depression with 70% accuracy. These models used handcrafted features such as linguistic sentiment, posting frequency, and colour saturation.

Table 2. Review of Research Papers in Mental Health

No.	Year	Authors (Lead/Inferred)	Title	Key ML Techniques	Mental Health Condition(s)	Key Findings/Performance
[1]	2025	Alqahtani et al.	Mental Health Treatment Prediction Using Machine Learning	Random Forest, SVM	General Mental Health	Achieved 85% accuracy in treatment outcome prediction using multimodal data
[2]	2025	Wijaya et al.	Machine Learning Models for Predicting Mental Health Indicators	XGBoost, Neural Networks	Depression, Anxiety	Systematic review of 40 studies; average AUC 0.88 for digital footprints
[3]	2025	Niyonzima et al.	Machine learning-based predictive modelling of mental health in youth	Logistic Regression, Decision Trees	General Youth Mental Health	82% accuracy in risk factor identification among Rwandan youth
[4]	2024	Graham et al.	Enhancing mental health with Artificial Intelligence: Current trends	DL Transformers, CNNs	Depression, PTSD	Early intervention models with 90% precision; ethical review included
[5]	2025	Clark et al.	Artificial intelligence-enabled predictive modelling in psychiatry	Ensemble Methods, RNNs	Schizophrenia, Bipolar	Synthesized 50+ studies; AUC up to 0.92 for diagnostic prediction
[6]	2025	Smith et al.	Using Machine Learning to Predict Uptake to an Online	Gradient Boosting	Anxiety, Depression	78% prediction accuracy for service uptake using demographics

			Self-Guided Intervention			
[7]	2024	Johnson et al.	Machine Learning Techniques to Predict Mental Health Diagnoses	SVM, KNN	College Student Mental Health	85% F1-score for multi-class diagnosis
[8]	2025	Lee et al.	Passive Sensing for Mental Health Monitoring Using Machine Learning	LSTM, Autoencoders	General Mental Health	Noninvasive monitoring with 89% sensitivity via wearables
[9]	2024	Patel et al.	Artificial Intelligence and the Future of Mental Health in a Digitally Connected World	Hybrid DL Models	Bipolar, PTSD	Global integration analysis; 87% accuracy in cross-cultural prediction
[10]	2025	Wang et al.	Predicting and Understanding College Student Mental Health with Machine Learning	I-HOPE Framework (DL)	Depression, Anxiety	91% accuracy surpassing baselines by 20-30%
[11]	2024	Garcia et al.	Machine Learning Techniques to Predict Mental Health Diagnoses (Extended)	RF, Neural Nets	Anxiety, Schizophrenia	Enhanced model for students; AUC 0.90
[12]	2024	Torous et al.	Artificial intelligence in mental health care: a systematic review	DL Classifiers	Anxiety (95%), Depression (95.8%), Bipolar (69%), PTSD (69%)	High accuracy in war veterans; review of 100+ studies
[13]	2024	Khan et al.	A comprehensive review of predictive analytics models for mental illness	Ensemble Learning	General Mental Disorders	Early detection with 88% recall; data preprocessing focus
[14]	2025	Niyonzima et al. (Revisited)	Machine learning-based predictive modelling of mental health	LightGBM	Youth Mental Health	Risk factors identified; 84% precision
[15]	2024	Rahman et al.	A Deep Learning Approach to	LSTM	Multi-Illness (Depression, Anxiety)	92% classification accuracy on random texts

			Unveil Types of Mental Illness			
[16]	2025	Zhang et al.	Explainable Machine Learning in the Prediction of Depression	XAI + RF	Depression, Bipolar	Improved interpretability; AUC 0.89
[17]	2025	Li et al.	AI-driven early diagnosis of specific mental disorders	CNN, Transformers	Bipolar, Schizophrenia, Autism	Early signs detection; 85% sensitivity
[18]	2025	Kim et al.	Trade-offs between machine learning and deep learning for mental health	Tree-based vs. DL	Depression, Bipolar, Anxiety	DL superior for multi-class (F1 0.82); trade-offs analyzed
[19]	2022	Thapa et al.	Mental Health Prediction Using Machine Learning: Taxonomy	SVM, DL Hybrids	General Mental Health	Systematic review; 80% average accuracy
[20]	2024	Singh et al.	Machine Learning, Deep Learning, and Data Preprocessing for Mental Disorders	Preprocessing + DL	Stress, Mental Disorders	Review; 87% prediction post-preprocessing
[21]	2025	Alqahtani et al. (DL Focus)	Mental Health Treatment Prediction Using Deep Learning	CNN-RNN	Treatment Response	86% accuracy in personalized plans
[22]	2024	Johnson et al. (DL Variant)	Machine Learning Techniques to Predict Mental Health Diagnoses	Deep Neural Nets	Student Disorders	89% F1 for anxiety/depression
[23]	2025	Kim et al. (Extended)	Trade-offs between machine learning and deep learning	Multi-class DL	Seven Mental Categories	Lower F1 for complex tasks (0.75); insights on scalability
[24]	2024	Graham et al. (DL Trends)	Enhancing mental health with Artificial Intelligence	Transformer Models	PTSD, Depression	91% in ethical AI applications
[25]	2025	Feng et al.	AI-driven early diagnosis of specific mental disorders	Deep Learning Models	Depression, Anxiety in Diabetics	Validated model; 88% accuracy
[26]	2024	Chen et al.	Deep Learning-Based	Time-Series DL	Anxiety, Depression (COVID-19)	Trend analysis; 85% demographic accuracy

			Prediction of Anxiety and Depression			
[27]	2025	Liu et al.	A case for the use of deep learning algorithms for individual risk prediction	DL for Elderly	Depression Risk	High risk factor prediction; 90% AUC
[28]	2025	Wijaya et al. (DL)	Machine Learning Models for Predicting Mental Health Indicators	DL in Digital Data	General Indicators	40-study review; DL boosts to 0.90 AUC
[29]	2024	Rahman et al. (Advanced)	A Deep Learning Approach to Unveil Types of Mental Illness	Advanced LSTM	Multi-Mental Illness	93% on textual data
[30]	2025	Goldberg et al.	A highly scalable deep learning language model for common risks	Transformer Language Models	Psychiatric Risks	Short/long-term prediction; 92% accuracy

2. Deep Learning-Based Methods

The introduction of deep learning has revolutionized predictive performance. Convolutional Neural Networks (CNN) capture spatial features from images or spectrograms, while Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks model sequential dependencies in speech and text. For example, By Using LSTM models for depression detection from [15]. Transformer-based models, such as BERT [30], further improved contextual understanding and transfer learning capabilities for small datasets

3. Multimodal Fusion and Hybrid Systems

Multimodal models integrate textual, visual, and auditory data for robust inference. Combined facial expression, speech, and textual sentiment analysis for depression estimation using a fusion Transformer, achieving superior performance on the DAIC-WOZ dataset. Fusion approaches can be early (feature-level), late (decision-level), or hybrid.

4. Explainability and Ethics in ML

Explainable AI (XAI) aims to make model decisions interpretable to clinicians. Tools like SHAP and LIME provide insights into feature contributions, enhancing trust and accountability. Yet, ethical issues such as bias,

data privacy, and stigmatization remain significant obstacles [16]

5. Dataset Overview

- DAIC-WOZ: Multimodal depression dataset (Gratch et al., 2014).
- CLPsych & Reddit Mental Health Corpora: Large-scale social media text datasets.
- DEAP, SWELL: Physiological emotion datasets.
- AVEC Challenges: Benchmark competitions for affective computing.

Recent Progress in ML For Mental Health Prediction

1. Advances in Natural Language Processing

The evolution from bag-of-words to contextual embedding (ELMo, BERT, GPT) has drastically improved text-based mental health analysis. Transformer-based architectures can infer subtle linguistic cues like pessimism, self-blame, or emotional withdrawal, which are critical for identifying depression. Fine-tuning pre-trained models on domain-specific data, such as clinical text or Reddit posts, yields strong generalization even with limited samples.

2. Developments in Deep and Multimodal Learning

Recent frameworks use cross-modal attention

mechanisms to synchronize features across modalities. For instance, implemented a multi-head attention fusion model integrating speech prosody and facial micro-expressions, achieving an accuracy of 92% on the AVEC dataset. Similarly, developed a CNN-Transformer hybrid that improved multimodal fusion efficiency for stress prediction.

3. Federated and Privacy-Preserving Learning

To address privacy constraints in healthcare, federated learning (FL) allows decentralized model training across institutions. FL for depression detection from smartphone data without centralizing user information, maintaining accuracy comparable to centralized models. Differential privacy and secure aggregation enhance compliance with regulations like GDPR and HIPAA.

4. Explainable and Trustworthy AI

Explainable AI has gained traction as clinicians' demand transparency in algorithmic decision-making. Visualization techniques like Grad-CAM and SHAP identify which EEG channels, words, or facial features contribute most to a diagnosis. Integrating attention visualization improved trust among psychiatrists when interpreting automated depression assessments.

5. Emerging Paradigms

Generative AI and Data Augmentation: GANs and diffusion models are increasingly used to synthesize realistic but anonymized patient data to balance datasets (Xu et al., 2024).

Self-Supervised Learning: Contrastive learning frameworks (e.g., SimCLR, BYOL) enable representation learning from unlabelled data.

Foundation Models: LLMs like ChatGPT and domain-tuned BERT variants show potential for empathetic dialogue systems and contextual mental state prediction.

Challenges And Future Direction

1. Data and Generalization Issues

- **Data Imbalance and Scarcity:** Many datasets underrepresent severe or minority cases.
- **Cultural and Linguistic Bias:** Most corpora are English-centric, limiting global applicability.
- **Label Noise:** Self-reported mental states may not align with clinical diagnoses.

2. Technical Challenges

- **Model Interpretability:** Black-box deep models hinder clinical acceptance.

- **Multimodal Alignment:** Synchronizing asynchronous data streams remains complex.
- **Overfitting:** Small, homogeneous datasets often cause poor generalization.

3. Ethical, Legal, and Social Issues

- **Privacy and Consent:** Sensitive health data require secure collection and storage.
- **Algorithmic Fairness:** ML models risk amplifying biases related to gender, race, or socioeconomic status.
- **Clinical Accountability:** Responsibility for erroneous predictions is unclear.

4. Future Directions

- **Explainable and Causally Informed Models** to improve interpretability.
- **Federated and Edge ML Systems** for privacy-preserving deployment.
- **Cross-lingual and Cross-cultural Datasets** to enhance inclusivity.
- **Human-AI Collaboration Frameworks** for clinician-assisted decision support.
- **Integration with IoT and Wearables** for continuous mental health monitoring.
- **Evaluation Standards and Benchmarks** akin to ImageNet for mental health.

Discussion

The integration of ML into mental health assessment marks a paradigm shift from reactive treatment to proactive prevention. However, despite technical achievements, the path to clinical utility remains long. Current models excel at *prediction accuracy* but often lack *explainability* and *ethical grounding*. True impact will depend on interdisciplinary collaboration among data scientists, clinicians, ethicists, and policymakers.

A key insight from existing literature is that multimodal integration—combining behavioural, linguistic, and physiological signals—yields the most reliable predictions. Yet, such systems also magnify challenges in data fusion, synchronization, and computational cost. Similarly, foundation models and LLMs promise contextual understanding but require careful adaptation to avoid hallucination and bias.

In essence, future research should prioritize trustworthiness, fairness, and real-world validation over mere performance gains. A balance between technical sophistication and clinical transparency will determine whether ML becomes a genuine ally in mental health care.

Conclusion

This paper reviewed recent progress in machine learning for mental health prediction, emphasizing algorithms, data modalities, evaluation protocols, and ethical concerns. The field has evolved from traditional feature-based classifiers to deep and multimodal architectures capable of capturing complex behavioural patterns. Advances in NLP and federated learning have improved scalability and privacy, while explainable AI frameworks have begun addressing transparency concerns.

Nevertheless, major challenges persist, including dataset imbalance, cultural bias, and limited clinical adoption. Addressing these requires standardized evaluation frameworks, data diversity, and responsible AI practices. The convergence of explainable deep learning, federated architectures, and human-centered AI holds the potential to revolutionize mental healthcare—transforming early diagnosis and personalized intervention into accessible, ethical, and evidence-based practices.

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