

A Review of Prediction of Depression Using Machine Learning Algorithms

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Abstract

Depression is a widespread and debilitating mental health disorder that significantly affects individuals' emotional, cognitive, and social functioning. Traditional diagnostic methods often rely on subjective assessments, which can delay timely detection and intervention. Recent advancements in artificial intelligence, particularly machine learning, have created opportunities to enhance depression prediction and diagnosis by leveraging diverse data sources. This study aims to review existing research on the application of machine learning algorithms for predicting depression, highlighting their strengths, limitations, and potential for improving mental health care. A review approach was employed, producing literature published between 2019 and 2025 from reputable databases such as IEEE Xplore, PubMed, Scopus, Web of Science, and Google Scholar. Eligible studies applied machine learning or deep learning techniques to structured and unstructured data sources, including clinical records, social media content, multimodal signals, and wearable devices, and reported performance metrics such as accuracy, precision, recall, and F1-score. The review reveals that machine learning models, particularly ensemble methods, deep learning architectures, and hybrid frameworks, demonstrate strong predictive performance across diverse datasets, achieving accuracies above 90% in several cases. However, challenges such as limited data availability, class imbalance, lack of interpretability, ethical concerns around privacy and bias, and difficulties in clinical integration persist. The findings underscore the need for explainable, ethically responsible, and culturally adaptable predictive systems that can be seamlessly embedded into healthcare workflows.

Keywords: Depression, machine learning algorithm, mental health disorder, prediction,

1. Introduction

Depression is a widespread and debilitating mental health disorder that extends far beyond ordinary mood fluctuations (Gbadamosi et al., 2022). It is primarily characterized by a persistent and overwhelming sense of sadness, emptiness, or a marked loss of interest and pleasure in activities that were once considered enjoyable. Unlike temporary emotional downturns, clinical depression is diagnosed when such symptoms persist continuously for at least two weeks and cause significant disruption to an individual's ability to function effectively in daily life (Moncrieff et al., 2023). This impairment often extends across multiple domains, including occupational responsibilities, academic performance, social interactions, and family relationships (Inungu et al., 2024). The World Health Organization reported that compared with many traditional diseases, depression has been identified as the most concerning disease in the world (Xia, 2022). From a clinical perspective, depression is not limited to emotional distress but encompasses a broad spectrum of psychological, cognitive, and physical manifestations (Kupferberg & Hasler, 2023; Rief et al., 2024). Common symptoms include difficulties with concentration and decision-making, noticeable changes in appetite and sleep patterns, fatigue, or psychomotor disturbances, which may present as either restlessness or slowed movements (Acoba, 2024; Leahy, 2023). Furthermore, individuals frequently experience overwhelming feelings of worthlessness, hopelessness, or excessive guilt, all of which reflect the intricate biopsychosocial roots of the condition (Frohn & Martiny, 2023; Czepczor-Bernat et al., 2025). If left untreated, depression gradually erodes an individual's energy levels, motivation, and capacity to maintain routine functioning, ultimately leading to severe disability and compromised quality of life (Li et al., 2025; Adriani et al., 2024). On a global scale, depression constitutes one of the leading contributors to the overall burden of disease and disability (Zhou et al., 2025). Estimates indicate that more than 332 million people worldwide were affected by depressive disorders in 2021, a number that underscores the pervasive and persistent nature of the condition (Ahamed, 2025). Despite minor yearly improvements in reducing prevalence rates, the overall global burden remains alarmingly high, signaling ongoing deficiencies in prevention, early diagnosis, and equitable access to mental health care services (Ngu et al., 2010; Colizzi et al., 2020). The consequences of depression extend beyond individual suffering, as the disorder is strongly linked with an elevated risk of chronic physical illnesses such as cardiovascular disease, diabetes, and weakened immune responses (Sobolewska-Nowak et al., 2023; Fanelli et al., 2025). It also significantly increases vulnerability to suicidal ideation and attempts, representing one of the most severe public health challenges of the modern era. Economically, depression reduces productivity and labor force participation, placing immense strain on families, communities, and national health systems. The introduction of predictive models to predict depression is of great importance in the healthcare system. Given its complex presentation and far-reaching impact, there is an urgent need for innovative strategies to enhance the detection, prediction, intervention, and management of depression. Recent advancements in artificial intelligence, particularly machine learning, offer promising avenues for identifying at-risk individuals earlier, analyzing vast and diverse health datasets, and designing personalized treatment approaches. This integration of technology into mental health care holds potential not only to alleviate the global burden of depression but also to transform prevention and therapeutic practices, making them more accessible, precise, and effective.

2. Related Works

In recent years, there has been a remarkable increase in research exploring how machine learning (ML) can be applied to the detection and prediction of depression. This growing body of work highlights the potential of data-driven methods to transform mental health diagnostics across various populations and data modalities. Researchers have developed innovative approaches that leverage clinical data, natural language inputs, multimodal signals, and wearable devices, underscoring the diversity and sophistication of current efforts. Assessed the effectiveness of user-generated social media texts in predicting depression and evaluate the influence of demographic, language, social media activity, and temporal features on predicting depression on social media texts through machine learning (Phiri et al., 2025) The survey searched studies from 11 databases (CINHAL [through EBSCOhost], PubMed, Scopus, Ovid MEDLINE, Embase, PubPsych, Cochrane Library, Web of Science, ProQuest, IEEE Explore, and ACM digital library) from January 2008 to August 2023. Also, included studies that used social media texts, machine learning, and reported area under the curve, Pearson r , and specificity and sensitivity (or data used for their calculation) to predict depression. Protocol papers and studies not written in English were not considered. Extraction of study characteristics, population characteristics, outcome measures, and prediction factors from each study. A random effects model was employed to obtain the effect sizes with 95% CIs. The study heterogeneity was evaluated using forest plots and P values in the Cochran Q test. Moderator analysis was performed to find the sources of heterogeneity. A total of 36 studies were considered. It was observed that a significant overall correlation between social media texts and $N_{depression}$, with a large effect size ($r=0.630$, 95% CI 0.565-0.686). Also, noted the same correlation and large effect size for demographic (largest effect size; $r=0.642$, 95% CI 0.489-0.757), social media activity ($r=0.552$, 95% CI 0.418-0.663), language ($r=0.545$, 95% CI 0.441-0.649), and temporal features ($r=0.531$, 95% CI 0.320-0.693). The social media platform type (public or private; $P<.001$), machine learning approach (shallow or deep; $P=.048$), and use of outcome measures (yes or no; $P<.001$) were significant moderators. Sensitivity analysis revealed no change in the results, indicating result stability. The Begg-Mazumdar rank correlation (Kendall $\tau_b=0.22063$; $P=.058$) and the Egger test (2-tailed $t_{34}=1.28696$; $P=.207$) confirmed the absence of publication bias. Conclusions: Social media textual content can be a useful tool for predicting depression. Demographics, language, social media activity, and temporal features should be considered to maximize the accuracy of depression prediction models. Bourkhime et al. (2025) conducted a comprehensive comparative analysis of eight distinct machine learning algorithms to predict depression among people with diabetes. The algorithms used included logistic regression (LR), k-nearest neighbors (KNN), decision tree (DT), random forest (RF), Adaptive Boosting (AdaBoost), support vector machine (SVM), Extreme Gradient Boosting (XGBoost), and Categorical Boosting (CatBoost). The study applied a dataset from Morocco, explicitly curated for this task, and employed the Synthetic Minority Over-sampling Technique (SMOTE) to balance the dataset. Feature selection was performed using ExtraTreesClassifier, while hyperparameter tuning was accomplished through a grid search approach. The results revealed the promising performance of the machine learning algorithms in the prediction of depression among people with diabetes. Especially, the RF and CatBoost classifiers emerged as top performers, achieving an impressive accuracy rate of 82%. Advancing the management and overall well-being of individuals with diabetes and coexisting depressive disorders. Investigation of the trends and risk factors of depression among adults in the USA (Inungu et al., 2024). The National Health Interview Survey

(NHIS) data were analyzed. The NHIS early release data provided the prevalence of depression from 2019 to 2022. Depression covariates were accessed by applying SPSS 29. The prevalence of depression decreased from 4.7% in 2019 to 4.5% in 2020, before rising to 5% in 2022. The 31,536 participants in the 2022 NHIS, 51.7% were female and 40% were 26 to 49 years old. Logistic regression showed that being female, obese, having diabetes, and having a lower level of education, as well as smoking cigarettes, were significantly associated with higher levels of depression. Conversely, being married and aged 60 years+ were significantly associated with a lower likelihood of depression. The decrease in the trends of depression at the onset of the pandemic underscores the need for further study. Targeted public health strategies and collaborative efforts are essential to mitigate depression's impact and improve mental health outcomes. Compared seven machine learning algorithms to identify depression predictors using publicly available datasets from standard health surveys (Jamali et al., 2024). Data were obtained from the National Health and Nutrition Examination Survey (NHANES) 2017–2020, including medical, mental, demographic, and lifestyle information from 8965 people aged 18 to 80 years. Also, identified strongly correlated features of depression and demonstrated that learning algorithms can accurately identify depression predictors. The performance of the algorithms was evaluated using standard metrics. Among the algorithms tested, the Neural Network algorithm showed the highest overall performance, with an area under the curve of 91.34 %, which significantly outperformed results obtained with traditional statistical methods such as logistic regression and nomograms. This study demonstrates how ML can mine standard health surveys and identify depression predictors in a more accurate and nuanced fashion than other approaches. The findings of this study further suggest that incorporating heterogeneous data can enhance the performance of ML algorithms. Predicted depression based on diverse data using machine learning algorithms (Mishra & Srivastava, 2025). The designed model identified early indicators of depression, providing a potential tool for proactive intervention and support in mental health by analyzing patterns in behavioural, physiological, and contextual data. Machine learning algorithms, such as decision trees, extra trees, XGBoost, Stochastic gradient descent, grid search CV, Stacking, and Voting classifiers, and so on, were used to predict depression in the early stage. This study emphasized the integration of machine learning techniques to enhance predictive accuracy and contribute to developing accessible and timely depression detection systems. The F1 score was added, which helped to identify the best machine learning algorithm among the ones applied. Experimental results achieved an accuracy of 92 % with random forest, which is 3% higher than the work previously done in RF. We also achieved a 0.99 F1 score using Linear SVM. López Steinmetz et al. (2024) developed and compared machine learning (ML) models for predicting depression in Argentinean students during the pandemic. The performance of classification and regression models was assessed using appropriate metrics.3) To identify key features driving depression prediction. A longitudinal dataset (N = 1492 college students) captured T1 and T2 measurements during the Argentinean COVID-19 quarantine. ML models, including linear logistic regression classifiers/ridge regression (LogReg/RR), random forest classifiers/regressors, and support vector machines/regressors (SVM/SVR), were employed. Assessed features encompass depression and anxiety scores (at T1), mental disorder/suicidal behaviour history, quarantine sub-period information, sex, and age. For classification, models' performance on test data was evaluated using Area Under the Precision-Recall Curve (AUPRC), Area Under the Receiver Operating Characteristic curve, Balanced Accuracy, F1 score, and Brier loss. For regression, R-squared (R²), Mean Absolute Error, and Mean Squared Error are assessed. Univariate analyses are conducted to assess the predictive

strength of each feature with respect to the target variable. The performance of multi- vs univariate models is compared using the mean AUPRC score for classifiers and the R2 score for regressors. The highest performance is achieved by SVM and LogReg (e.g., AUPRC:0.76, 95% CI: 0.69, 0.81) and SVR and RR models (e.g., R2 for SVR and RR: 0.56). Evaluation of depression experienced by college students, using the depression scale questionnaires (PHQ-9) (Majeed et al., 2023). Data was collected from 300 students of the GCET Jammu, where they were questioned simply about how they felt in situations they might have encountered within the previous two weeks. Answers were given some amount of weight that helped to compute a score to analyze the depression level of students. Five machine learning algorithms (MLAs) were used: Support Vector Machine (SVM), Decision Tree (DT), k-nearest neighbour (KNN), Random Forest (RF), and Naïve Bayes. The results showed that, when compared to other algorithms, SVM gave the highest accuracy of 94.8%. Leahy (2023) gave an overview of the causes, symptoms, and treatment strategies related to mood disorders. The types of mood disorders discussed in the review included Major Depressive Disorder (MDD), Bipolar Disorder, Persistent Depressive Disorder (PDD), and Seasonal Affective Disorder (SAD). The causes of mood disorders are multifactorial, involving genetic, biological, environmental, and psychological factors. Neurotransmitter imbalances, brain structure and function abnormalities, life events, and chemical imbalances contribute to the development of mood disorders. Common symptoms include persistent sadness, loss of interest, changes in appetite and sleep patterns, and thoughts of death or suicide. The treatment approaches, which encompass psychotherapy, medication, lifestyle changes, support groups, and Electroconvulsive Therapy (ECT) in severe cases, were mentioned. It was suggested that early detection and effective management are crucial to improving the quality of life for individuals affected by mood disorders. Seeking professional help from mental health experts and accessing appropriate support can offer hope and relief for those facing mood disorder challenges. Gbadamosi et al. (2022) provided more information on the prevalence of depression in Sub-Saharan Africa (SSA), its pathophysiology, risk factors, diagnosis, and the experimental models available to study depression within the sub-region. Also, the contribution of the sub-region to the global research output of depression was evaluated, as well as bottlenecks associated with the complete exploitation of the sub-region's resources to manage the disorder. Application of machine learning algorithms to predict depression (Khan, Chaudhary, & Kadam, 2023). To use these algorithms, data was gathered from people from different backgrounds, including students, employed and unemployed individuals, and homemakers, from diverse cultures and communities via the PHQ-9. The machine learning algorithms predicted depression across four levels of severity with high accuracy, making them especially effective in predicting mental health issues. Sharif et al. (2022) applied the burns depression checklist as the gold standard for the diagnosis of depression and the support vector machine, decision tree, and light gradient boosting method as algorithms to build models capable of diagnosing depression on a dataset of 604 surveyed participants. This work showed the efficiency of machine learning algorithms within the field of mental health. This study increased the body of knowledge by training insufficiently researched algorithms on a frequently used depression detection dataset with the goal of reaching or surpassing the level of performance seen in current research. This experimental research has found the decision tree classifier to be the best approach for predicting depression, with an accuracy of 95.66% while that of the support vector machine classifier and the light gradient boosting classifier were 91.48% and 94.58%, respectively. Depression is a worldwide health problem that has progressively affected people's daily lives (Xia, 2022). The study mentioned that in the vulnerability model, low self-

esteem makes people more susceptible to depression. In disparity to the vulnerability model, the scar model points to people with depression can have low self-esteem outcomes, and the common factor model argues that depression and self-esteem are the same construct, but are two extremes of a continuum. The expected effect of self-esteem on depression has been explored in many studies, but no study has explored the effect of depression on self-esteem. Furthermore, it indicated that the deep effects of depression on self-esteem can be a new direction of future research. Aleem et al. (2022) performed a review on different machine learning algorithms used to detect and diagnose depression. The ML-based depression detection algorithms are categorized into three classes: classification, deep learning, and ensemble. A general model for depression diagnosis involving data extraction, pre-processing, training a machine learning classifier, detection classification, and performance evaluation is presented. Moreover, it presents an overview to identify the objectives and limitations of different research studies presented in the domain of depression detection. Furthermore, it discussed future research possibilities in the field of depression diagnosis.

3. Methodology

This study adopted a systematic review approach to synthesize existing research on the application of machine learning algorithms for the prediction of depression. The methodology was designed to ensure rigor, reproducibility, and clarity in identifying, screening, and analyzing relevant studies. A comprehensive literature search was conducted across multiple academic databases, including IEEE Xplore, PubMed, Scopus, Web of Science, ScienceDirect, and Google Scholar, covering publications between 2019 and 2025. The search employed carefully selected keywords and Boolean operators such as “depression prediction,” “machine learning in mental health,” “natural language processing for depression,” “multimodal depression detection,” “EEG depression classification,” and “wearable sensor depression detection.” To ensure scientific credibility, only peer-reviewed journal articles, conference proceedings, and high-quality preprints were considered. Eligibility was determined through explicit inclusion and exclusion criteria. Studies were included if they applied machine learning or deep learning models for depression prediction, diagnosis, or monitoring, utilized structured or unstructured data sources such as electronic health records, social media text, voice and facial expression data, EEG signals, or wearable devices, and reported evaluation metrics such as accuracy, precision, recall, F1-score, or AUC. Only studies published in English were considered. Excluded works were those that focused exclusively on clinical psychology without computational modeling, lacked performance evaluation of the proposed models, or were duplicates, non-peer-reviewed, or purely opinion-based. For each eligible study, relevant details were extracted systematically, including bibliographic information, the type of data modality used, algorithms applied, evaluation metrics reported, methods of explainability or interpretability, and ethical considerations discussed. Studies were then categorized according to their primary data modality, such as electronic health records, natural language processing, multimodal systems, wearable or physiological signals, and privacy-preserving frameworks. This categorization allowed for meaningful comparisons of algorithmic performance across different contexts and for identifying dominant trends in methodological approaches. The synthesis of findings was conducted narratively, focusing on cross-study comparisons in terms of algorithmic accuracy, robustness, generalizability, and clinical viability. Special attention was given to the role of explainable artificial intelligence in promoting transparency, the challenges of

applying models across different cultural and linguistic populations, and the emergence of federated and privacy-preserving techniques as ethical safeguards. Ethical concerns such as informed consent, fairness in training data, risks of false positives and false negatives, and data privacy were also carefully considered, as these factors strongly influence the clinical adoption of machine learning systems in mental health care. By employing this methodological framework, the review provides a structured and comprehensive understanding of how machine learning algorithms have been applied to depression prediction, the successes achieved, the limitations encountered, and the gaps that require future exploration.

4. Results and Discussions

Despite the remarkable progress of machine learning (ML) in mental health research, the development and deployment of predictive models for depression face several critical challenges. A major limitation lies in the availability and quality of data. Depression datasets are often scarce, imbalanced, and heterogeneous, making it difficult to build models that accurately capture the wide variability of symptoms across individuals. In many cases, depressed individuals are underrepresented compared to non-depressed samples, leading to biased predictions. Furthermore, mental health data is highly sensitive, raising privacy and confidentiality concerns that restrict data sharing and cross-institutional collaboration. The cultural and linguistic diversity of patients further complicates model applicability, as most datasets remain Western-centric, limiting transferability to other populations and clinical contexts. Model-related challenges also pose significant barriers. Machine learning models, particularly deep learning architectures, are often criticized for their lack of interpretability, functioning as “black boxes” that provide little insight into their decision-making processes. This lack of transparency undermines clinician trust and hinders integration into medical practice. Overfitting is another recurrent issue, where models perform well on training datasets but fail to generalize to unseen or real-world data. Multimodal systems that combine textual, audio, visual, and physiological signals hold promise but are computationally complex and technically demanding to implement. Ethical and legal considerations add further complexity. Biases present in training data can perpetuate or even amplify existing inequalities related to gender, ethnicity, or socioeconomic status, thereby raising concerns about fairness. Misclassification also presents risks: false positives can lead to unnecessary psychological distress and stigmatization, while false negatives may delay critical interventions. Beyond this, ensuring informed consent, protecting patient autonomy, and adhering to strict data protection laws such as GDPR and HIPAA remain ongoing challenges. From a clinical standpoint, real-world implementation introduces additional obstacles. Many predictive models are validated on controlled datasets rather than in dynamic clinical environments, limiting their reliability when applied to diverse populations. Integration into existing healthcare systems requires tools that are not only accurate but also seamless, efficient, and user-friendly for clinicians. Without sufficient interpretability and validation, healthcare professionals may hesitate to trust or adopt such systems. Moreover, depression is an episodic condition, which means predictive models must demonstrate longitudinal reliability, adapting to temporal fluctuations in symptoms over extended periods. Finally, technical difficulties such as computational costs, feature engineering complexities, and issues of scalability remain pressing concerns. Deep learning algorithms, for instance, require substantial computational resources, and the extraction of meaningful features from modalities such as EEG signals, speech, or

facial micro-expressions demands advanced techniques. Scaling these models for large populations while maintaining fairness, accuracy, and efficiency is another unresolved challenge. In summary, while machine learning has shown considerable promise in predicting depression, its translation into clinical practice remains constrained by data-related, methodological, ethical, clinical, and technical barriers. Addressing these challenges will require interdisciplinary collaboration among data scientists, clinicians, psychologists, ethicists, and policymakers to ensure the development of robust, interpretable, and ethically responsible predictive systems.

5. Conclusion

Depression is a complex mental health disorder with philosophical implications for people, families, and societies. Its prompt detection and accurate diagnosis remain serious challenges in clinical practice, especially given the subjective nature of traditional assessment methods and the stigma that often surrounds mental illness. In recent years, machine learning has emerged as a promising tool to increase mental health diagnostics by leveraging large-scale data and uncovering hidden patterns that may elude conventional approaches. This review has produced a wide range of studies applying machine learning techniques to predict depression across diverse data sources, including structured clinical records, unstructured social media content, wearable sensor data, and multimodal inputs. The findings reveal that ML models, particularly ensemble methods, deep learning architectures, and hybrid frameworks, can achieve high predictive performance when trained on well-curated datasets. However, the success of these models is often contingent upon factors such as data quality, feature engineering, algorithm selection, and the contextual relevance of the input data. Despite these advances, several limitations persist. Many studies suffer from small sample sizes, a lack of external validation, and limited demographic diversity, which restricts the generalizability of their findings. Moreover, the interpretability of complex models remains a barrier to clinical adoption, as healthcare professionals require transparent and explainable systems to make informed decisions. Ethical concerns, including data privacy, algorithmic bias, and the potential for misuse, must also be addressed through rigorous governance frameworks and stakeholder engagement. Looking ahead, future work should prioritize the development of interpretable and ethically sound machine learning models that can be seamlessly integrated into clinical workflows. This includes leveraging federated learning to preserve privacy, incorporating culturally sensitive features to enhance inclusivity, and fostering interdisciplinary collaboration between data scientists, clinicians, and mental health experts.

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