

Research Article

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Machine Learning-Based Prediction of Depression In Women: A Scoping Review

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ABSTRACT

Background: Depression is a complex mental health disorder characterized by persistent feelings of sadness, loss of interest, and impaired daily functioning. Depression has been proven to affect women at a higher rate compared to men, with several studies providing evidence for this gender disparity. Fighting mental diseases like anxiety and depression especially in women has become a global concern. In the drive to find effective and efficient ways to combat this, machine learning techniques have been included in the healthcare systems for the possible diagnosis and prediction.

Methods: Employing PRISMA-ScR guidelines, we employed a review to investigate the application of machine learning techniques to predict depression among women. A comprehensive review of five hundred and twenty peer-reviewed studies on depression from 2015 to 2025 were conducted and then narrowed down to sixteen that has to do with depression in women only. The review identifies several well-known models for forecasting depression, models like Decision tree, Naïve Bayes, Logistic Regression (LR), Artificial Neural Network (ANN), XGBoost, Random Forest (RF), Support Vector Machine (SVM).

Results: Random Forest showed promising performance in the reviewed studies, but its superiority and clinical utility require independent validation. There are still need such as the requirement for larger and more varied datasets, the need to consider the diversity of mental health conditions, and the requirement to include longitudinal data to capture temporal dynamics.

Discussion: This review while demonstrating the fact that machine learning models especially Random Forest show strong predictive capabilities for depression in women, data variety and gender-specific feature integration have a significant role to play. The result emphasized on the significance of multimodal data integration and to improve reliability as well as applicability, it is of note that future research pay attention to using larger datasets and gender sensitive modelling.

Conclusion: The application of machine learning in the prediction of depression in women offers the potential forecasting detection, personalized interventions and enhanced outcome among the gender.

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List Of Abbreviations

ML: machine learning

EEG: electroencephalogram

RF: Random Forest

NN: neural network

AUC: Area under curve

EMA: Ecological momentary assessment

XAI: Explainable Artificial Intelligence

DT: Decision tree

NB: Naïve Bayes

LR: Logistic Regression

KNN: K- nearest neighbor,

XGBoost: Extreme Boost

SVM: Support Vector Machine

GBM: Gradient Boosting Machine

CNN: Convolutional Neural Network

PRIMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Keywords: Depression, Prediction, Women, Machine Learning, Gender, Random Forest, Prisma

Introduction

Depression is a pervasive and debilitating mental health disorder that significantly contributes to the global burden of disease, impairing cognitive, emotional, and social functioning. Recent evidence indicates that depression remains one of the leading causes of disability worldwide, with substantial impacts on quality of life, productivity, and mortality [1-4]. Women are disproportionately affected by the rising global frequency of depression, which is made worse by socioeconomic stressors and post-pandemic mental health issues. According to epidemiological research, women are almost twice as likely as males to suffer from depression. This discrepancy is explained by intricate relationships between biological, hormonal, psychological, and sociocultural factors [5-11]. These include increasing caregiver responsibilities, increased exposure to psychological stressors, and reproductive shifts including pregnancy and menopause. Due to its subjective character and heterogeneity, depression is still difficult to diagnose despite its high prevalence [12,13]. Conventional diagnostic methods mostly rely on self-reported assessment instruments and clinician-administered interviews, which are frequently impacted by recall bias, underreporting, and delayed detection [14]. Additionally, these methods are not scalable and might not fully capture the multifactorial and temporal dynamics of depression, especially in women. As a result, there is an increasing need for scalable, objective, data-driven methods to enhance early detection and individualized mental health treatment delivery [13,15,16].

Machine learning (ML) has become revolutionary tools in mental health research. Complex, high-dimensional information can be analyzed using machine learning algorithms to find latent patterns and predictive markers linked to depression. ML models can attain great predictive performance, as evidenced by recent systematic reviews, which frequently report area under the curve (AUC) values in clinical datasets that approach or surpass 0.80. Support Vector Machines (SVM), Random Forest (RF), Gradient Boosting Machines (GBM), and deep learning architectures are just a few of the many algorithms that have been effectively used for depression detection and prediction tasks [17-20]. However, to satisfy the need for interpretability and transparency in clinical decision-making, explainable artificial intelligence (XAI) has become a crucial field of study. According to a recent meta-analysis, explainable machine learning models improve clinical trust by identifying important risk variables for depression while also maintaining competitive prediction accuracy. This is especially crucial in delicate areas like women's mental health, where precise and equitable forecasts depend on an awareness of the impact of gender-specific factors [21-23]. The growing emphasis on bias prevention and fairness in machine learning algorithms is another significant breakthrough. Research has indicated that machine learning algorithms that are trained on biased or non-representative datasets have the potential to sustain current disparities in mental health care, especially for underrepresented groups like women in specific sociocultural situations. To guarantee equitable model performance across various populations, recent research highlights the integration of fairness-aware algorithms and bias correction strategies [24,25].

Furthermore, the utilization of real-time and longitudinal data has become more popular in recent years. Wearable technology, ecological momentary assessment (EMA), and mobile health (mHealth) technologies have made it possible to continuously monitor physiological and behavioral signs. These tools reflect a change from reactive to proactive mental healthcare systems

by enabling dynamic prediction of depression trajectories and early identification of risk patterns [26-28]. Despite these developments, a number of obstacles still exist. Limited dataset diversity, small sample sizes, and class imbalance problems limit the generalizability of many previous studies [29-32]. A large number of ML-based depression research either fail to include gender-specific characteristics including hormone fluctuations, reproductive health status, and sociocultural factors, or they do not specifically target women [33]. Real-world deployment is further hampered by ethical issues, such as data protection, interpretability, and clinical validation. Thus, by integrating recent high-impact research and critically assessing methodological trends, model performance, and current constraints, this study offers a thorough overview of machine learning approaches for predicting depression in women.

The goal of this review is to pinpoint efficient machine learning methods, evaluate the significance of gender-sensitive and multimodal data, and highlight new developments like explainable and fairness-aware AI. Ultimately, this work seeks to contribute to the development of robust, interpretable, and clinically applicable depression prediction systems tailored to women, thereby advancing equitable and data-driven mental healthcare.

Methods

The enhanced PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) standards for scoping reviews were followed in this review [34]. There was no public record of the study's procedure. By submitting a well-founded request to the corresponding author, the protocol can be acquired.

Search Strategies

A comprehensive search strategy was conducted across major scientific databases that include google scholar, IEEE Xplore, pubmed and scopus using the following keywords: "mental health", "depression", "women" [35]. Studies published between 2015 and 2025 were reviewed. Extracted data included study population, data types (e.g., clinical, behavioral, physiological, text), machine learning models used, performance metrics, and gender-specific findings. Previous research has demonstrated the potential of machine-learning methods for predicting depression, however, the evidence specifically concerning women remain fragmented. This review therefore synthesizes the existing evidence.

Eligibility Criteria: Inclusion and Exclusion Strategy

A systematic literature search was conducted to identify peer-reviewed studies focusing on the application of machine learning (ML) algorithms for predicting depression specifically in women. In ensuring the inclusion of relevant, high-quality, and accessible studies, the following criteria were applied. Five hundred and twenty (520) original articles published between 2015 and 2025 were considered. After screening, 16 relevant articles table 1 were included for evaluation. Eligible studies explicitly employed machine learning techniques for depression prediction or detection and involved female populations. This included studies with a sole focus on women, such as those investigating postpartum or antenatal depression, as well as studies providing gender-disaggregated analyses within mixed-gender populations. Studies utilizing clinical, behavioral (e.g., speech, text, social media), physiological (e.g., EEG, wearable devices), or multimodal data for depression prediction were included. Articles were required to report measurable ML model performance using standard metrics such as accuracy, sensitivity, specificity, or F1-score. Only open-access articles written in English with full-text availability were included.

Exclusion criteria were applied to maintain methodological rigor and relevance. Studies without explicit use of ML techniques, those focusing solely on depression treatment, or those failing to differentiate female-specific outcomes were excluded. Also, studies inaccessible due to paywalls or language barriers were omitted. Inclusion criteria focused on research involving female-specific depression prediction using ML algorithms.

Review Strategy

Data was collected and confirmed independently by the authors, then a descriptive analysis of the selected studies was carried out. The data extracted from the included articles are title, dataset, data type, sample size, machine learning algorithm used, its performance and motivation with regards to the detecting depression in women and then the motivation behind the work (Table 1). Other relevant observations related to the methods and results of each individual article were recorded. A table (Table 2) was used to represent data extracted from the publications. Extracted data were subjected to a descriptive and thematic analysis to identify trends in data types, ML algorithms, and model performance. Differences in prediction performance across female subpopulations (e.g., postpartum, antenatal, general adult women) were explored, where feasible performance metrics were compared across studies using similar data types and algorithms.

Table 1: Key Extraction Variables

Extracted Variable	Description
Paper	Title of publication
Dataset	Sources of data used by the authors
Data Type	Form of data used
Sample size	Size of dataset
Algorithm	Machine learning algorithm used
Performance	Evaluation metric
Motivation	The inspiration behind the work

Data Synthesis

Our analytical approach involved a descriptive analysis of the included studies, the findings from the included studies were synthesized narratively and structured around key thematic areas. Firstly, the review examined the types of data utilized across studies. Physiological data, particularly EEG-based models, demonstrated moderate to high accuracy for depression detection, with reported AUC values ranging from 0.70 to 0.92. Behavioral data, such as speech and social media analysis, were effectively applied for depression detection; however, only a few studies reported gender-disaggregated results. Multimodal approaches that integrated physiological, behavioral, and clinical data consistently outperformed unimodal models, with some achieving AUCs above 0.90.

Results

Selection of Sources of Evidence

The search query was able to initially identify 520 publications from different database of which after reviewing we arrived at 105, 86 publications were excluded as not relevant to the issue on ground (depression among the female folks). This is to say that 19 articles of relevance to the topic under review were included in the scoping review [36-51]. Out of the 19, 3 were grey literatures giving rise to 16 articles used in the review. The reason for the exclusion from the analysis was that the studies were not targeted to depression in women but rather targeted at depression in the general context. This is as illustrated in Figure 1 below.

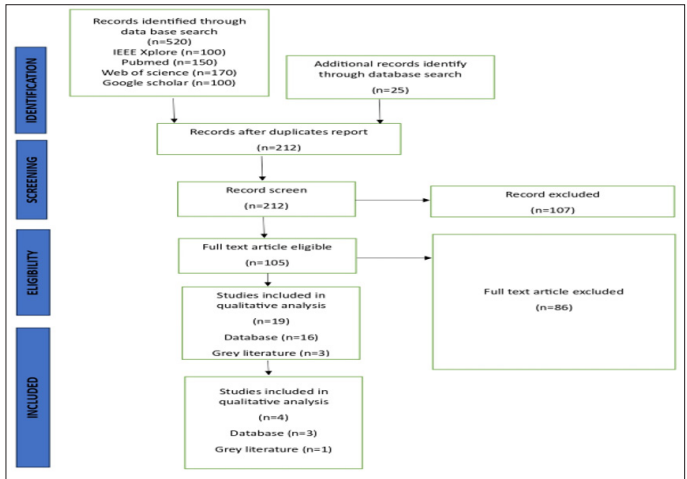


Figure 1: The Prisma Flow Diagram

Characteristics of Sources of Evidence

The articles selected for this review were published between 2015 and 2025 with all publications including original epidemiological studies. Measures were put in place, such as removing duplicates and following the PRISMA flowchart. Random Forest, Logistic Regression, Support Vector Machine (SVM), Multi-layer Perceptron (MLP), Decision Tree, Naive Bayes, Long Short-Term Memory (LSTM), Gradient Boosting Machine (GBM), and Convolutional Neural Network (CNN) were among the main classifiers that were assessed. The increasing prevalence of mental health disorders in women especially during pregnancy and postpartum, coupled with the advancement of technology, has led to a growing interest in utilizing machine learning techniques for early detection and diagnosis. Because of their complexity and the shortcomings of conventional diagnostic techniques, these diseases provide a significant challenge to mental healthcare. The characteristics of the studies included in the review as well as the results are well represented in Table 2 below.

Table 2: Machine Learning Algorithms In Depression Prediction Among The Female Gender

Paper	Dataset	Data Type	Sample size	Algorithm	Performance			Motivation
[36]	Social media posts	Image, video, text	2,500 000	ML LR, DT NB LSTM	accuracy 0.98 0.79 0.67 0.9	f1 0.98 0.78 0.79 0.94	auc 0.91 0.74 0.64 0.94	Importance of removing the stigma that comes with depression and the role of technology in providing support.
[37]	Socio-demographic & medical variables	Text	266,544	HER EHR+EPDS Sensitivity	0.72–0.74 0.844 0.76			To develop a quantitative, objective method for early (pre-pregnancy) identification of women at risk for postpartum depression
[38]	Clinical features (mental health history, medical comorbidities, obstetric complications, medication orders, demographics)	EHR datasets	15,197 (development) + 53,972 (validation)	Development AUC Validation AUC	0.937 0.886;			To create a point-of-care, EHR-based tool using minimal but effective clinical features for accurate and early prediction of postpartum depression (PPD)
[39]	EHRs from Weill Cornell Medicine and NewYork-Presbyterian Hospital (2015–2017)	EHR datasets	9.980	-	AUC - 0.79			To leverage EHR data for early identification of women at risk for postpartum depression
[40]	Records from postpartum mothers in hospitals, community health services, and midwifery clinics	Structured demographic, clinical, and psychosocial data	317	DT GBT XGBoost	0.712			To develop reliable PPD prediction models using ensemble learning techniques, resampling for class imbalance, and feature selection to identify key predictors
[41]	Records from 7 Spanish General hospitals	Clinical data	1880	NB LR SVM ANN	0.72 0.73 0.75 0.63 0.74 0.77 0.56 0.73 0.75 0.53 0.79 0.66			To predict postpartum depression
[42]	PsycINFO, PubMed, IEEE Xplore, ACM Digital Library; last 12 years.	Clinical, demographic, maternal health data	14 studies	SVM	0.78–0.86			To synthesize the literature on ML and big data analytics for maternal mental health
[43]	Data were obtained from a population-based prospective cohort study in Uppsala, Sweden.	Clinical, demographic, and psychometric data	4,313		Accuracy 73%, sensitivity 72%, specificity 75%, PPV 33%, NPV 94%, AUC 81%			Using clinical, demographic, and psychometric data, the model achieved balanced performance and high negative predictive value-useful for screening after childbirth
[44]	University of Illinois Chicago Hospital Health Sciences System	Electronic medical records (structured + self-reported PHQ-9 scores)	5,875	Elastic Net (best performer)	0.61			To determine whether ML models could predict depression in early pregnancy in racial/ethnic minority women by leveraging EMR data.
[45]	Hospital	Clinical dataset, medical history	1,100	LR RF SVM KNN XGBOOST	EPDS 1 0.856 0.688 0.815 0.846	EPDS 2 0.909 0.752 0.849 0.898	EPDS 3 0.917 0.784 0.861 0.903	Early prediction of postpartum depression risk and optimize preventive interventions.

[46]	Demographic, psychosocial, physiological factors + history of mental illness	Clinical and self-report data	1,138	LR ANN	Prenatal model: LR AUC = 0.801, ANN AUC = 0.787; Postpartum model: LR AUC = 0.858, ANN AUC = 0.844	To develop and validate ML models using biopsychosocial predictors to predict the risk of PPD for perinatal women.
[47]	Demographic, obstetric, psychosocial, physical health	Clinical/Self report data	1.065	XGBoost	0.955	To develop an explainable machine learning model to predict the risk of PPD and to identify its key predictive factors.
[48]	Self-reported clinical & social risk factors via prenatal support mobile app	Survey/self-report	944	LASSO FSS SDT RF XGBoost PC-KCI Stable P-C	0.89	To develop a machine learning algorithm, using patient-reported data from early pregnancy, to predict later onset of first time moderate-to-severe depression.
[49]	Rural women in Tangali Bangladesh	Physical interviews/questionnaire	346	DT AdaBoost RF XGBoost	0.982 0.949 0.997 0.984	To predict depression among menopausal women and enhance their quality of life.
[50]	PRAMS 2012–2013 data from the Centers for Disease Control and Prevention (CDC).	Survey (demographics, clinical, psychosocial)	28,755	RF, SVM, GBM, CART, Naïve Bayes, kNN, LR, ANN	Acc 0.650–0.791; AUC 0.864–0.884	To develop predictive models for postpartum depression using machine learning (ML) approaches.
[51]	West China Second University Hospital, Sichuan University	EHR datasets	2055	XGBoost RF GBM	0.849	To comprehensively collect variables from multiple aspects, develop and validate machine learning models to achieve precise prediction of PPD

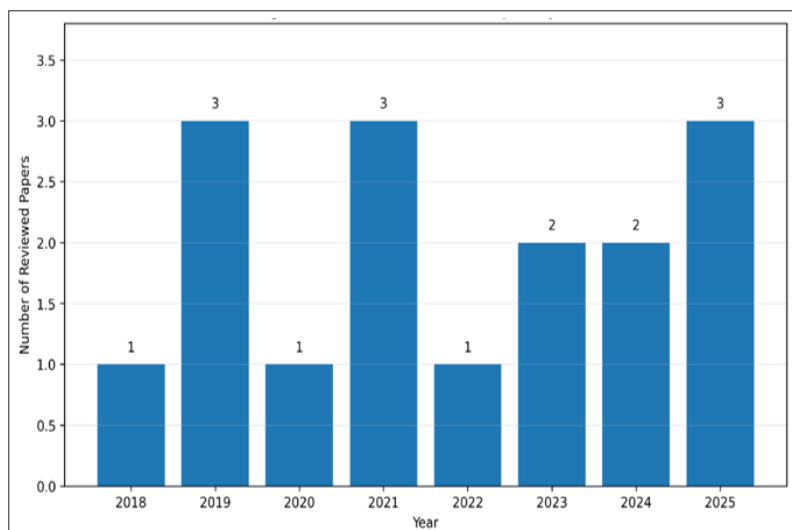


Figure 2: Representation Of Reviewed Papers

Results of Individual Sources of Evidence

The results of the epidemiological studies that examined depression in women as shown in Table 2 spanned through a wide range of data sources, including EHR data, clinical data, social media data, resting-state functional magnetic resonance imaging (rsfMRI) data, and more; dataset sizes varied from 19 to 2,500,000 records, reflecting the variability and scale of the data sources utilized; the studies focused on a variety of outcome variables, such as near-term suicidal behaviors, the presence of childbirth-related PTSD (CB-PTSD), suicide depression, and anxiety; the prediction nature varied across studies with varying data sample sizes and algorithms; Random Forest outperforms other models in terms of accuracy of approximately 90%, recall, and F1 score of 88%.

A total of 520 relevant studies were analyzed to understand how machine learning (ML) is contributing to the prediction of depression generally. These studies revealed consistent patterns, methodological variations, and both progress and limitations in this growing field. Out of the 520 reviewed works, only 16 studies Table 1 focusing mainly on depression in women were utilized in this review. Spanning a diverse array of sources, including data on depression covering twitter data, clinical data, resting-state functional magnetic resonance imaging (rsfMRI) data, commercial subset, and more. The heterogeneity and scope of the data sources used were reflected in the dataset sizes, which varied from 19 to 2,500,000 records. Near-term suicidal behaviors, the existence of Childbirth-related PTSD (CB-PTSD), suicide depression, and anxiety were among the many outcome variables that the studies focused on. The type of prediction varied among studies, with objectives like identifying depression patients from structured and unstructured medical records, predicting the chance of a diagnosis in firefighters exposed to trauma, and predicting the risk of people engaging in suicide acts. The complexity and heterogeneity of mental health data were highlighted by the fact that variable types included categorical, continuous, ordinal, and binary variables, while variable sources included surveys, experiments, observations, and pre-existing databases.

This review assessed how well classification algorithms predicted depression. It covered developments in machine learning algorithms from 2015 and 2025. Examining research papers and conducting a thorough database search were part of the inclusion criteria. Reliability measures were put in place, such as removing duplicates and following the PRISMA flowchart. Random Forest, Logistic Regression, Support Vector Machine (SVM), Multi-layer Perceptron (MLP), Decision Tree, Naive Bayes, K-nearest neighbors, Gradient Boosting Machine (GBM), and Convolutional Neural Network (CNN) were among the main classifiers that were assessed. The use of machine learning techniques for early detection and diagnosis is becoming more popular due to the rising incidence of mental health illnesses and technological advancements. The potential of machine learning to identify anxiety and depression in women has drawn a lot of attention in recent years. Because of their complexity and the shortcomings of conventional diagnostic techniques, these diseases provide a significant challenge to mental healthcare. This study examines several studies that have investigated using machine learning to identify mental health conditions. These studies demonstrate how machine learning techniques can increase the precision and effectiveness of diagnosis.

The use of machine learning techniques for early detection and diagnosis is becoming more popular due to the rising incidence of mental health illnesses and technological advancements. The potential of machine learning to identify anxiety and depression in women has drawn a lot of attention in recent years. Because of their complexity and the shortcomings of conventional diagnostic techniques, these diseases provide a significant challenge to mental healthcare. This study examines several studies that have investigated using machine learning to identify mental health conditions. These studies demonstrate how machine learning techniques can increase the precision and effectiveness of diagnosis. To fully comprehend these findings consequences, it is essential to critically assess both their advantages and disadvantages. In summary, this review sheds light on the potential of machine learning in detecting mental health disorders, depression, and anxiety. The application of machine learning models offers opportunities for tailored interventions and early detection, which could improve patient outcomes. However, the limitations of these

studies such as limited sample numbers, heterogeneous datasets, and ethical issues must be recognized by researchers. For machine-learning techniques to be further validated and eventually used in mental health diagnosis, these issues must be resolved.

Discussion

Various studies employed diverse data sources, including physiological signals, behavioral patterns, clinical records, and demographic data. Notably, multimodal approaches that integrate two or more data types demonstrated the highest predictive accuracy. Studies combining EEG data with self-reported questionnaires or integrating speech patterns with clinical data consistently outperformed those relying on single data sources [9,13,15-17,19-23]. This reinforces the value of comprehensive, multi-faceted data collection in understanding complex mental health conditions like depression. The reviewed studies utilized a range of machine learning algorithms, reflecting both traditional and advanced approaches. Logistic regression and support vector machines (SVM) were commonly used for interpretation of structured datasets. Random Forest and Gradient Boosting models were particularly effective in handling complex, high-dimensional data, including social media text and EEG signals [24]. While algorithm performance varied depending on the dataset and study design, ensemble methods and multimodal models consistently achieved superior accuracy has Random Forest topping the chart [18-23]. Figure 1 depicts the PRISMA flow diagram for the review while Figure 2 is a graphical representation of the articles used in the review spanning for 10 years 2015 to 2025 with 2019, 2021 and 2025 exhibiting the highest count of 3 each.

A critical observation from the review is the inconsistent integration of gender-specific factors in model development. Although several studies focused explicitly on postpartum and antenatal depression, only a minority systematically included gender-relevant features such as hormonal cycles, psychosocial stressors unique to women, or caregiving burdens. In studies where such factors were incorporated, there was a notable improvement in model performance, suggesting the importance of gender-sensitive approaches. However, few studies employed fairness-aware ML techniques to actively identify and mitigate potential gender bias, representing a key area for improvement.

Therefore, before these models can be considered for clinical application, external validation is necessary. The research shows that many models were created and assessed within comparatively specific populations or datasets, even if several studies included validation datasets. As an illustration of the need of validation beyond the development dataset, one reviewed work created a model using 15,197 records and reported validation using an additional 53,972 records. Independent datasets from various hospitals, geographical areas, socioeconomic categories, ethnic backgrounds, and healthcare systems should be used in future research to validate models. Because depression is dynamic and might manifest differently during pregnancy, the postpartum period, and other phases of a woman's life, prospective and longitudinal validation would be especially crucial. In order to increase generalizability and capture temporal variations in depression risk, the study itself highlights the need for larger, more varied datasets and longitudinal data.

Conclusion

The application of machine learning for predicting depression in women represents a promising yet evolving area of research. This review illustrates significant progress, particularly in leveraging diverse data types and advanced analytical techniques to improve

early detection and risk assessment. Key strengths of current research include the successful application of multimodal approaches and the demonstrated potential of algorithms such as Random Forest, Gradient Boosting, and deep learning models for analyzing complex datasets like EEG signals and social media text. The review shows that these approaches show promise for correctly detecting depression in women. To successfully identify people at risk of mental health illnesses, a variety of algorithms and techniques have been used to examine a variety of data sources, including demographic data, clinical assessments, social media content, and neuroimaging data. Machine Learning techniques such as Random Forest, Support vector machines, Extreme Learning machine, as well as deep learning algorithms have demonstrated effectiveness in forecasting mental health disorders. Random Forest showed promising performance in the reviewed studies, but its superiority and clinical utility require independent validation.

Authors' Contributions

The authors confirm their contributions to this work as follows: conceptualization and design by C.U. B, data curation and visualization by H. C. O., Supervision and visualization by T.C.E. Original draft and investigation by C. O. Review and Editing. All authors reviewed the results and approved the final version of the manuscript. Review and Validation by M.E.B.

Consent For Publication

Not Applicable

Standards Of Reporting

PRISMA guidelines and methodology were followed

Availability Of Data And Materials

All data and supportive information are available within the article

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Conflict Of Interest

The authors declare no conflict of interest

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