

Detection and Analysis of Depression in Women Using Machine Learning Approaches

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Abstract - Depression is a widespread mental health condition marked by ongoing sadness, reduced interest in activities, and emotional detachment. Unlike normal mood changes, it significantly impacts daily life, relationships, and productivity. This study presents a new, more reliable approach for identifying depression, which was tested using the Mental Screen Inventory. The method showed improved accuracy over existing techniques. The findings offer valuable insights for mental health professionals and researchers aiming to better understand and manage depression.

I. Introduction

Millions worldwide face depression each year, often without timely diagnosis or support. It can lead to other mental disorders and affects women more frequently due to hormonal, genetic, and social factors. Life stressors like grief, work pressure, and caregiving duties are known triggers. Hormonal shifts during the menstrual cycle can also worsen symptoms, sometimes resulting in conditions like premenstrual dysphoric disorder (PMDD). Tools like the Menstrual Distress Questionnaire help assess such issues. This research introduces a machine learning-based detection method that outperforms current systems, offering a promising step toward early and accurate diagnosis of depressive disorders.

II. Proposed Methodology

It emphasizes the shortcomings of traditional approaches while emphasizing the potential benefits of using machine learning techniques to improve classification accuracy and efficiency.

Machine Learning Models

The four major categories of machine learning algorithms are supervised, semi-supervised, unsupervised, and reinforcement learning, each based on a different learning strategy.

Supervised Learning: To create predictions, supervised learning algorithms use labeled datasets.

Unsupervised learning systems use Unsupervised Learning Unlabeled data. This learning method labels unlabeled material by categorizing it or expressing its type, form, or structure.

Semi-Supervised Learning The purpose of these methods is to apply the knowledge gained from labeled data to classify unlabeled data.

Gathering and Preparing Data

We began our research by preparing the dataset required to train and evaluate our model. For this purpose, we collected printed versions of standardized psychological assessment tools from the psychology department of a multi-specialty hospital. These tools targeted two prevalent mental health conditions: anxiety and depression. Specifically, we used the Depression Scale created by Rahman and Uddin (2005) and the Anxiety Measurement Scale developed by Farah Deebea and Roquia Begom (2004) [11].

Proposed Model

To explore the role of machine learning in diagnosing mental health disorders, we reviewed an extensive range of scholarly articles and journals, focusing on studies involving diverse age groups and individuals who prefer to remain anonymous. One notable system, the Monash Interview for Liaison Psychiatry (MILP), was developed using constraint-based reasoning aligned with diagnostic standards such as DSM-III-R, DSM-IV, and ICD-10. The framework was implemented using Constraint Logic Programming (CLP) and offered a relatively simple diagnostic process. Additionally, researchers have applied various AI techniques—including rule-based reasoning, fuzzy logic, and fuzzy-genetic algorithms—to identify and manage mental health conditions effectively.

The depression severity was divided into various categories using the scores for the responses listed in Table 1.

The Intensity of Depression	Range of scores that correlate
Minimum	30-100
Mild	101-114
Moderate	115-123
Severe	124-150

Anxiety was divided into four severity categories based on the calculated total score, as shown in Table 2.

The Intensity of Anxiety	Range of scores that correlate
Mild	54 and less
Moderate	55-66
Severe	67-77
profound	78-135

III. Results

Standards of Evaluation The model's output was assessed using its recall, accuracy, and precision values. The metrics were computed by adding up the accurate forecasts (false positives, FP, and false negatives, FN) and inaccurate predictions (true positives, TP, and true negatives, TN)

Accuracy: The system's overall number of predictions across all prediction kinds is called accuracy (Aj).[13]

Precision: A measurement metric called precision (Pn) is used to compare the precise forecast of actual positive instances, which include both true positives and false positives under the category of positive cases, in comparison to the total optimistic predictions"[13].

Recall: A parameter called recall (Rn) quantifies the percentage of accurately recognized positive examples among all real positive patterns [13].

Model Performance Assessment

For anxiety and depression, three distinct algorithms are utilized to examine recall, accuracy, and precision in Figure 1 and 2, respectively: LDA, KNN, and SVM.

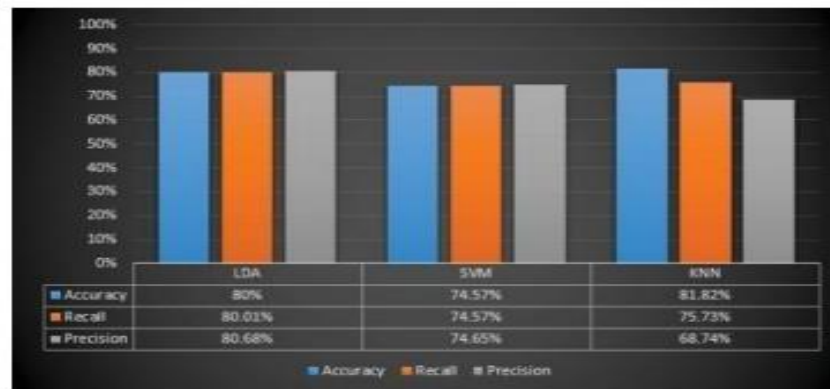


Figure 1: Depression comparison with LDA, KNN and SVM

SVM and CNN showed the best and lowest scores for precision and recall, respectively, among these techniques. The data above lead us to the conclusion that the accuracy of all the algorithms is about the same. CNN, on the other hand, registered 96.8% for melancholy and 96% for anxiety, giving it the highest accuracy. KNN, on the other hand, produced the least accurate results, scoring 81.82% for both depression and anxiety. While the default value for anxiety and depression is typically 100, the CNN was set to 45 epochs.

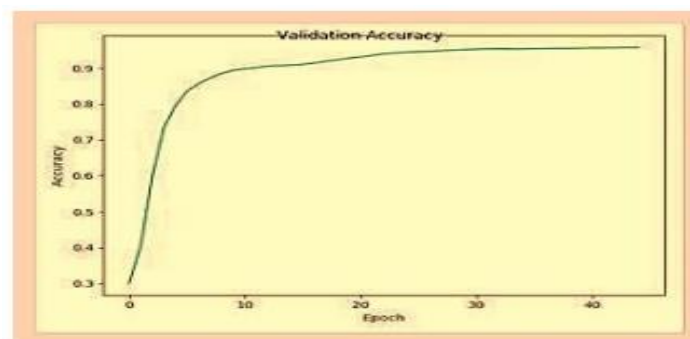


Figure 2: Anxiety -Validation Accuracy

IV. Experimental Results

Our findings indicate that linear regression is not a reliable method for predicting anxiety and depression outcomes. The Root Mean Square Error (RMSE) values for both conditions fall within a moderate range—neither significantly high nor notably low—suggesting that the model produces only average predictions. This outcome can be attributed to the nature of linear regression, which assumes a linear relationship among variables. Since our dataset does not exhibit any clear linear trend, the model struggles to establish meaningful connections between input features and target variables, resulting in limited predictive accuracy. To improve performance, we compared three alternative machine learning algorithms—Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM)—in terms of accuracy, precision, and recall for both anxiety and depression. The comparative results are illustrated in Figures 3.

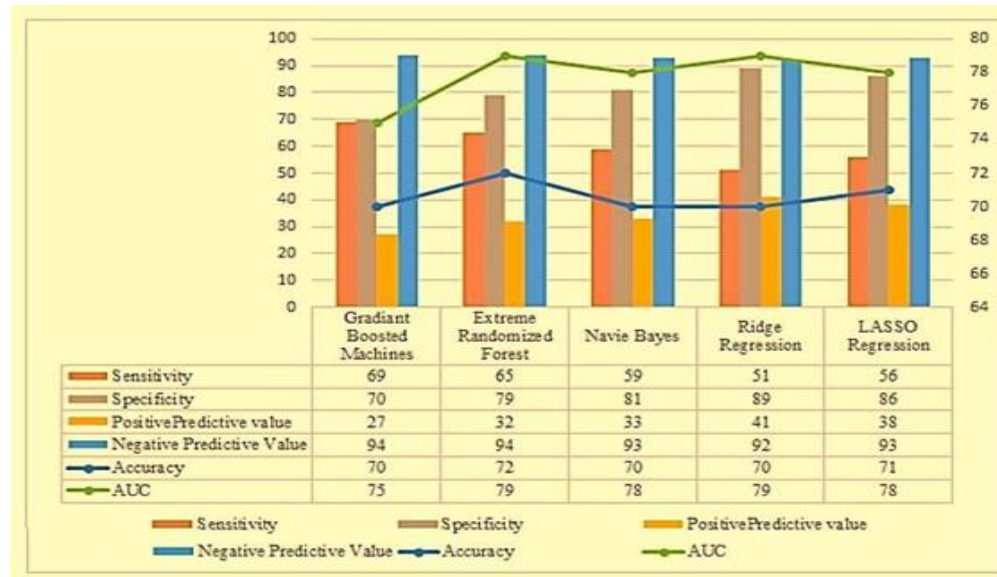


Figure 3: Performance Measure -1

V. Conclusion

In India, depression is common among women of all ages but often goes undiagnosed due to stigma. Stress from balancing multiple roles contributes to conditions such as PMS, postpartum depression, and PMDD. Routine screenings for domestic violence and early detection should be prioritized in primary care. Antidepressants must be freely available, and combining medication with therapies like cognitive-behavioral therapy leads to better outcomes. This study also reviews key feature selection (FS) methods used in mental health prediction, including Ratliff filter, IG filter, SFS wrapper, RFE-SVM, LASSO, and RIDGE. Each method was evaluated for its strengths and limitations. To handle data imbalance, future research could apply techniques like POS tagging. The study also highlights a strong link between depressive symptoms and women's quality of life, with the proposed method showing improved reliability. However, further data enrichment is needed to assess depression severity more accurately.

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