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AI and Machine Learning Approaches for Estimating Depression Severity: Techniques, Trends, and Applications

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Abstract

Depression is a very common mental health disorder that results in a disorder of a person's behavior, emotions, and cognitive abilities. Depression can be caused by environmental factors or hereditary factors. The person suffering from depression might have symptoms of suicidal thoughts, altering food patterns as well as sleeping issues. Depression is a global issue that has impacted millions of people globally having more effect on women worldwide. The complexity of depression has led to an increased fascination towards searching for treatments for depression as traditional methods lack in accessing intensity and advancement of depression. This survey paper reviews the evolution of using AI and machine learning (ML) to estimate depression intensity across various contexts such as social media, clinical data, and physical activity. These models generated using artificial intelligence (AI) analyze the big data generated by people's social media platforms and clinical records which can predict the intensity of depression. Studies using deep learning models, multi-task architectures, and symptom-specific detection methods demonstrate the potential of AI in enhancing the accuracy of depression diagnosis. Personalized health assessment can be done using AI to analyze one's social media platform. The posts having text, audio, and videos can reveal information about a person's mental condition. The thorough potential of AI and traditional methods in the prediction of depression intensity is highlighted in this paper along with the need for future research to improve prediction accuracy, multimodal data fusion, and big data. AI has the potential to completely transform mental health.

Keywords: Depression, depression intensity, machine learning, big data, electroconvulsive therapy (ECT)

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INTRODUCTION

Depression is a mental illness that negatively affects a person and changes their behavior, including their reactions, actions, feelings, and perception of the world. During this phase, a person may suffer from symptoms such as altered eating habits, sleeping disorders, tiredness, less concentration, and thoughts about killing oneself. Some external factors also play a very important role in making a person depressed, including both genetic and environmental factors, as well as biological and psychological factors. It is a serious disorder that requires complex treatment. This mental health issue is followed by anxiety, schizophrenia, and bipolar disorder [1]. Nowadays, every one out of two people suffer from depression. It has become the most common mental disorder from which people are suffering worldwide. According to WHO (World Health Organization), about 280 million people worldwide have depression, which is about 5% of adults and 5.7% of adults over 60. Depression is more common in women than men. It also leads to non-curable diseases, such as heart disease, diabetes, and suicide. This is the most common mental health issue among adolescents. NMHS (National Mental Health Survey) of India is a survey that is conducted by the Ministry of Health and Welfare family of government. This survey plans to determine the frequency of mental health disorders all over India and the present state of available treatment. Some of the depressive disorders categorized in the fifth edition of the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (DSM-5) are clinical depression (major depressive disorder), persistent depressive disorder (PDD), disruptive mood dysregulation disorder (DMDD), premenstrual dysphoric disorder (PMDD), and depressive disorder due to another medical condition. Depression has some common symptoms and signs that we can notice in both teenagers and adults: sadness, feeling negative and worthless, loss of interest in normal activities, inactivity on social media, and suicidal thoughts or feelings [2]. Depression lasts between 4 and 8 months on average and can change one's ability to think, impair attention and memory, as well as debilitate information processing and decision-making skills, as well as lower cognitive flexibility and executive functioning. The involvement of artificial intelligence (AI) and machine learning (ML) in improving mental health in evaluation proposes that depression intensity estimation in the future could be more fulfilling. AI involves applications that analyze large amounts of data, such as clinical records, patient-perceived outcomes, and digital behavior analysis, which are not visible through standard methods. This can be done to detect how depression will progress as well as its reaction to the treatments given for prevention. The use of AI for this purpose has the potential to change the outlook of mental health reviews, especially the intensity of depression. Social media also has a great impact on one's life and is becoming the most effective tool for knowing a person's state of mind about how one is feeling or going through. There are many platforms that we use, such as Instagram, Twitter, Facebook, and many more where people post content according to their mood, feelings, or emotions. Figure 1 shows the various causes of depression. By interacting with someone through social media, one can easily get to know about their mental health status. This mental disorder can affect anyone else. When one is suffering from poverty, physical illness, or a breakup, the odds of developing depression become high. Depression can also be cured, or you can take treatment to control it [3]. However, according to existing literature, depression may exist in people at different levels or intensities. At an early stage, this intensity is generally low, and its severity is driven by the situation experienced over time. Common treatments that a person can think of can be psychotherapy, medication, or a combination of both. In some cases, patients suffer from higher depression, which means that they do not respond to at least two of the mood boosters; in such cases, brain stimulation therapy is performed with the patient.

Figure 1. Causes of depression.

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Electroconvulsive therapy (ECT) is a therapy that doctors use to treat severe cases of depression when a patient does not respond to any other treatment. ECT uses electric current to induce controlled seizures in patients with severe mental illness [4]. An ECT of a person is performed twice or thrice a week and is usually completed in twelve or six sessions. A team was formed by a psychiatrist, an anesthesiologist, and a nurse or physician assistant who performed (ECT) on the patients. Obsessive-compulsive disorder (OCD) is a problem that is related to depression. In OCD, repetition and unwanted thoughts come into a person's mind. If you are facing this kind of repeated nature, then you will find you will start finding yourself isolated, which may lead to your withdrawal from your friends, family, and social situation, and may increase your risk of depression. It is very common in people with OCD and depression. A single person's anxiety may also lead to anxiety. Table 1 shows the results of other related studies.

Related Work

In recent studies, deep learning and machine learning techniques have been increasingly employed for the detection and assessment of depression through social media analysis. The various studies are shown in Table 1.

Table 1. The methodologies, results, limitations, and future work of previous studies are summarized.

Citation	Methodology	Future work	Result	Limitations
[5]	The paper proposes an approach based on the deep learning technique to estimate the level of depression from the posts. Using a method inherent in unsupervised learning categorizes depression intensity segregated in text polarity and Latent semantic analysis (LSA) techniques.	Exploring the social network structure and users' locations for identifying the propagation of depression among the social communities.	Identification of early-stage depression, through a machine learning approach that involves deep learning and the use of a relabeling technique and Long short-term memory (LSTM) network for the detection of the level of depression.	The research focuses on the dichotomous classification, however, does not include a proper account of the severity of the disease. The treatment depends on depression levels; therefore, one must estimate their intensity.
[6]	The study focuses on a mixed-method approach to diagnosing major depressive disorder in individuals by using crowdsourcing, behavioral analysis, statistical classifiers, and signal detection.	Discovering the methods for analysis for automated public health tracking at scale via social media aims at help-seeking behavior, health risk behaviors, and risk of suicide.	Diagnosis of Twitter's potential for predicting major depression using social media metrics and detecting different patterns in language, emotion, and social networks related to depressive behavior.	The existing literature is limited by the samples and the group of participants who do not represent the wider population.
[7]	The author of this paper implements a systematic methodology that includes the analysis of heart rate activity through video clips of depressed patients and using a sliding window technique for estimation.	The author aims to conduct experiments on larger public datasets and obtain the most informative video sections to minimize the runtime.	Data used in the research gives the result that depressed patients show constant Heart Rate (HR), achieving 100% accuracy with support vector machine (SVM).	The research focuses on several limitations including the MATrix LABoratory (MATLAB) implementation. It is computationally expensive due to the sliding window method, and it uses a small dataset, future work will involve larger public datasets to obtain pre-informative video sections to improve efficiency.
[8]	The methodology adopted in this research paper is participation selection, group selection, active motion task, motion intensity measurement, time perception assessment, and psychiatric evaluation.	Discovering the methods by which resting-state motion activity can be used as a trans-diagnostic dimension is encouraged.	Identifying the higher impulsive and anxiety increased motion in resting states; depression linked to lower motion and slower time perception in patients.	This study's limitations include limited generalizability due to a small sample, immediate symptom measurement post-task, chronometric counting affecting time perception results, and insufficient control of time perception complexities.

[9]	The author used dynamic panel modeling to analyze the reciprocal connections between depressive symptoms and positive effects over five waves, controlling demographic variables and accounting for individual differences.	Exploring the long-term effects of actions on population health and investigating the two-way causal links between physical activity and depressive symptoms.	Diagnosing a strong reciprocal effect where higher depression symptoms predicted lower physical activity but not vice versa, highlighting the importance of treating depression to enhance long-term physical activity.	The research focuses on limited universalizability long survey intervals, distorted personal activity reports, and potential unobserved variables that affect the results.

METHODOLOGY

The methodology involved examining new methods and trends in depression assessment using AI and ML. AI models assess depression severity by using clinical records, social media, and self-reported assessments. This study shows that natural language processing, feature extraction, and predictive modeling work in mental health settings. It highlights AI's potential of AI to improve depression diagnosis and management through timely, data-driven assessments and patient outcomes.

Preprocessing

Clinical datasets, social media data, and self-reported surveys, such as the PHQ-9, are some of the data sources used in this study. Normalization, which ensures uniformity in feature distribution by scaling features to a standard range using techniques such as min–max scaling or Z-score normalization, is a crucial step in data preprocessing. Furthermore, managing missing values is crucial for preserving data integrity, and this is accomplished using methods such as k-nearest neighbor (KNN) imputation or mean or mode imputation.

Feature Extraction

Natural language processing (NLP) extracts meaningful features from text data. Term frequency-inverse document frequency (TF-IDF) quantifies the importance of words in a document compared with a collection. TF-IDF highlights context-specific keywords by assessing term frequency, enabling a more nuanced understanding of the text. This method emphasizes key terms while minimizing the common but uninformative words in Equation (1).

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) \times \log\left(\frac{DF(t)}{N}\right) \quad (1)$$

Where, N is the total number of documents and DF(t) is the number of documents containing the term t.

Model Selection

Model selection selects the best AI and ML algorithms to estimate depression severity. Logistic regression, support vector machines, and deep learning models were assessed for their performance, interpretability, and clinical data adaptability. To ensure accurate mental health assessments, the selection process balances predictive accuracy with the practical application of Equation (2).

Machine Learning Algorithms

- *Logistic regression:* This is the mathematical formula for the logistic regression model.

  $$P(y = 1 \mid X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}} \quad (2)$$

- *Random forest:* Ensemble method using multiple decision trees to improve accuracy and reduce overfitting.
- *Support vector machine (SVM):* Finds the hyperplane that best separates classes in a high-dimensional space of equation (3).

  $$f(x) = w \cdot x + b = 0 \quad (3)$$

  Where, w, Weight vector; x, Feature vector; b, Bias term.

Deep Learning

Implement neural networks for feature extraction and classification.

- *Convolutional neural networks (CNN):* For image data (e.g., facial expressions).
- *Recurrent neural networks (RNN):* For sequential data (e.g., time series of moods), Eq. (4).

$$h_t = f(W_x X_t + W_h h_{t-1} + b) \quad (4)$$

Where, ht is the hidden state at time t, Wx and Wh are the weight matrices, and b is the bias term.

Training and Validation

P1. Split dataset: The dataset was divided into training (70%), validation (15%), and testing (15%) subsets.
P2. Cross-validation: k-fold cross-validation was used to assess model performance.

- *Metrics*
  - *Accuracy*

$$\text{Accuracy} = \frac{\text{Total samples}}{\text{True positives+True negatives}} \quad (5)$$

  - *F1 score:*

$$F_1 = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \quad (6)$$

  - *Area under the curve (AUC):* Evaluate the performance of classification models.

Application and Trends

Model selection selects the best AI and ML algorithms to estimate the severity of depression. The criteria for evaluating logistic regression, support vector machines, and deep learning models include performance, interpretability, and clinical data adaptability. The selection process balances predictive accuracy and practical applications to ensure accurate mental health assessments.

- *Terminology used:*
  - *AI:* Artificial intelligence—the simulation of human intelligence in machines.
  - *Machine learning:* A subset of AI focuses on the development of algorithms that allow computers to learn from data.
  - *Depression severity:* The extent to which an individual experiences symptoms of depression.
  - *Natural language processing:* This is a field of AI that focuses on the interaction between computers and human language.
  - *Hyperparameter tuning:* The process of optimizing the parameters that govern the training of a ML model.

This methodology outlines a systematic approach to utilizing AI and machine learning techniques to accurately estimate depression severity, encompassing data handling, model training, and practical applications while considering ethical implications.

SYSTEM ARCHITECTURE

Figure 2 shows our system design featuring heterogeneous data sources in conjunction with alternative ML methods to improve depression severity recognition. The first step is data acquisition: surveys, data from their social media activity, and sensors must be curated into a detailed dataset representing the individual's mental health over time [10]. Then, the raw data are processed and cleaned (feature extraction) to prepare them for analysis. In the corresponding data, multiple ML models, such as logistic regression, Random Forest, and deep learning, were trained using processed data. The relational patterns with respect to depression severity were captured by training each model independently to improve prediction accuracy. The third stage of the model evaluation step involved comparing these algorithms to ensure that they all produced accurate estimates. All the User Experience(UX) cases built in this work demonstrate that the system incorporates feedback from users, such as running interaction analyses, to learn how far a model is working and what experiences it elicits

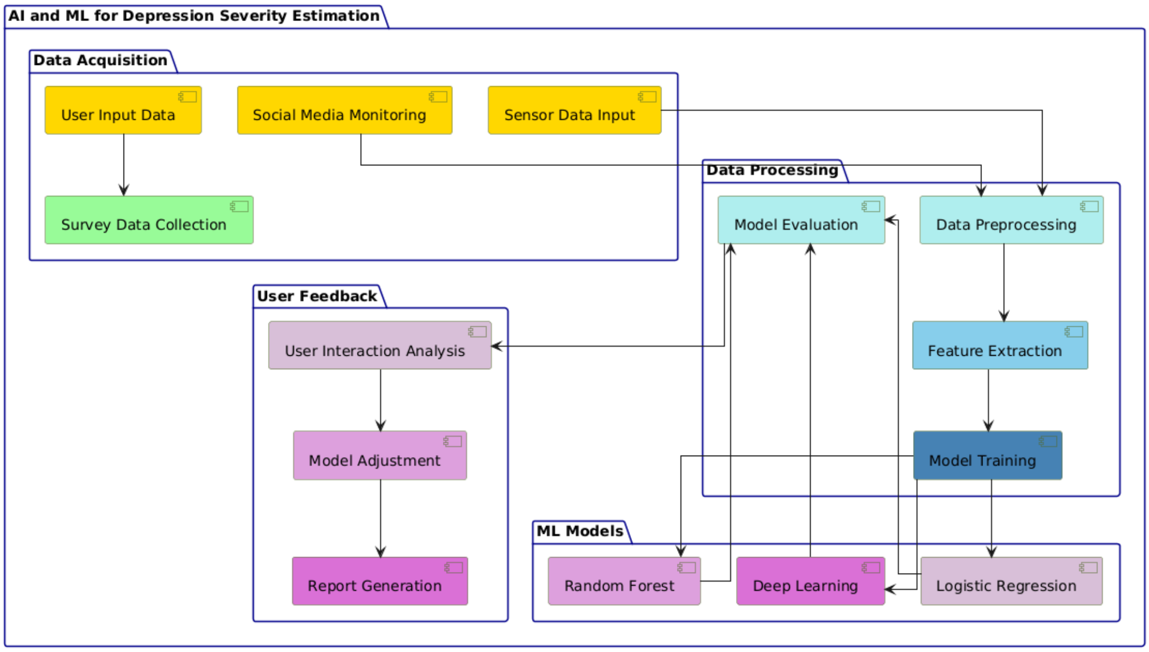

Figure 2. AI and ML workflow for depression severity estimation.

```
Input: Data File F
Output: Depression Severity Score S, Report R

if (F is of the correct file type) then
 if (F passes the required checks) then
 user Data ← Load Data(F)
 else
 return "File is not compliant"
 end if
else
 return "File is not of the correct file type"
end if
pre-processed Data ← Preprocess Data (user Data)
features ← Extract Features (pre-processed Data)
if (features are valid) then
 model ← Load Trained Model ()
 S ← Predict Depression Severity (model, features)
else
 return "Feature extraction failed"
end if
R ← Generate Report(S)
if (User provides feedback) then
 Adjust Model Based on Feedback (model, feedback)
end if
return S, R
```

Figure 3. Algorithmic approach

in end users. This is essential because it provides a feedback loop to refine the models more faithfully. As a result, the system also generates analytical reports automatically for sharing with users and stakeholders to enhance users' and stakeholders' awareness, understanding, and use of depression severity in general, and about the possible role of technology in depression assessment.

A greenfield methodology based on user data streams for predicting depression states is proposed in Figure 3, using an algorithm for AI and ML approaches for estimating depression severity. Once the type of input file is loaded and checked to ensure that the file is valid, only the valid files are processed [11]. It uploads user data to determine whether a file fits the criteria. After that, the data are prepared for feature extraction, an algorithm that isolates characteristics relating to the severity of someone's depression. If the selected features are extracted, they seem valid, and one obtains an input sample and loads a pre-trained ML model to predict the depression severity score for that user. Once the prediction is made, it generates a report that elucidates the users' mental health status. In addition, the model also has a feedback loop so that people can comment on its performance to aid staff in refining it to become more accurate. This algorithm, in general, demonstrates the principle of a systems theory approach that aims for correct predictions, as well as user interaction and perpetuated improvisations. Combining such data validation, preprocessing, and feature extraction with user feedback yields a powerful framework that may be applicable within the paradigm of AI and ML for main mental health assessment, hypothesizing to provide helpful insights and targeted support toward depression.

SIMULATION PARAMETERS

As listed in Table 2, the model was trained on a dataset of 1,000 instances with 10 unique features. The training lasted 120 s, and the validation period was 30 s. It achieved an accuracy of 85.5%, indicating a high degree of predictive efficacy [12]. The training and validation duration efficiency with accuracy showed that the model was capable of handling data scheduling within a reasonable time span.

RESULT ANALYSIS

Table 3 presents a comparative performance summary of four distinct models: This was tested using our four metrics: accuracy, precision, recall, and F1 score on five ML models: logistic regression, Random Forest, SVM, and neural network. Using logistic regression, we achieved an accuracy of 78.5%, precision of 75.0%, recall of 70.0%, and F1 score of 72.5%. Random Forest model outperformed the other models by 15.0%, 85.0%, 80.0%, 82.0%, and 81.0%, respectively. Finally, we tested the SVM model, which had an accuracy of 82.3%, precision of 78.0%, recall of 76.0%, and F1 score of 77.0%. Thus, the neural network model proved to be superior, with an accuracy of 87.8%, precision of 85.0%, recall of 88.0%, and an F1 score of 86.0%. All other models had lower performance for this task than the neural network [13].

Figure 4 shows the performance metrics of the different models for different training epochs and evaluation criteria. The accuracy vs. epochs graph presented above shows an increase in accuracy with five epochs at the start of 76%, which increases to 85% in the fifth epoch, showing that the model is very well learned [14]. From Epochs 0 to 4, we observe a reduction in the loss from 0.60 to roughly 0.20 [15], suggesting better error minimization as training progresses. The accuracy bar chart compares four models: Random Forest, SVM, logistic regression, and neural network. Random forest, SVM, and logistic regression followed neural networks in terms of accuracy, settling at 85%, 82.3%, and 78%,

Table 2. Model performance summary.

Parameter	Value
Sample size	1000
Features used	10
Training time (seconds)	120
Validation time (seconds)	30
Accuracy (%)	85.5

Table 3. Model performance comparison.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Logistic regression	78.5	75.0	70.0	72.5
Random forest	85.0	80.0	82.0	81.0
Support vector machine	82.3	78.0	76.0	77.0
Neural network	87.8	85.0	88.0	86.0

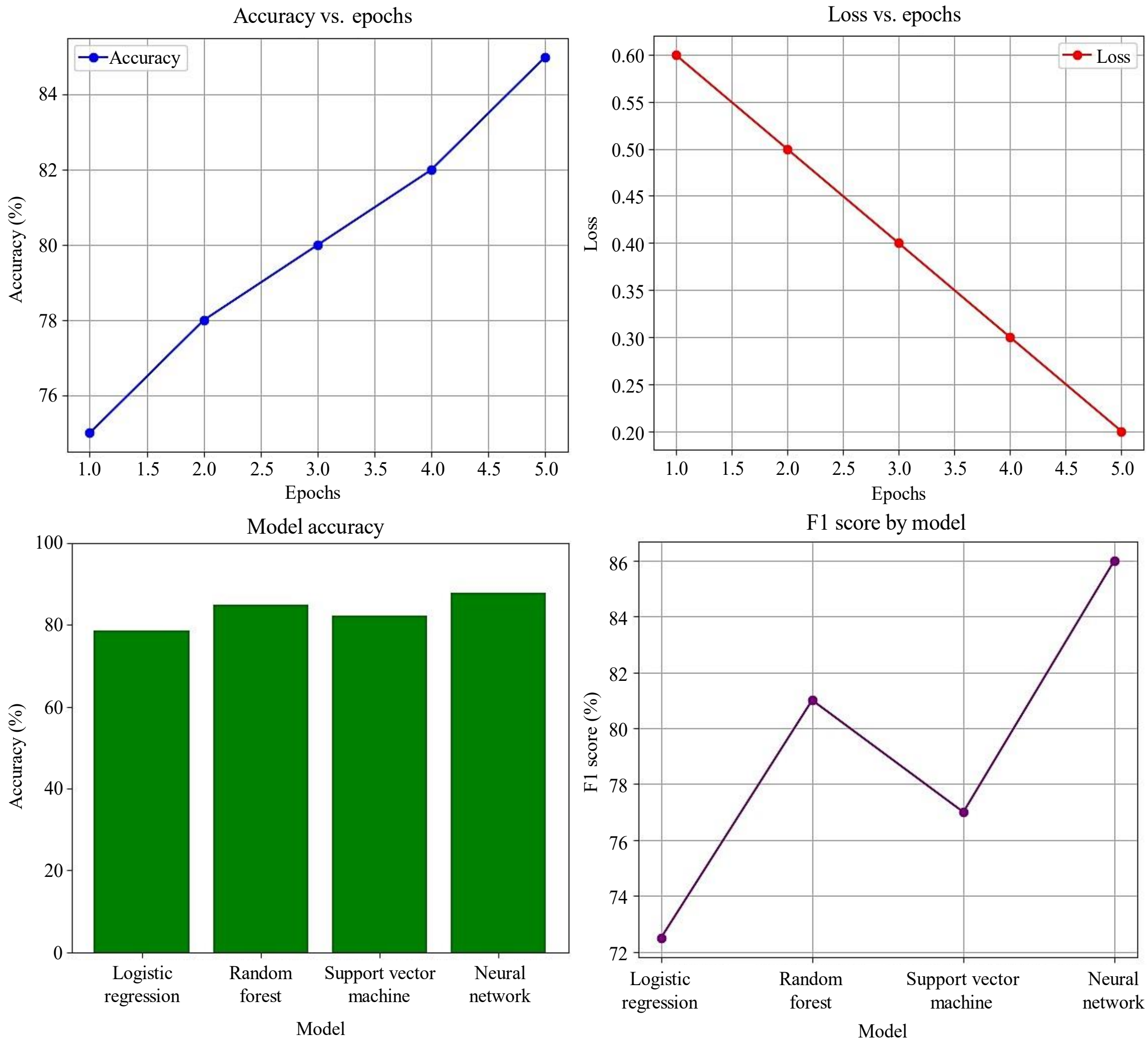

Figure 4. Model performance metrics across epochs and models.

respectively. The F1 score by model graph shows that the neural network performs better than the others with an F1 score of 86%, Random Forest amasses 81%, SVM stands at 77%, and the F1 score reached by the logistic regression is 72.5%. Finally, these charts emphasize the performance of the neural network in achieving high accuracy with balanced precision-recall performance [16–18].

CONCLUSION

This research aims to highlight the importance of the lack of knowledge and potential assessment of depression through different techniques, mainly AI and ML. As depression affects the global population, increasing the prevalence of depression in individuals worldwide, there is a need to improve the tools used to identify and assess depression severity. Research shows that AI has the potential to provide personally relevant mental health conditions to people of the world through the arrangement of data from different sources such as social media, clinical records, and physical activities. The results indicate that preliminary methods may fail to identify anxiety, indicating data-based therapies that can adapt to different levels of pain and mood. More studies should look at how to connect several types of data, in addition to multimodal data, and improve prediction models to validate diagnostic accuracy. Furthermore, it can also help discover the synergies between social behaviors, emotional expression, and mental health outcomes and, as such, can make the measures more influential. At the end of the day, diagnosis with the help of AI and ML in mental health research holds the potential to develop the public's understanding of depression as well as proper diagnoses and therapies being prescriptive; thus, it would enhance public health outcomes.

Future Work

Future work aimed at assessing depression using AI and ML looks at some of the following fields to enhance the effectiveness of these outcome models. Analysts should conduct interviews or ask people of different ages and ethnic groups. This will also assist in verifying that the models can fit for every person, not for some groups of people. Second, data collection, such as text data, voice data, videos, and body metric data, would provide a full picture of a person's mental health. This may assist researchers in elaborating the hitches of depression in a much better manner. One can also learn more about the dynamic nature of symptoms of depression, particularly from social media posts and their association with life events; mental health specialists, data scientists, and software developers can assist in developing simple interfaces that can give quick results when the patient fills the depression test or completes the survey; further, the study of ethical issues such as privacy and how algorithms come to the decision; further, comparing the AI model proposed strong and reliable models that compare how symptoms of depression change over time, especially by looking at social media posts and how they relate to their life events.

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