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A COMPREHENSIVE REVIEW OF RECENT ADVANCES IN AI-BASED BIOSIGNAL PROCESSING SYSTEMS FOR DEPRESSION DETECTION

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ABSTRACT

Depression represents one of the most common neurological and mental health issues worldwide, imposing a significant burden on quality of life and contributing to high rates of morbidity and mortality. Traditional diagnosis methods are primarily based on clinical interviews and self-reporting, which can be subjective and time-consuming, thereby motivating the need for alternative approaches. Artificial Intelligence (AI) and intelligent biosignal processing represent a promising direction in depression detection, offering increased objectivity and precision. This study provides a comprehensive survey of recent literature on AI-based biosignal processing for depression detection, covering EEG, speech, physiological signals, facial expressions, textual data, and multimodal approaches. This study discusses the current state-of-the-art in machine learning and deep learning algorithms, including Convolutional Neural Networks (CNN), Long Short-Time Memory (LSTM), Transformers, Graph Neural Networks (GNN), Attention Mechanisms, and Explainable AI (XAI) for health. The results demonstrate that deep learning algorithms are generally more effective than traditional machine learning methods, achieving classification accuracy in some cases exceeding 95%. Multimodal approaches were also found to be more accurate and robust than unimodal ones. The study highlights the key limitations of the current research, including the lack of standardized data sets and external validation, as well as the need for increased model interpretability and clinical applicability. This study concludes that future directions in intelligent depression detection include multimodal learning, XAI, wearables, and large-scale clinical investigations. The results of this study contribute to the growing body of literature on AI-based biosignal processing for depression detection and can help clinicians and researchers identify viable options for developing novel biosignal processing algorithms.

Keywords: Depression Detection, Artificial Intelligence, Biosignal Processing, Electroencephalography, Deep Learning.

1. INTRODUCTION

Neurological Disorder (ND) constitutes one of the most significant global health challenges, which affects millions of people all over the world, across ages and socio-economic classes. NDs are chiefly attributed to the malfunction of brain cells. They are characterized by their effect on the automatic nervous system and muscles (Fahoum and Zyout, 2023). NDs encompasses over 600 disorders which includes Parkinson's disease, depression, epilepsy, Alzheimer disease, stroke, spinal cord injury among other neurodegenerative and neurophysiological conditions (Tawhid et al., 2020). All these diseases are associated with progressive deterioration of brain functions, reduced quality of life and massively contribute to global mortality rate. To effectively manage this problem, early detection and timely intervention are vital to slow down progression of the disease and improve output in patients (Alvi et al., 2023).

Advances in medical studies have contributed massively to increase the expectancy of life and quality, however NDs has continued to threaten life sustainability. As per the World Health Organization (WHO) records, 6.8 million people are affected by NDs every year (WHO, 2022). The primary goal of this dissertation is to modelling of an intelligent biosignal processing system for early detection of the most prevalent neurological disorder called depression. Depression (DD) is chronic and debilitating condition that leads to feelings of sadness, emptiness, anger, irritability, pessimism, fatigue, social isolation and self-harm such as suicide (Fahoum and Zyout, 2023). According to the data from the World Health Organization, approximately 280 million people worldwide are affected by this debilitating condition, suggesting a global health crisis (Liu et al., 2024). Tragically, approximately 720,000 individuals die each year of depression (Wardig et al., 2024) with up to 53% of the suicides occurring among those affected by this condition (Fox et al., 2021). Thus, depression has become the leading cause of death among various mental disorders owing to its high mortality and morbidity rates. Additionally, compared to healthy individuals, Enkhbayar et al. (2025) revealed that patients with depression are at an increased risk of developing chronic conditions, including cancer, neurological disorders, and cardiovascular diseases.

Healthcare providers diagnose depression through established diagnostic criteria, patient self-report questionnaires, and various clinical tests. Nevertheless, certain physicians may lack sufficient expertise, empathy, or up-to-date knowledge when addressing patient concerns, leading to disagreements, excessively high therapy fees, and ultimately suboptimal treatment outcomes (WHO, 2022). Consequently, there is a pressing demand for depression diagnostic methods that are reliable, precise, cost-effective, and widely accessible. To meet this challenge, researchers and clinicians have increasingly explored signal processing and machine learning techniques applied to electroencephalogram data, presenting a promising approach to enhance both diagnostic accuracy and affordability (Azizi et al., 2021).

EEG is the primary neuroimaging modality employed for identifying depression and related neuropsychiatric conditions. Other imaging techniques, including Positron Emission Tomography (PET), Magnetoencephalography (MEG), Magnetic Resonance Imaging (MRI), and Computed Tomography (CT), are also utilized in diagnosing depressive disorders (DD) (Suzuki et al., 2024). However, these modalities are often prohibitively expensive and time-intensive. An alternative assessment tool is the mini-mental state examination, which relies on structured personal interviews (Elnaggar et al., 2025). Despite these options, EEG continues to be the most commonly adopted technique for detecting neurophysiological biomarkers in neurological and psychiatric disorders (Fahoum and Zyout, 2023).

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In recent years, EEG has gained prominence as a more economical and rapid diagnostic tool for distinguishing depressive disorders from healthy controls (HSs). EEG signals capture the dynamic electrical activity of the cerebral cortex, recorded via electrodes positioned on the scalp to measure fluctuating voltage potentials. Some of the studies that applied EEG for detection of DD include Huang et al. (2024) who applied pre-trained model for DD detection from voice. Prama et al. (2024) applied AI-based deep depression model. Nusrat et al. (2024) used AI for multi classification of DD. Liu et al. (2024) applied capsule networks with contrastive learning for the prediction of DD, while Patil et al., (2025) applied convolutional neural network (CNN) for detection of depression. Despite the success, these works are isolated to either clinical or a combination of clinical and physiological data; however Slimmen et al. (2024) and Ellissa et al. (2025) argued that depression are multi-dimensional and are influenced through complex interactions of social, behavioral, environmental and digital factors.

While there has been considerable progress in artificial intelligence (AI)-powered depression detection, the research findings are fragmented in terms of individual data types, such as EEG, speech, facial expressions, text, physiology, and social media. While multi-modal methods have proven more effective than individual data sources, the approaches for integrating multiple data types are not unified, and there are challenges in terms of interpretability, clinical validation, standardization, and practical application in real-world settings. At the same time, recent advances in depression detection include the use of Transformers, XAI, large language models, and foundation models, which have not been systematically reviewed in terms of the context of depression diagnosis. Therefore, there is a need to review the latest advances in AI-based depression detection to provide an in-depth understanding of the state-of-the-art methods, their strengths, weaknesses, and opportunities for advancing the field. This study aims to review recent research on bio-signal processing and machine learning, with a focus on deep learning and multi-modal learning, in the context of depression detection. The review also discusses the current methods, standardized datasets, evaluation criteria, and clinical applicability, research directions, and technical opportunities for building intelligent systems for depression detection and personalized healthcare.

2. LITERATURE REVIEW

Saeedi et al., (2026) did a systematic literature review of rest-state fMRI in the application of deep learning in the diagnosis of Major Depressive Disorder (MDD). Both supervised and unsupervised methods were explored, as well as multimodal methods, with Graph Neural Networks (GNNs) consistently outperforming other approaches in modelling brain connectivity and reported performance, although this performance was dependent on the graph construction and heterogeneity of the data sets. Various methods were then considered, including autoencoders, GANs, transfer learning, and multimodal fusion (performing fusion of structural MRI, demographic, and functional data), which was found to significantly enhance classification accuracy.

In this mini-review, Hussain et al., (2026) provide an overview of depression detection using deep learning and Large Language Models (LLMs) on multimodal datasets. The study shows that EEG is the most physiologically informative unimodal modality, with accuracies ranging from 88% to 99% on laboratory datasets such as SEED-IV, and multimodal methods consistently outperform unimodal methods, with an accuracy of 90%-95% on the laboratory SEED-IV dataset and F1-scores of 0.80-0.90 on the community datasets DAIC-WOZ. Transformer-based fusion models were effective for extracting multimodal cues, and attention-guided models were excellent for extracting multimodal cues as well, whereas LLMs gave a boost in robustness and interpretability through contextual reasoning, embeddings, and few-shot learning.

Xu and Sun (2024) developed a depression detection model using deep learning and included CNNs for facial expression analysis, Long Short-Term Memory (LSTM) for processing text and speech, and other machine learning algorithms to analyze physiological biomarkers like HRV. The model was trained and validated on a large-scale clinical dataset with an impressive accuracy of 0.95 and F1 score of 0.93, which is much better than a traditional decision tree-based method. Ablation studies showed that the features extracted from speech emotion-free talk tasks were the most useful in improving detection accuracy, and that using multiple emotional categories was more stable for classification.

To capture the depression detection and prediction using EEG signals with deep learning algorithms, a systematic literature review was done by the researchers, Safayari and Bolhasani, (2021). Altogether, 22 studies in the period 2016-2021 were analysed, and CNN-based architectures (CNN, 1D-CNN, 2D-CNN and 3D-CNN) were the most frequently used, accounting for almost half of the classifiers, followed by the use of CNN alone, which accounted for approximately one-third of the classifiers. The combined CNN-LSTM models consistently outperformed with reported accuracy rates even above 95% and, in some instances, even above 99%, due to the feature extraction capability of CNN and the temporal memorisation capability of LSTM. The methods used for feature extraction were diverse, but the most popular methods were convolutional layers as end-to-end methods, FFT, band-pass filters, and wavelet transforms to capture frequency and connectivity features.

Lu et al., 2025 performed a systematic review and meta-analysis of speech feature-based depression detection models based on Traditional Machine Learning (TML) and Deep Learning (DL) models. Based on a pooled sensitivity of 0.82, specificity of 0.83, and AUC of 0.89 across 25 studies, TML models performed on average with a sensitivity of 0.82, specificity of 0.83, and AUC of 0.89, which were comparable to those of DL models, whose pooled sensitivity was 0.83, specificity was 0.86, and AUC was 0.91. The results of the subgroup analyses showed that the diagnostic accuracy differed across the subgroups (sample size, validation strategy, language, and diagnostic criteria).

Fisher et al., (2026) conducted a systematic review and meta-analysis of studies using NLP and ML for depression detection from spoken and written text. They searched in different databases, identified 123 eligible studies, and used quantitative synthesis using 40,983 text samples across 43 datasets. Pooled performance metrics were: accuracy 0.80, precision 0.78, recall 0.76, AUC 0.79 and balanced accuracy 0.71. Subgroup analyses showed that accuracy was highest when studies were structured clinical interviews, non-English language, and embedding based linguistic features, but meta-regression analysis verified that text source was the only significant factor influencing accuracy variance. The important emerging findings are that, although depression detection using text has shown potential diagnostic accuracy, there is significant variation across the methods (heterogeneity) and a need for standardization, validation, and clinical implementation prior to large-scale use.

Ren et al., (2025) have done a bibliometric and visual analysis of AI applications in depression detection and diagnosis between 2015-2024. By analyzing 2,304 publications, they found that the number of publications and citations has grown exponentially over time with a sharp increase since 2018, due to developments in deep learning, multimodal fusion and objective biomarkers like EEG and facial expression recognition. The research underscores the potential of XAI, longitudinal evaluation and multi-modal data as key components in advancing from academic innovation to equitable real-world mental health solutions.

Khafaga et al., (2023) suggested a new deep learning framework, named Multi-Aspect Depression Detection with Hierarchical Attention Network (MDHAN), which uses Adaptive Particle Swarm and Grey Wolf optimisation for feature selection to detect depression from Twitter data. The model was tested and trained with a dataset of more than 4000 tweets from the Kaggle platform, and the result was an excellent accuracy of 99.86%, a perfect precision of 99.15% for depressed tweets, a recall rate of 97% and an F1-measure of 99.32%.

Su (2025) developed a multimodal deep learning depression prediction system, PsyGuide-Net, that combines the three information modalities of speech spectrogram, text semantic vector, and standardised psychological features supervised using the PHQ-8 score. On the DAIC-WOZ and AVEC 2014 datasets with 5-fold cross validation, the model obtained an accuracy of 0.848, an F1-score of 0.778 and an AUC-ROC of 0.898 for the prediction of the PHQ-8 score, and the Pearson correlation coefficient was 0.732. Importantly, PsyGuide-Net outperforms baseline models like MMD-Transformer, DepAudioNet, MC-MLP and Hierarchical Fusion with statistically significant improvements at $p < 0.05$ or $p < 0.01$. The most important outcome highlighted is that PsyGuide-Net not only achieves high inference speed (106ms average), robust retention (95% retention rate) and sensitive identification of severe depression cases (F1-score of 0.878), but also its psychological feature gating mechanism offers interpretable insights into depression detection, bringing a higher level of clinical applicability for counsellors, campus services and telemedicine platforms.

Amanat et al., (2022) designed a deep learning model for depression detection using textual information, with a particular emphasis on social media posts like tweets. They built their model using a combination of a Recurrent Neural Network (RNN) and LSTM layers, and applied some preprocessing methods such as stemming, lemmatization, and PCA to achieve strong feature extraction. The system was evaluated on the Kaggle dataset containing more than 4000 tweets and performs extremely well: 99.66% accuracy with 10-fold cross validation, precision of 99% in depressed tweets, and 97% in non-depressed tweets, recall of 98-100%, and average F1 score of 0.98. In comparison with the traditional frameworks like SVM, Naive Bayes, CNN and DBN, the proposed LSTM-based framework outperformed them in all the cases, thereby minimizing false positives and having a good generalization.

Pan (2025) proposed a multimodal deep learning depression diagnosis framework named Dynamic Dolphin Echolocation-tuned Effective Temporal Convolutional Networks (DDE-ETCN). Physiological signals (EEG, heart rate), behavioural cues (facial expressions), and biometric data (activity level) are included in the model along with the preprocessing steps of wavelet transformation, normalization, and median filtering. Fast Fourier Transform (FFT) was used to extract the features and fused at the feature level to improve performance. model outperformed standard diagnostic techniques and other deep learning-based models with an accuracy of 98.72%, precision of 98.13%, recall of 97.81%, and F1-score of 97.65% in experiments. It was also validated by error measurements: the MAE was decreased to 3.09, while the RMSE was lowered to 3.59.

In an extensive review, Squires et al. (2023) explore the use of ML and DL tools for detecting, diagnosing, and treating depression. Many studies claim high levels of predictive accuracy, but the review outlines some key areas of limitation which make it difficult for the study to be adopted clinically. The most important of these is model validation, which is predominantly done internally, with only a handful tests on independent data sets and no randomised controlled trials. It is unclear whether the shift to clinical practice will occur unless validated and externalised. Small sample size is also a significant problem, particularly for prediction of treatment response, where the number of subjects in the sample is typically under 150. This increases potential overfitting and overclaiming for performance, reducing generalizability. The review also notes uncertainty quantification as an area where models generally do not convey confidence in their predictions, and is therefore important for clinical decision making and where the area is underexplored. Lastly, although detection research has moved towards transformer-based embeddings (BERT) and multimodal fusion, the prediction of treatment response is still not as advanced, and is still based on traditional algorithms such as SVM, which are not applied directly to raw neuroimages.

Das and Naskar (2024) presented a deep learning model for depression detection, which uses Mel-Frequency Cepstral Coefficients (MFCC) and CNN features based on spectrograms derived from the audio signals. They use a mixture of frequency-domain features derived from the MFCC and spectrogram features derived using a novel CNN architecture optimized by the use of residual blocks and an initialisation function called “glorot uniform”. This model was tested on standard datasets such as DAIC-WOZ, MODMA, emotion recognition dataset RAVDESS, etc. Detection accuracy of more than 90% was obtained for DAIC-WOZ and MODMA, and more than 85% for RAVDESS, outperforming state of the art baselines.

Weber et al., (2025) examined depression diagnosis via multimodal ML of patient interviews, combining speech pattern, language and structured clinical data. Different models were developed for each modality and fused to capture the complexity of psychiatric evaluations. The multimodal fusion approach achieved the highest AUROC (0.88) and macro F1 score (0.75) and had also good calibration and higher NNB (NB of 0.54) than the baseline models.

In this systematic review, Mao et al., (2023) systematically analyzed 264 studies published in the last ten years using speech, text, and facial expression features to diagnose and characterize depression in the PRISMA framework. The review collated results from all modalities, identifying acoustic indicators including lower fundamental frequency, jitter, shimmer and a less precise articulation; semantic indicators such as negative sentiment and social media activity patterns; and facial indicators such as changes in eye gaze, nodding and landmark variations. Importantly, the results highlighted that although some of the models performed well with above 0.80 in accuracy and an F1 score range of 0.78-0.93, there are challenges with small datasets, no external validation and limited generalizability of the models in the field.

Squarcina et al., (2024) published a mini-review on the application of deep learning for the prediction of treatment response for depression, using patient data with clinical, genetic, neuroimaging and biomarker data. The reviewed studies used models like Multi-Layer Perceptrons (MLPs), Dense Neural Networks (DNNs), and other deep learning models, sometimes in comparison with classical regression or support vector models. In total, across eight included studies, deep learning models demonstrated an accuracy of approximately 80% in the prediction of outcomes and achieved significant results, such as an AUC of 0.823 in the prediction of response to Selective Serotonin Reuptake Inhibitors (SSRI) treatment and a 30% improvement in remission prediction in some of the data sets.

Lin et al., (2024) gave a comparative review of the resting-state EEG-based depression diagnosis with both TML and DL approaches. The presentation reviewed 49 articles that utilized classifiers like KNN and SVM for TML and CNNs and variants for DL, which were typically evaluated using n-fold cross-validation, LOOCV, LOSOCV, and nested CV to reduce overfitting. Across the literature, the accuracy rate of DL was found to be extremely high, even outperforming traditional methods as it was able to automatically extract features from raw EEG signals. The review noted, however, that most of the studies had small sample sizes and were not independently validated by external researchers, which limits the generalizability of the findings. The most important finding was that although the diagnostic accuracy of DL models was higher than that of TML, it had limitations in its interpretability and limited data availability, which hampers clinical use. The authors recommended further studies focusing on multimodal data fusion, large standardized datasets and interpretable models as key elements to foster precision psychiatry.

Thoduparambil et al., (2020) created an automatic clinical depression detection model using deep learning techniques which integrates CNN and LSTM network. The CNN extracted local features from EEG signals and the LSTM learned the sequential dependencies: the classification was achieved using fully connected layers. The model was tested with EEG signals from both hemispheres with random splitting. The results were impressive: the system correctly identified depressed individuals from healthy controls with a 99.07% accuracy for right hemisphere signals and 98.84% for left hemisphere signals.

Taoussi et al., 2025 examined improvements in the ML and DL models for depression detection with a particular focus on data preprocessing and augmentation methods to tackle the challenge of class imbalance, including SMOTE. They tested a number of architectures such as RoBERTa (transformer-based), CNN-LSTM (hybrid deep learning) and XGBoost (ML) using the Counsel Chat Dataset. The outcomes were very encouraging: RoBERTa outperformed top-of-the-line baselines with an accuracy of 91.55%, an F1 score of 0.91 and a recall of 92.10%. CNN-LSTM reached 91.67% accuracy (95% CI: 0.8987-0.9312), while XGBoost attained the highest accuracy among ML models at 93.06% (95% CI: 0.921-0.941). These models were shown to be statistically superior, with very low p-values (5.48e-13 for RoBERTa, 3.41e-16 for XGBoost).

Liu et al., (2024) performed a systematic review and meta-analysis of deep learning (DL) models based on speech samples for depression detection. Twenty-five studies were reviewed, with 8 studies included in the meta-analysis, all of which used CNNs. The pooled diagnostic performance was strong: accuracy of 0.87 (95% CI: 0.81-0.93), specificity of 0.85 (95% CI: 0.78-0.91), and sensitivity of 0.82 (95% CI: 0.71-0.94). The best pooled accuracy was from models with handcrafted acoustic features with a score of 0.89 (95% CI: 0.81-0.97) which was higher than end-to-end models.

3. CONCEPT OF NEUROLOGICAL DEPRESSION, CAUSES AND RISK FACTORS

Understanding depression from a neurological perspective requires examining its multifactorial etiology, encompassing biological, genetic, environmental, and psychosocial determinants. This subsection explores the conceptual foundations of neurological depression, its clinical and socioeconomic causes and risk factors, and the conventional diagnostic methods currently employed in clinical practice as shown in Figure 1.

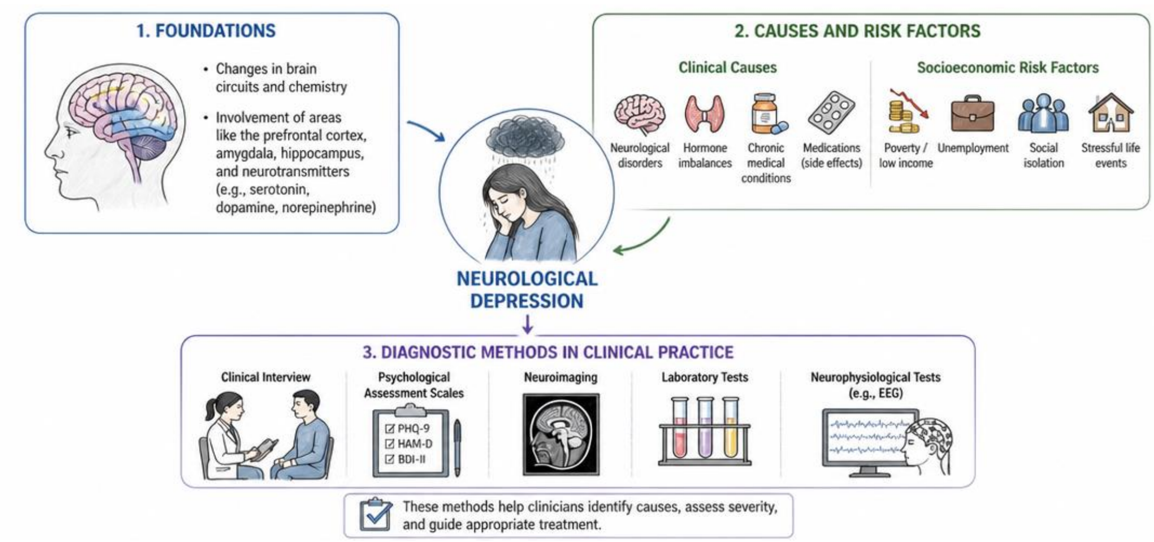

Figure 1: Foundational Concepts of Depressive Disorder

3.1 Causes and Risk Factors of Depression (Clinical and Socioeconomic Causes)

Major Depressive Disorder (MDD) is a complex mental disorder influenced by various biological, environmental, genetic, and neurological factors (Cui et al., 2025). Biologically, MDD is traditionally associated with the monoamine hypothesis, which suggests that deficits in neurotransmitters such as serotonin, norepinephrine, and dopamine in the central nervous system may contribute to the disorder (Liao et al., 2024). However, the delayed onset of antidepressant efficacy and the heterogeneity of treatment responses suggest the involvement of additional mechanisms, such as alterations in brain structure and function (Yang et al., 2021), inflammatory responses (Bhatt et al., 2023), gut-brain axis dysregulation (Riggott et al., 2024), and hypothalamic-pituitary-adrenal (HPA) axis dysfunction (Freimer et al., 2022).

Genetic studies indicate that MDD has a moderate heritability ranging from 30% to 50% (Kendall et al., 2021). Children of parents with MDD have twice the risk of developing the disorder compared to those without such a family history (Agerbo et al., 2021). Gene-environment interactions are significant, with environmental factors like childhood trauma influencing the risk of MDD through epigenetic mechanisms (Normann & Buttenschøn, 2020). Environmental risk factors include childhood emotional or physical abuse, low socioeconomic status, and inadequate social support (Berk et al., 2023). Conversely, protective factors such as a positive family environment, extroverted personality traits, and higher self-esteem can enhance psychological resilience (Metts et al., 2021).

3.2 Conventional Methods for Depression Diagnosis

The diagnosis of depression has traditionally been made based on clinical criteria, including patient current symptoms and history. This process is widely used but relies on subjective interpretation. To standardize both the data obtained and data interpretation, various interview-based instruments and non-interview methods exist for screening and testing for depression in various clinical settings. Traditional tools include physician-administered or patient self-administered interview tools that have reasonable clinical accuracy depending on the threshold score and may lead to a full diagnostic evaluation for high-risk patients (Akpınar & Akpınar, 2021).

The clinical interview is the essential procedure for the diagnosis of depression, with the International Classification of Diseases (ICD) and Diagnostic and Statistical Manual of Mental Disorders (DSM) providing agreed criteria to rely upon. Due to the existence of different factors that may affect the progress, course, and severity of depression, it is recommended to evaluate features of the episode including duration, number and intensity of symptoms, and comorbidity, as well as psychosocial assessment encompassing social support and interpersonal relationships, degree of associated dysfunction and disabilities, risk of suicide, and response to previous treatment (Akpınar & Akpınar, 2021).

Newer diagnostic methods such as genomics, proteomics, and metabolomics are technically sophisticated and objective and are beginning to emerge in psychiatry (Elnaggar et al., 2025). Although promising, further evaluation of these methods is needed to fully demonstrate their clinical value and accuracy. The management of depression in adults should be performed as a stepped care and collaboration model between primary care and mental health, so that interventions and treatments are tailored to the status and evolution of the patient.

3.3 EEG Biomarkers Associated with Depression and Feature Extraction Techniques for the Signals

EEG features extracted for depression diagnosis fall into several categories, with spectral features and functional connectivity metrics being the most prevalent (Elnaggar et al., 2025). Spectral features include absolute and relative band power, Power Spectral Density (PSD), and differential entropy. Temporal and nonlinear dynamics features have appeared in fewer studies but offer valuable insights into the complexity of EEG signals (Elnaggar et al., 2025). Ahmadi et al., (2025) computed time-domain Hjorth parameters including activity, mobility, and complexity in beta and gamma bands. Entropy measures, while relatively rare, have shown promising results.

The feature extraction process is of utmost importance as models are not equipped to handle data with high dimensions, such as EEG signals, which may lead to overfitting (Elnaggar et al., 2025). Existing studies have used a variety of techniques to extract characteristics for depression diagnosis. Statistical, nonlinear, spectral, and wavelet transform-based characteristics are the four categories into which these techniques are subdivided. These features have been extracted using methods like FFT, the Autoregressive (AR) model, functional connectivity-based brain networks, nonlinear analysis methods including Second-Order Difference Plot (SODP) and phase space trajectories, statistical methods, and DWT, Wavelet Packet Decomposition (WPD), and Empirical Wavelet Transform (EWT). Of all the feature categories, nonlinear analysis characteristics are employed most frequently for both machine learning and deep learning approaches. The method in this category that has been most thoroughly studied is entropy-based computation (Elnaggar et al., 2025).

3.4 Application of AI for EEG Signal Analysis

The application of artificial intelligence for EEG signal analysis represents a paradigm shift from subjective clinical assessment to objective, data-driven diagnostic approaches. Deep learning, in particular, has demonstrated remarkable capabilities in automatically extracting hierarchical features from raw EEG data, bypassing the limitations of handcrafted feature engineering. This subsection examines the role of deep learning in EEG signal analysis and explores emerging technologies in bio-signal analysis for neurological disorders.

3.4.1 Deep Learning for EEG Signal Analysis

Deep learning has emerged as a dominant approach in EEG-based depression detection, with CNNs showing strong capabilities in learning local spatial and temporal patterns directly from raw or minimally processed EEG data (Elnaggar et al., 2025). An international collaborative study applied deep learning algorithms to EEG data from six independent global datasets, successfully distinguishing patients with MDD from healthy controls and predicting treatment response to Selective Serotonin Reuptake Inhibitors (SSRIs) (Teng et al., 2025). The research team employed a CNN deep learning model using only 10-channel EEG recordings at a sampling rate of 250 Hz. Gradient-weighted class activation mapping (Grad-CAM) analysis revealed that alpha-band activity in frontal and parietal regions served as key biomarkers, with the right frontal F4 electrode carrying the highest weight (Teng et al., 2025).

Several specialized deep learning architectures have been developed for EEG-based depression detection. Wang et al. (2025) proposed a multi-task model (M-MDD) for enhanced robustness, while Ahire (2025) demonstrated that deep learning models, particularly 1D-CNN, outperform traditional algorithms. Hou et al. (2025) developed a lightweight convolutional transformer neural network (LCTNN) that combines dynamic channel weighting and sparse attention mechanisms to achieve optimal classification with reduced computational cost.

XAI has become increasingly critical in EEG-based depression diagnosis (Saghab Torbati et al., 2025). Techniques such as SHAP values, LIME, and attention mechanisms enable researchers to pinpoint EEG features that distinguish between mental health conditions. Shen et al. (2025) used a Random Forest with SHAP-based feature selection to grade depression severity, with SHAP highlighting left-parietal beta and occipital alpha power as top predictors of more severe depression. Chen et al. (2024) reported a multi-dimensional attention CNN for MDD versus control classification. Metin et al. (2024) used CNNs and Class Activation Mapping in bipolar disorder versus control classification, with CAMs highlighting prefrontal channels as most discriminative.

4. FINDINGS

The research findings of this review article revealed that artificial intelligence has been a ground-breaking concept for the early detection of depression based on biosignals processing via deep learning and multi-modal learning approaches. Figure 2 presents the summary of these findings

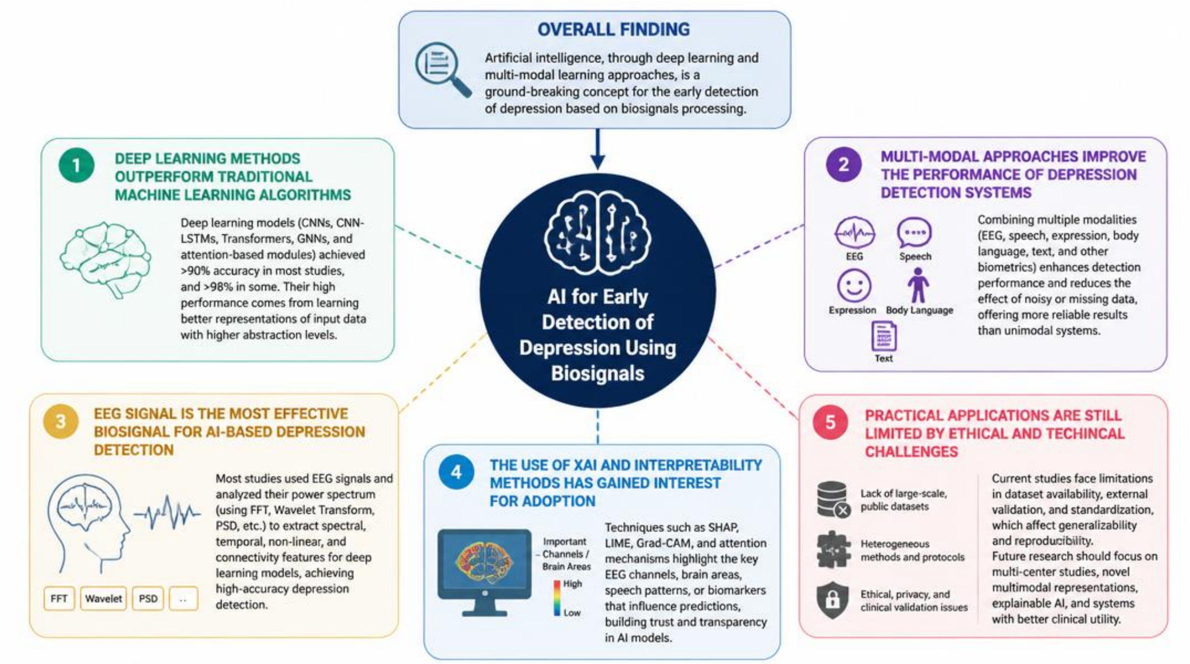

Figure 2: Summary of Findings

4.1 Deep Learning Methods Outperform Traditional Machine Learning Algorithms

The study found that deep learning-based classification methods had superior performance over traditional machine learning algorithms in all reviewed articles for detecting depression. The CNNs, CNN-LSTMs, Transformers, GNNs, and attention-based modules achieved accuracy rates of over 90% in most studies, and over 98% in some research. Their high performance is attributed to the models' ability to learn better representations of input data with higher abstraction levels.

4.2 Multi-Modal Approaches Improve the Performance of Depression Detection Systems

The review also found that using multi-modal inputs improves the performance of depression recognition systems and reduces the effect of noisy or missing data. Several recent studies combined EEG signals with other biometrics, speech, expression, body language, and text analysis to create better depression detection systems that offer more reliable results than unimodal systems.

4.3 EEG Signal Is the Most Effective Biosignal for AI-Based Depression Detection

The study revealed that most research used EEG signals for intelligent depression detection, which is a promising biosignal for building such systems. All reviewed articles showed interest in analyzing the power spectrum of EEG signals using FFT, Wavelet Transform, PSD, and other similar methods to extract spectral, temporal, non-linear, and connectivity features for classification using deep learning algorithms. Those features are then used to train artificial intelligence models to recognize depression with high accuracy, proving the effectiveness of EEG-based biosignal processing using deep learning approaches.

4.4 The Use of XAI and Interpretability Methods Has Gained Interest for Adoption

One of the latest trends in AI-enabled depression detection system design is utilizing techniques from the XAI field to make the models more interpretable and transparent. The latest studies demonstrated that it is possible to use SHAP, LIME, Grad-CAM, and attention mechanisms to explain which EEG channels or brain areas, speech patterns, or physiological biomarkers contribute most to depression detection results, enabling clinicians to understand the black-box models and have more trust in AI-enabled depression detection.

4.5 Practical Applications Are Still Limited by Ethical and Technical Challenges

This review also identified several gaps in the current research on AI for depression detection, including the lack of large-scale, publicly available datasets or the validation of results on external test sets. The reviewed studies mostly utilized the same standard open-source databases, which limits the performance comparison of different methods and negatively impacts the overall generalizability of results. In addition, most articles used different pre-processing steps, feature extraction methods, and evaluation protocols, which reduces the comparability of studies and casts doubt on the reproducibility of results. Therefore, future research should focus on multi-center depression studies, novel multimodal biosignal representations, developing explainable artificial intelligence models, and building intelligent systems with better clinical utility.

5. CONCLUSION

AI has been a ground-breaking innovation for early depression detection based on biosignals processing and multimodal learning. The review found that deep learning-enabled methods allow building efficient automatic recognition systems with higher accuracy than traditional machine learning approaches. Moreover, most studied utilized EEG signals for intelligent depression detection, which proved to be an effective approach for constructing such systems. Several research papers demonstrated that combining different biosignal modalities, such as EEG, speech, facial expression, and others, results in higher classification accuracy than using only one signal type. Finally, the majority of recent studies are focusing on developing methods for building more explainable and interpretable AI models for depression detection, which increases the level of trust clinicians can have in AI-powered systems.

Nevertheless, the survey also identified certain ethical and technical challenges that need to be addressed by the scientific community. The majority of studies did not validate results on large-scale, multi-center datasets, which impacts the generalization of results and may introduce biases into such systems if they are not built using appropriate data. Thus, future research into AI-based depression detection should concentrate on constructing systems with better practical utility while following the FAIR principles and utilizing novel methods for multi-modal biosignal processing for creating more trustworthy and transparent deep learning models for mental health monitoring. Those systems would enable clinicians and patients to manage depression more efficiently by offering reliable early detection and round-the-clock monitoring to improve the quality of care and have a better understanding of the disease.

5.1. Recommendations

1. Future studies should consider designing novel multi-modal depression detection systems that utilize speech, EEG, facial expressions, and other biosignal data for higher accuracy and reliability.
2. More research is needed to make AI-powered depression detection tools more accessible and scalable, which is why future work should concentrate on building models using large-scale, multi-center datasets.
3. The papers should include more methods for model interpretability and explainability to improve the level of trust clinicians and patients can have in those systems.
4. The next generation of biosignal-based depression detection systems should utilize novel IoMT-enabled wearable technologies for continuous patient monitoring.
5. The collaboration between computer science researchers, neurologists, psychiatrists, psychologists, and other healthcare professionals can result in more efficient AI-based depression recognition systems that can improve early treatment.

AI Declaration

The authors declare that this manuscript was not prepared entirely using any artificial intelligence (AI) tool. The conceptualization of the study, literature search, critical review, synthesis of the reviewed studies, interpretation of findings, and preparation of the manuscript were undertaken by the authors. Grammarly was used solely for grammatical corrections and language refinement, while PicAI.com and Microsoft Copilot were used only to assist in the creation of illustrative figures that support the presentation of the review. These tools were not used to generate the scientific content, conduct the literature review, analyze evidence, interpret findings, or formulate the conclusions. The authors accept full responsibility for the originality, accuracy, integrity, and scholarly content of this manuscript.

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