International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Depression Detection and Diagnosis: Using an AI Perspective

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Abstract

Depression is a widespread and complex mental health disorder requiring accurate and timely diagnosis. This review explores the potential of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in enhancing depression detection through diverse data sources such as EEG, fMRI, audio, and text. Models like SVM, CNN, LSTM, and BERT, combined with hybrid approaches, have demonstrated significant accuracy, especially when used with preprocessing techniques and explainable AI tools like SHAP and LIME. The integration of linguistic, behavioral, and neurophysiological data improves early diagnosis and supports clinical outcomes. However, challenges such as data heterogeneity, limited sample sizes, and generalizability issues persist. Future research should prioritize the development of scalable and interpretable systems to aid healthcare professionals in delivering personalized care.

Keywords: Depression, Machine Learning, EEG, fMRI, Deep Learning, SHAP, LIME, Text Analysis, Multimodal Data

1. Introduction

Depression is a complex mental health issue that affects millions of people worldwide It goes beyond everyday emotional ups and downs, manifesting instead as a lasting sense of sadness, disinterest in regular activities, and difficulty with thinking or concentration These symptoms often persist for extended periods, disrupting a person's ability to manage responsibilities at work, school, or in personal life.[1]

The roots of depression can often be traced to a mix of psychological, social, and biological influences Events such as prolonged stress, personal loss, or a lack of social connection are commonly linked to its onset Over the past few decades, the global impact of depression has grown significantly According to the World Health Organization, it now affects a substantial share of the population each year, with women—especially during and after pregnancy—being more frequently affected

Despite its widespread nature, depression often goes unrecognized and untreated, particularly in low- and middle-income regions where access to mental health services is limited This gap in care not only places individuals at risk but also has broader social and economic effects, such as decreased job performance and rising medical costs

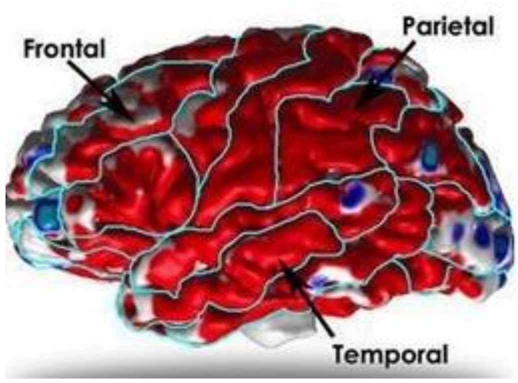

Figure (a) Brain structure during depression

In response to these challenges, computer science has begun playing an important role in the field of mental health Emerging technologies are opening the door to innovative solutions that can help detect and monitor depression more efficiently By using techniques from ML, natural language processing, and biosignal analysis, researchers are now able to explore patterns in speech, brain activity, and online behavior These methods have the potential to support mental health professionals by offering timely insights and aiding in early diagnosis

This research focuses on leveraging such computational tools to better understand and identify depressive symptoms, contributing to the development of intelligent systems for mental health support

2. Previous research works

Numerous studies have investigated the potential of AI and ML in detecting depressive symptoms using multimodal data sources.

Hanshu Cai (2018), explores a novel approach to detecting depression using EEG signals collected from 213 participants (92 depressed patients and 121 controls) via a three-electrode system targeting prefrontal sites (Fp1, Fp2, Fpz) in both resting and sound-stimulated states The raw EEG data underwent extensive preprocessing using techniques such as Finite Impulse Response filtering, Kalman derivation, Discrete Wavelet Transformation, and Adaptive Predictor Filtering, ensuring high-quality signal extraction From this data, 270 linear and nonlinear features were extracted, with the dimensionality reduced using the minimal-redundancy-maximal-relevance (MRMR) feature selection method The study evaluated four classifiers—SVM, KNN, Classification Trees, and ANN—using 10-fold cross-validation, identifying KNN as the top performer with an accuracy of 7927% Notably, the absolute power of the theta wave was consistently present in the best-performing feature combinations, highlighting its potential as a biomarker for depression The study also underscores the feasibility of employing a three-electrode EEG system for depression screening, offering a portable, accessible, and objective tool for early detection These findings pave the way for leveraging compact EEG systems in clinical and real-world settings, bridging gaps in mental health diagnostics with technology-driven innovations.[2]

Shuang Gao (2018), reviews ML applications in major depressive disorder (MDD) using neuroimaging data, focusing on classification and treatment prediction Out of 2045 articles screened, 66 studies were analyzed, most of which used small sample sizes and various neuroimaging modalities, with resting-state fMRI showing the highest accuracy for MDD classification and prediction Preprocessing steps, including feature selection and extraction, were highlighted as critical for optimizing ML pipelines Support Vector Machines (SVM) were the most commonly used algorithm, alongside Gaussian Process Classifier (GPC), Linear Discriminant Analysis (LDA), and Decision Trees Despite achieving varying levels of accuracy, the field is still exploratory, with challenges such as data heterogeneity and limited sample sizes The review underscores the potential of combining ML with MRI data for individual-level analysis and clinical applications in MDD, while emphasizing the need for further research to address current limitations and enhance reliability.[3], [4]

Md Zia Uddin (2021), investigates the use of Long Short-Term Memory (LSTM)-based Recurrent Neural Networks (RNN) to detect depressive symptoms from textual data, leveraging a large dataset collected from a Norwegian youth-focused public information channel The dataset includes 11,807 and 21,470 posts for two experiments, annotated by psychologists for depression-related features Preprocessing steps involved text cleansing, tokenization, and feature selection based on 189 depression-specific symptoms validated by experts Features were encoded using one-hot encoding, creating binary representations of symptom presence, and analyzed using Linear Discriminant Analysis (LDA) for visualization and robust separation between depression and non-depression classes The model architecture comprised RNN with LSTM layers and an attention mechanism to prioritize critical depressive features, enabling accurate predictions for time-sequential data Explainability was ensured using Local Interpretable Model-Agnostic Explanations (LIME), which highlighted key features influencing predictions, fostering trust in model decisions The system achieved superior results, with accuracies of 98% and 99% for the two datasets, outperforming traditional models such as SVM, CNN, and Logistic Regression (maximum 91% accuracy) This interpretable and robust system demonstrates potential for real-time mental health diagnostics and intelligent chatbot applications Future work includes extending the dataset and adapting the model for multilingual and broader applications. [4]

Egils Avots et. al (2022), investigates the potential of EEG features and ML techniques to detect depression and its long-lasting effects Using EEG data from 20 age- and gender-matched participants (10 healthy and 10 previously diagnosed with depression), the research explores both linear (eg, relative band power, spectral asymmetry index) and nonlinear (eg, Higuchi fractal dimension, Lempel-Ziv complexity) EEG features Data were recorded via an 18-channel Cadwell Easy II EEG system, with feature selection algorithms like F-tests and ReliefF applied to enhance classification accuracy Multiple classifiers, including SVM, LDA, NB, kNN, and D3, were evaluated, achieving accuracy rates between 80% and 95% The best-performing method was an ensemble approach with ReliefF-selected features and equally weighted predictions across all feature types Notably, specific EEG features, such as A_rbpO1, A_rbpO2, and B_rbpO2, were sufficient to classify subjects with high accuracy, suggesting a streamlined and targeted approach for depression detection This research highlights the promise of EEG-based diagnostics in mental health, emphasizing how ensemble techniques and simplified feature sets could improve accessibility, efficiency, and accuracy in clinical applications for detecting both ongoing and long-term effects of depression. [5]

Amna Amanat et. al. (2022), investigates the application of DL models, specifically Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM), for detecting depression from textual data, such as tweets The dataset, sourced from Kaggle, comprises over 4000 tweets labeled as depressed or non-depressed Preprocessing involved data cleansing, tokenization, stemming, and lemmatization, followed by feature extraction using One-Hot Encoding and dimensionality reduction with Principal Component Analysis (PCA) The proposed model employs LSTM with two hidden layers, coupled with an attention mechanism, to enhance feature selection and prioritize critical depressive traits Evaluation metrics, including precision, recall, F1-score, and accuracy, were assessed using 4-fold and 10-fold cross-validation The model achieved 99% accuracy, outperforming traditional methods like SVM, Naive Bayes, and CNN The framework demonstrated robust performance, effectively identifying depressive features with minimal false positives Future research will explore hybrid RNN models and larger datasets to enhance generalizability in real-world scenarios.[6]

Matthew Squires et. al. (2023), examines the application of AI, ML , and DL in psychiatry, with a focus on depression detection, diagnosis, and treatment response prediction Preprocessing techniques include natural language processing (eg, LIWC, BERT), audio signal processing (eg, COVAREP), and neuroimaging (eg, EEG coherence, fMRI connectivity), while DL models automate feature extraction Datasets span text (Twitter, Reddit), multimodal data (DAIC), and neuroimaging (EEG, MRI), but small sample sizes and limited generalizability remain significant challenges Supervised algorithms (SVM, Random Forest) and unsupervised methods (hierarchical clustering) are employed, with DL models (CNN, LSTM, BERT) achieving superior performance, particularly with multimodal data integration However, treatment response prediction models require robust external validation to ensure clinical applicability The study highlights the need for standardization, larger datasets, and causal AI frameworks to improve the scalability, interpretability, and efficacy of AI-driven precision psychiatry systems[7]

Vandana et.al. (2023),presents a hybrid DL model for automated depression detection, combining textual and audio features to address limitations of traditional diagnostic methods The DAIC-WOZ Depression Database, comprising audio, text, and questionnaire data from 189 sessions (59 depressed and 130 non-depressed participants), is used for training, validation, and testing Preprocessing involves feature extraction from text using Word2Vec embeddings and audio features like Mel spectrograms and MFCC, with segmentation for noise removal and balancing to mitigate data imbalance Three models are developed: Textual CNN, Audio CNN, and a Hybrid LSTM/Bi-LSTM model integrating both feature sets Results show Audio CNN achieving the highest accuracy (98%) with a loss of 01, while the Hybrid Bi-LSTM model demonstrates improved sequential learning (88% accuracy, 02 loss) The findings emphasize the efficacy of integrating multimodal features for depression detection, with future work exploring additional video features for enhanced multimodal analysis. [8]

Clinton Lau et. al. (2023), introduces a novel approach to automatic depression severity assessment using DL and parameter-efficient tuning techniques The proposed dual encoder model integrates depression-adapted embeddings via prefix-tuning with general-purpose embeddings from a pretrained sentence transformer Using the DAIC-WOZ dataset, the model predicts PHQ-8 scores from clinical interview transcriptions and achieves state-of-the-art performance, with a root mean square error of 467 and a mean absolute error of 380 on the PHQ-8 scale The study highlights prefix-tuning as a more efficient alternative to conventional fine-tuning, requiring fewer parameters (< 6%) and demonstrating robustness in low-data settings By combining depression-specific and general-purpose embeddings, the model delivers complementary insights, outperforming prior text-based and multimodal methods This research underscores the potential of parameter-efficient techniques to address data scarcity in mental health applications and challenges assumptions about the superiority of multimodal approaches, emphasizing AI's promise in supporting mental health evaluation tasks.[9]

Biodoumoye George Bokolo et. al. (2023), presents a comprehensive approach to detecting depression from social media posts, specifically tweets, using a combination of traditional ML techniques and advanced transformer-based models By repurposing the Sentiment140 dataset, the researchers creatively addressed the scarcity of dedicated depression datasets, transforming it into a depression detection dataset comprising 632,000 tweets The study applied extensive preprocessing, including text cleaning, TF-IDF vectorization, and label encoding, to prepare the data for analysis A range of models, from logistic regression and random forests to transformer models like RoBERTa and DeBERTa, were rigorously evaluated using cross-validation and performance metrics such as accuracy, precision, recall, and F1 score Among the models, RoBERTa outperformed others, achieving a remarkable accuracy of 981% on the evaluation set and 97% across cross-validation folds The research highlights the effectiveness of ML, particularly transformer models, in identifying depression-related patterns in tweets, offering a scalable and accessible approach for early detection and monitoring of mental health risks This innovative dataset transformation and the detailed comparison of methodologies underscore the potential of AI-driven tools in digital mental health support.[10]

Yang Liu et. al. (2024), explores the integration of ChatGPT with explainable DL (XDL) frameworks to optimize depression intervention strategies The research aims to evaluate the reliability of AI-generated content (AIGC) compared to human-generated content (HGC) in providing effective psychological counseling Two datasets were utilized: (1) HGC, consisting of 9,257 samples from a Chinese psychological counseling platform, and (2) AIGC, generated using ChatGPT The datasets were preprocessed, cleaned, and divided into training (80%) and testing (20%) subsets Linguistic and sentiment analyses were performed to identify stylistic and semantic differences between HGC and AIGC

The study employed pre-trained models, including BERT and RoBERTa, for feature extraction and classification, with RoBERTa achieving the highest accuracy (9376%) SHAP (Shapley Additive Explanations) was integrated to enhance interpretability by identifying influential words and phrases in the text, enabling transparent decision-making Results revealed that AIGC maintained a neutral tone and objective structure, while HGC exhibited personalized and emotional language.

The findings highlight the efficacy of ChatGPT and XDL models in depression intervention, offering tailored, interpretable, and reliable counseling support Future research will focus on validating the models through clinical trials and expanding datasets to ensure generalizability and scalability in mental health applications.[11]

3. Mathematical and Classification Models in Depression Detection

To effectively detect depression using artificial intelligence (AI), it is important to understand the basic mathematical concepts and models behind each method. The process usually involves several steps: preparing the data (such as EEG signals or text), applying machine learning models to classify the data, evaluating the model's performance, and making the results explainable. The table below presents an overview of commonly used techniques, their key formulas, and their roles in depression detection based on recent research. This helps highlight how mathematical tools contribute to building smarter and more accurate AI systems in mental health analysis.

Table 1: Mathematical Techniques and Models

Aspect	Technique / Model	Mathematical Formula / Concept	Use / Purpose
Preprocessing	DWT	Wave decomposition into EEG bands	EEG signal filtering
Preprocessing	TF-IDF	$\text{TF-IDF}(t,d) = \text{TF}(t,d) \times \log\left(\frac{N}{\text{DF}(t)}\right)$	Text feature weighting
Preprocessing	PCA	Eigen decomposition of covariance matrix	Dimensionality reduction
Classification Models	SVM	$w^T x + b = 0$	Binary classification
Classification Models	Logistic Regression	$\hat{y} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}}$	Binary/multiclass prediction
Classification Models	CNN	$(f * g)(t) = \sum_{\tau=-\infty}^{\infty} f(\tau) \cdot g(t-\tau)$	Feature extraction from images/audio
Classification Models	LSTM	$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$	Sequence learning (EEG, text)
Classification Models	BERT / Transformers	$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$	Contextual text representation
Evaluation Metrics	Accuracy	$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$	Overall correctness
Evaluation Metrics	Precision	$\text{Precision} = \frac{TP}{TP + FP}$	Correct positive predictions
Evaluation Metrics	Recall	$\text{Recall} = \frac{TP}{TP + FN}$	True positive rate
Evaluation Metrics	F1-Score	$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	Harmonic mean of Precision & Recall
Evaluation Metrics	RMSE	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$	Regression error measure

Evaluation Metrics	MAE	$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} \lvert y_i - \hat{y}_i \rvert$	Absolute error
Explainable AI Tools	SHAP	$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{\lvert S \rvert! \cdot (\lvert N \rvert - \lvert S \rvert - 1)!}{\lvert N \rvert!} [v(S \cup \{i\}) - v(S)]$	Feature importance using Shapley values
Explainable AI Tools	LIME	Linear regression on perturbed input samples $\mathrm{Explanation}(x) = \arg\min_{g \in G} \mathcal{L}(f, g, \pi_x) + \Omega(g)$	Local model interpretability

The mathematical methods shown above highlight the wide range of techniques used in AI-based systems for detecting depression. Preprocessing tools such as DWT, TF-IDF, and PCA help clean and simplify the data by breaking it down and reducing its complexity. Machine learning models like SVM, CNN, and LSTM use different mathematical ideas to recognize signs of depression in the data. Accuracy and other evaluation measures are used to check how well these models work. In addition, tools like SHAP and LIME explain how the models make decisions, which helps build trust in their use. When combined, these methods create a strong and explainable approach to analyzing and understanding mental health using AI.

4. Types of Depression

Depression encompasses a spectrum of disorders, each distinguished by specific diagnostic criteria and clinical manifestations Depressive conditions are categorized into several key types, reflecting differences in symptom severity, duration, and etiology.[12]

Major Depressive Disorder (MDD)

MDD, commonly termed clinical depression, is among the most prevalent and debilitating forms of depression Individuals diagnosed with MDD typically experience persistent feelings of sadness, emotional emptiness, and diminished interest in routine activities These symptoms persist for a minimum of two consecutive weeks and are often accompanied by disturbances in sleep, appetite changes, and cognitive difficulties, substantially impairing daily functioning

Persistent Depressive Disorder (PDD)

Also known historically as dysthymia, PDD represents a chronic form of depression characterized by a depressed mood lasting for at least two years While the intensity of symptoms may be less severe than in MDD, the long-term nature of the condition can have a significant cumulative impact on an individual's quality of life and psychosocial functioning

Disruptive Mood Dysregulation Disorder (DMDD)

DMDD primarily affects children and is marked by severe and recurrent temper outbursts that are disproportionate to the situation, along with a persistently irritable or angry mood Symptom onset generally occurs before the age of ten and is associated with long-term emotional regulation challenges, often affecting academic and social development

Premenstrual Dysphoric Disorder (PMDD):

PMDD is a hormonally influenced condition that presents as a severe extension of premenstrual syndrome (PMS) It is characterized by mood-related symptoms such as irritability, anxiety, and depressive episodes occurring in the luteal phase of the menstrual cycle These symptoms typically resolve shortly after menstruation begins but can be severe enough to impair daily activities and interpersonal relationships

Depression Secondary to Medical Conditions

In certain cases, depressive symptoms arise as a direct physiological response to medical illnesses Conditions such as hypothyroidism, cardiovascular diseases, neurodegenerative disorders, and oncological diagnoses can precipitate depressive episodes Addressing the underlying medical pathology often leads to improvement in mood and emotional well-being

Subtypes of Major Depressive Disorder

Major Depressive Disorder (MDD) is not a single, uniform condition; rather, it manifests in various subtypes that reflect differences in triggers, symptom patterns, and physiological context Recognizing these subtypes is crucial for tailoring clinical assessment and improving treatment strategies

Seasonal Affective Disorder (SAD)

One well-documented form of depression is Seasonal Affective Disorder, which typically emerges during the fall and winter months when daylight hours are reduced Individuals with SAD may experience a significant drop in mood, energy levels, and motivation, with symptoms often improving naturally during spring and summer This cyclical pattern points to a possible connection between mood regulation and seasonal changes in light exposure

Peripartum Depression (Prenatal and Postpartum)

Some individuals develop depressive symptoms in relation to pregnancy and childbirth When these symptoms occur during pregnancy, the condition is termed prenatal depression If they arise shortly after delivery—usually within four weeks—it is known as postpartum depression Both types are collectively referred to in diagnostic criteria as “MDD with peripartum onset” Hormonal fluctuations, combined with emotional and physical stressors, are thought to play a significant role in their onset

Atypical Depression

Atypical depression is characterized by a distinctive symptom profile that sets it apart from more conventional forms of MDD A key feature is mood reactivity—individuals may temporarily feel better in response to positive events Other common symptoms include increased appetite, excessive sleeping, and heightened sensitivity to interpersonal rejection Despite its name, this form is relatively common and requires careful clinical attention

Depressive Episodes in Bipolar Disorder

In individuals with bipolar disorder, depressive episodes are interspersed with periods of mania or hypomania Although the depressive symptoms can be similar to those seen in unipolar depression, their presence alongside mood elevation episodes is a defining characteristic of bipolar disorder These mood shifts are essential for accurate diagnosis and influence the selection of appropriate therapeutic approaches

5. Symptoms of Depression

Depression can affect individuals of all age groups, including both children and adults we should know that the depression is a multifaceted mental health disorder characterized by a diverse range of emotional, behavioral, cognitive, and somatic symptoms Although the specific presentation may vary across individuals and subtypes, several core symptoms are commonly recognized in clinical settings These include:

Figure (b) symptoms of depression

- **Persistent Depressed Mood**: Individuals often report ongoing feelings of sadness, hopelessness, or emotional emptiness In children and adolescents, this may manifest predominantly as irritability rather than overt sadness
- **Loss of Interest or Pleasure (Anhedonia)**: A significant reduction in interest or enjoyment in activities that were previously considered pleasurable is a hallmark feature, often leading to social withdrawal

- **Irritability and Frustration**: Increased emotional sensitivity and a low threshold for frustration are frequently reported, particularly in adolescents and younger adults
- **Appetite and Weight Changes**: Depression may be associated with increased or decreased appetite, resulting in noticeable weight gain or loss without deliberate dietary changes
- **Sleep Disturbances**: Individuals may experience insomnia, characterized by difficulty falling or staying asleep, or hypersomnia, which involves excessive sleep duration and difficulty waking
- **Fatigue and Low Energy**: A pervasive sense of tiredness, even after adequate rest, is commonly observed, often impairing day-to-day functioning
- **Cognitive Difficulties**: Problems with concentration, decision-making, and memory are often reported and can negatively impact academic or occupational performance
- **Somatic Complaints**: Physical symptoms such as headaches, gastrointestinal discomfort, or sexual dysfunction frequently accompany depressive episodes and may occur in the absence of an identifiable medical cause
- **Suicidal Ideation**: In severe cases, individuals may experience thoughts of self-harm or suicide, which require immediate clinical attention and intervention

These symptoms, particularly when persistent and impairing, warrant professional evaluation Early diagnosis and timely treatment are crucial to reduce the personal, social, and economic burdens associated with depression

6. Key Factors That Can Lead to Depression:

- **Brain Chemistry Imbalance:** When certain brain chemicals—particularly serotonin and dopamine—are not functioning properly, it can affect how a person feels and processes emotions, often contributing to depressive symptoms
- **Genetic Vulnerability:** People with a close biological relative, like a parent or sibling, who has experienced depression may be more likely to develop it themselves Still, many individuals without any family history can also be affected
- **Challenging Life Events:** Emotionally distressing experiences—such as bereavement, relationship breakdowns, exposure to trauma, or long periods of social isolation—can trigger depressive episodes, especially when support systems are weak or absent
- **Chronic Medical Conditions:** Ongoing physical health issues, including illnesses that cause persistent pain or require long-term care (like diabetes or autoimmune disorders), often have a negative impact on mental well-being, potentially leading to depression
- **Medications and Substance Use:** Some prescription medications may list depression as a side effect In addition, frequent use of alcohol or recreational drugs can increase the risk of developing depressive symptoms or intensify existing ones

7. Approaches to Managing and Treating Depression

Depression is widely recognized as one of the most treatable mental health conditions A large majority of individuals who receive appropriate care—between 80% and 90%—experience meaningful improvement in their symptoms over time

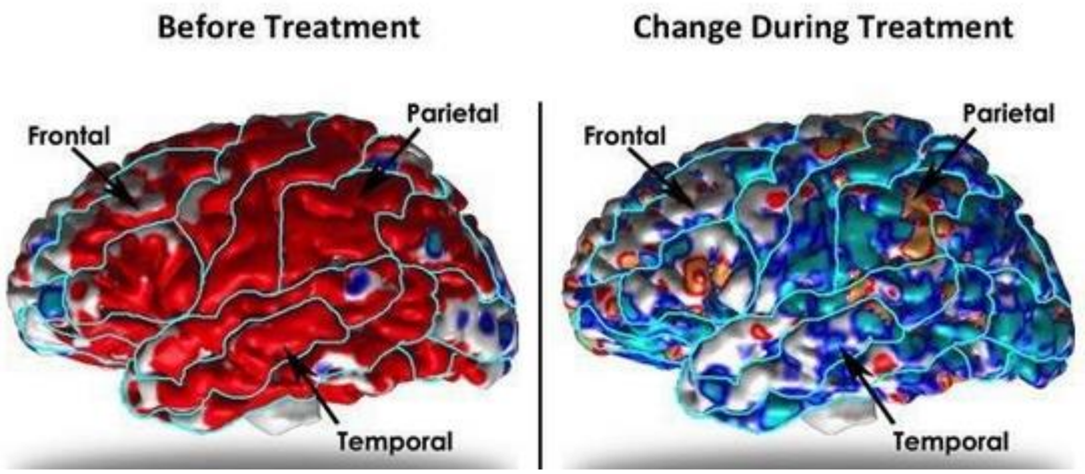

Figure (c) depict brain scans of individuals with chronic depression, captured before and during treatment

- **Before treatment (Left image):** Depressed patients showed increased thickness in the cortex of the frontal, temporal, and parietal regions (highlighted in red) compared to healthy individuals
- **After 10 weeks of treatment (Right image):** These regions, now marked in blue, showed no significant difference in thickness when compared to the brains of healthy controls

1 Psychotherapy (Talk Therapy)

- This form of treatment involves speaking with a licensed mental health professional to explore emotional challenges and reshape negative thinking patterns
- One of the most effective approaches is *Cognitive Behavioral Therapy (CBT)*, which focuses on identifying and modifying unhelpful thoughts and behaviors
- Some people benefit from short-term therapy, while others find long-term support more helpful depending on the nature and severity of their condition

2 Antidepressant Medication

- Antidepressants are commonly prescribed to help correct chemical imbalances in the brain that are believed to contribute to depression
- There are various types of these medications, and finding the most suitable one may involve a period of adjustment
- While side effects can occur, they typically subside with time If not, adjusting the dosage or switching medications under professional guidance may be necessary

3 Complementary Therapies

- These are often used alongside conventional treatments to support overall emotional well-being

- Options include acupuncture, massage, hypnosis, and biofeedback, which may be particularly beneficial for those with mild symptoms or ongoing low mood

4 Brain Stimulation Techniques

- For individuals with treatment-resistant or severe forms of depression, brain stimulation therapies may offer relief
- These methods include:
  - Electroconvulsive Therapy (ECT)
  - Transcranial Magnetic Stimulation (TMS)
  - Vagus Nerve Stimulation (VNS)
- These treatments are typically considered when other options have not been effective

5 Lifestyle and Self-Care Strategies

In addition to clinical interventions, certain daily habits can help support recovery and prevent relapse:

- Engaging in regular physical exercise
- Establishing and maintaining healthy sleep routines
- Eating a balanced and nutritious diet
- Reducing or avoiding alcohol consumption, as it can worsen symptoms
- Staying connected with supportive friends and family members

8. Discussion

The application of AI in depression detection is advancing rapidly, offering transformative solutions for early diagnosis and intervention. This paper presents a range of approaches—from EEG-based classification and neuroimaging analysis to text mining and social media sentiment evaluation. Notably, deep learning models such as LSTM, BERT, and hybrid networks consistently demonstrate high performance, especially when paired with explainability tools like SHAP and LIME. These tools contribute to the transparency and clinical acceptance of model predictions. However, despite these advancements, the field faces significant challenges, including limited dataset sizes, inconsistent labeling standards, and a lack of real-world validation. Addressing these gaps through collaborative research and larger, standardized datasets will be essential for deploying AI systems in real clinical settings.

9. Conclusion

AI-driven technologies are reshaping the landscape of mental health diagnostics. Through advanced algorithms and multimodal data integration, these systems offer promising tools for early and accurate depression detection. Nonetheless, the long-term success of AI in psychiatry will depend on overcoming current limitations by ensuring model interpretability, promoting ethical design practices, and integrating seamlessly with clinical workflows. With further research and refinement, AI holds immense potential to support mental health professionals in delivering timely and effective care.

10. Acknowledgement

I sincerely thank the University Grants Commission (UGC) for their support, which made this research possible. I am also grateful to the Department of Computer Science and IT at Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhajinagar (MH), India, for providing the necessary facilities to carry out this work. Special thanks to Dr. Mukta G. Dhopeshwarkar for her invaluable guidance and support throughout this research journey.

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