Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 12
December 2023

"A Supervised Learning-Based Machine Learning Method for Detecting Depression and Anxiety"

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Abstract

Anxiety and depression are two of the main factors contributing to significant disability in emerging nations. India ranked top in the World HealthOrganization's (WHO) South East Region report on anxiety disorders, with women suffering from the condition twice as badly as men. Since treating these problems later on would be more expensive and ineffectivethan intervening early, we have developed a model that diagnoses the various stages of these mental disorders using machine learning algorithms in conjunction with a regular psychological assessment. We've identified five distinct AI algorithms—Convolutional Neural Networks, Support Vector Machines, Linear Discriminant Analysis, K Nearest Neighbor Classifiers, and Linear Regression— that have proven effective in our proposed model when applied to both anxiety and depression datasets. In assessing diverse measurement criteria like accuracy, recall, and precision, our model employing the CNN algorithm demonstrates superior performance. Specifically, it achieves 96% accuracy for anxiety and 96.8% for depression, surpassing other algorithms in these aspects. Furthermore, our data reveals that 15.6% of urban women aged 18 to 35 experience chronic depression, and 7.4% experience severe anxiety.

Keywords- Support vector machine; Convolution neural network; Linear Regression; K Nearest Neighbor Classifier; Linear discriminant analysis; Machine Learning; Depression; Anxiety;

I. Introduction

Global Health Data report an approximate global count of 450 million individuals facing mental health challenges. Furthermore, depressive disorders currently hold the fourth position globally with regard to the event of disease and are anticipated to ascend to the foremost position by the year 2020 [1].Depression is a prevalent yet highly hazardous mental state that impairs a person's ability to focus on work, school, and other daily duties by causing persistent emotions of melancholy and disinterest. In any given year, depression affects one in fifteen persons, indicating a major contributing factor to almost half of all suicide attempts [2]. Approximately 30% of adults encounter another substantial psychological concern during various levels of their lives, which is anxiety. According to the latest survey carried out by the World Health Organization,6.9 million individuals, constituting 4.1% of the nation's total population, experience anxiety, while 6.4 million, accounting for 4.4%, grapple with depression in India [3]. In the WHO's reports, India stands out with the highest prevalence of anxiety disorders among all countries. Women are diagnosed with these diseases twice as often as men are (4.6% versus 2.6% globally) [1]. In this research, we have suggested a machine learning algorithm-based diagnostic system for the two aforementioned frequent psychological disorders: anxiety and depression. Determining the patient's disorder's severity will be helpful. After conversing with psychologists across multiple hospitals, it became evident that a standard scale is frequently employed by the majority of Indian psychologists during the initial diagnosis of prevalent mental illnesses. These standard scale questionnaires for anxiety and depression were gathered from the Bharathmultispeciality hospital of psychology department and completed by urban patients, ages 18 to 35. Before employing the five machine learning methods these data were pre-processed.

II. Related Studies

We've analyzed numerous articles and academic journals to grasp how machine learning contributes to identifying mental health disorders among individuals of diverse age groups who prioritize anonymity.The 1980s saw the beginning of this topic's research.In the research conducted in [4] introduced an expert system named MILP (Monash Interview for Liaison Psychiatry), utilizing constraint-based reasoning to diagnose mental disorders, referencing DSM-III-R, DSM-IV, and ICD-10 criteria.The framework was created utilizing the Constraint Logic Programming (CLP) language.Still, it was a rather simple procedure [4]. Nevertheless,in [5] researchers utilized three artificial intelligence reasoning methods—rule-based reasoning, fuzzy logic, and fuzzy-genetic algorithm—to identify and treat mental health patients. Also, their suggested model offered consumers recommendations for appropriate therapy regimens [5]. Furthermore,researchers in [7] designed a hybrid system merging Mamdani's fuzzy logic controller with a feed-forward multilayer neural network to detect adult depression utilizing a neuro-fuzzy technique.The system achieved a diagnostic accuracy of 95.5 percent in identifying depression.The Multiclass Classifier demonstrated superior accuracy in producing results in accordance with the selected attributes [7].

Nevertheless, several investigations used image analysis to scrutinize nonverbal cues of patients, aiming to enhance the precision of ascertaining a user's psychological condition [8]. David DeVault, Ron Artstein, and colleagues introduced a prototype named SimSensei Kiosk, aiming to create a conducive environment for patients to comfortably discuss their concerns with an interviewer in person.This virtual human interviewer could analyze a patient's gestures to identify indicators of depression, anxiety, or post-traumatic stress disorder (PTSD) [9]. Other research studies utilized data from social media platforms for the purpose of detecting

Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 12
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various disorders. Researchers and their collaborators developed a multimodal depressive dictionary learning model by examining a Twitter dataset that revealed behavioral differences between users affected by depression and those who were not [10][17][18].

A. GATHERING AND PREPARING DATA

A. Acquiring Dataset

We started our investigation by getting our model's dataset ready. In accomplish this, we have gathered hard copies of distinct standard scale questionnaires from the psychology department of the multispeciality hospital for the two common psychological disorders, anxiety and depression.We utilized two questionnaires for our study: the depression scale developed by Rahman and Uddin in 2005 and the anxiety measurement scale devised by Farah Deeba and Roquia Begom in 2004 [11].The development of both datasets prioritized urban patients and included questions linked to lifestyle that are related to our nation's climate, culture, and way of life.

The depression scale consists of thirty questions, each offering five possible responses carrying weights ranging from 1 to 5.The score aids in assessing the severity level of the patient's depression. Utilizing the scores outlined in TABLE I for the responses, the depression severity was categorized into distinct groups. The anxiety measurement scale comprises thirty-five questions.Every question offers five choices, where each choice, ranging from 0 to 4 in terms of weight, contributes to determining the ultimate score.Based on the computed total score, anxiety was categorized into four levels of severity, as specified in TABLE II.

TABLE I
CATEGORIES OF DEPRESSION SEVERITY SCALE

The intensity of depression.	Range of scores that correlate.
Minimum	30-100
Mild	101-114
Moderate	115-123
Severe	124-150

TABLE II
LEVELS OF ANXIETY SEVERITY MEASUREMENT

The intensity of anxiety.	Range of scores that correlate
Mild	
Moderate	55-66
Severe	67-77
Profound	78-135

All the participants who filled out the form were females aged between 15 and 35 years old.Among them were professionals from corporations, homemakers, and students.We have employed it to document information in distinct CSV files. Following that, we conducted data preprocessing by removing irregularities From every individual file independently. To verify if the outcomes adhered to the specified range in the questionnaire forms, the sums of the results from each column were initially computed. The noise-containing column was completely eliminated. Subsequently, we examined each column to identify any instances of missing values. whether so, we eliminated the entire column. Thirdly, we eliminated any columns that had multiple values. The data was preprocessed in this manner.

B. Dataset for Training and Testing

Subsequently, we implemented various methods to preprocess our datasets. Our dataset underwent division through K-fold cross-validation, resulting in the creation of training and testing sets. We partitioned our dataset using K-fold cross-validation, separating it into training and testing sets. Employing a stochastic method, the dataset is divided into k groups or folds, each of roughly equal size. During model training, k-1 folds are utilized, and the testing is performed on fold 1. The procedure is repeated k times, utilizing distinct folds or groups of data points on each iteration for validation purposes [12]. On the flip side, opting for a smaller value of k results in heightened bias and diminished cost-effectiveness in the model.Conversely, as k increases, the model's cost increases but its bias decreases. Moreover, employing higher values of k may introduce significant variability in the model. We have decided that 10 is the most reasonable figure for k, keeping everything else in mind.

III. METHODOLOGY OF THE STUDY

Model training consisted of utilizing five machine learning algorithms.They are Linear Regression,K nearest neighbor (KNN),Support Vector Machines (SVM),Linear Discriminant Analysis (LDA),Convolutional Neural Network (CNN)

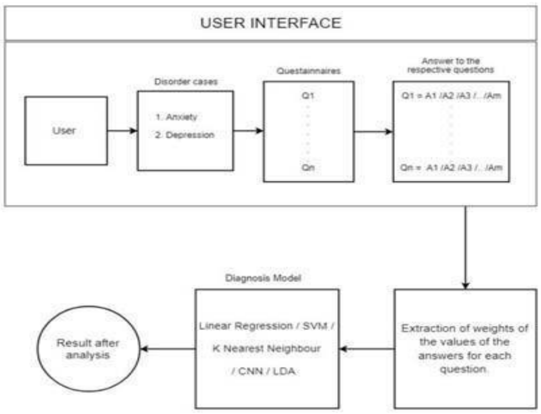

Fig. 1. System Architecture Design.

The optimal approach for evaluating anxiety and depression levels in adults aged 15 to 35 is subsequently delineated, considering various performance metrics such as accuracy, precision, and recall. Fig. 1 describes the architecture of the system.

A. Linear Regression

Regression analysis is frequently employed to evaluate various factors and establish the correlation between two variables. T(x1, y1), T(x2, y2), and T(x n, y n) denote a collection of random data points for two numerical variables, X and Y, where X serves as a predictor for Y.

A straight line in X, Y space is created by a perfectly linear relationship between X and Y in this linear regression analysis. This linear regression will result in a straight line if X and Y are perfectly linearly correlated in the X, Y space.

$$y = ax + b \quad (1)$$

A questionnaire is considered variable X in our system, while an outcome is considered variable Y. Straight lines are produced to illustrate the trend in the data. As the distance between the data points and line decreases, the accuracy of the data increases.

Our dataset was used to determine the optimal parameter values for linear regression using Grid Search Algorithm.0.1 was chosen as the minimum tolerance parameter. Collinear features must be eliminated with a minimum tolerance.A value of 2 is assigned to the ridge parameter.Ridge regression should be conducted using the specified ridge parameter.

B. K nearest neighbor (KNN)

Supervised machine learning is done with the K Nearest Neighbor (KNN) algorithm. It stands out as a straightforward, practical, and uncomplicated algorithm among all machine learning approaches.Regression and classification problems are resolved by KNN.

As previously mentioned, KNN algorithms can be applied to accomplish tasks in both classification and regression. Nevertheless, in our work, we are employing it to address a classification problem.Consequently, a sample is assigned a category determined by the majority vote from its neighbors, and it is placed in the class with the highest degree of commonality among its k nearest neighbors.

Furthermore, in our study, we employed parameter tuning to determine the optimal value of k, resulting in the best possible outcome. Subsequently, distance metrics such as Euclidean, Hamming, Manhattan, and Minkowski distances are employed to compute the distances between data points. The distance is used to find K closest neighbors. Subsequently, points are classified according to the majority vote from their k neighbors. Voting for each object is done according to class. Subsequently, the prediction is established by choosing the class that garnered the highest count of votes.By implementing the Grid Search technique for parameter tuning, we've discovered the most suitable parameters for the KNN algorithm. K's values are within the range of 1 and 133. In this instance, the value happened to be 1. An additional crucial element for our dataset is the mixed measure. Distance between data points is measured with this metric.Euclidean distance is well-suited for the analysis of our dataset. Data points connected by a line segment are measured by Euclidean distances. The kernel type argument is the third crucial one Our dataset demonstrated optimal performance with radial kernels.

C. Support Vector Machine (SVM)

Backing A group of comparable supervised learning techniques used for regression and classification are called support vector machines. When we integrate n features into the data, we visualize it in n-dimensional spaces.There is a value assigned to each coordinate corresponding to each feature. Each category is defined by a line since the Support Vector Machine (SVM) processes the data as inputs.The identification of the hyperplane, which effectivelyseparates the two classes, concludes the classification process.

Amongst the attributes of the SVM, specifically the Radial Basis Function (RBF) kernel, the effective ones are denoted as c and gamma. The training example's influence is shown by the gamma parameter. Generally speaking, high numbers are denoted as "close," and low ones as "far." Conversely, c operates as the SVM regularization parameter. By adjusting training example classifications in opposition to the decision function's margin maximization, it manages the trade-off. For the analysis of depression, the gamma parameters were set to "poly" with a degree 4 polynomial kernel.

D. Linear discriminant analysis (LDA) algorithm

A popular method for dimension reduction issues and feature extraction, Linear Discriminant Analysis (LDA) is similar to a pre-processing stage for machine learning and pattern classification applications.

A default set of parameters were used for anxiety, including solver, shrinkage, priors, ncomponents, and store covariance. Without calculating covariance matrices, Singular Value Decomposition (SVD) is the default solver for both transformation and classification.In scenarios with more features, this is quite advantageous. Tol, however, is set to 0.0001. "Tol serves as a threshold utilized by the SVD solver for approximating the rank without copying any content."The solver parameter for depression is set to lsqr, which is a crucial algorithm that performs well for classification and can be used in conjunction with shrinkage. Tol has once more been set to 0.0001, and shrinkage is assigned to 0.999. The default values are assigned to other parameters such as store covariance, components, and priors.

E. Convolutional Network (CNN) algorithm

Among the primary types of neural networks that performs object detection, picture classification, image recognition, and many other functions on visual input is the convolutional neural network. In principle, within deep learning, CNNs are constructed to recognize items by assigning probabilistic scores ranging from 0 to 1. This involves training and assessing individual input images as they traverse a chain of convolutional layers equipped with filters, pooling operations, dense layers, and the final utilization of the Softmax function. The depiction of images with respect to input and output dimensions is conveyed mathematically through multi-dimensional matrices as they progress across every layer within the network.The number of epochs was adjusted to 45 specifically for addressing anxiety and sadness, whereas the standard preset value is typically 100. Due to overfitting observed with a 100-epoch size, the decision was made to reduce it to 45 for the model's training.Therefore, extending the period might improve accuracy, but there might be modifications that lead to the model becoming overfit. An epoch signifies the count of iterations or cycles the program

Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 12
December 2023

undergoes in an effort to minimize errors during training. After each epoch, a comparison is made between the initial outcome and the past finding result. Consequently, it aims to minimize errors by updating the functionality of the layers.

IV. Result Analysis

A. Evaluation Criteria

The evaluation of the model's output was based on its precision, accuracy, and recall values. The metrics were calculated by summing the correct predictions (true positives - TP, true negatives - TN) and incorrect predictions (false positives - FP, false negatives - FN).

1) Accuracy: Accuracy (Aγ) is the total number of predictions the system made across all prediction types[13]

2) Precision:Precision (Pn) is a measuring metric utilized to contrast the accurate prediction of true positive instances against the total positive predictions, encompassing both true positives and false positives within the category of Ppsitive instances"[13].

*3) Recall:*Recall (Rn) is a metric that measures the proportion of correctly identified positive instances among all actual positive patterns [13].

B. Assessment of Model Performance

Our findings indicate that linear regression is not a reliable method for making predictions. In the case of linear regression, the RMSE for anxiety and depression is neither very high nor very low. It is possible to conclude that the model produces an average forecast since the data points do not closely match the projected value of the model. This is due to the fact that linear regression works best with linear models in which the data exhibits a certain trend. However, due to the absence of a discernible pattern in our data, the model fails to establish a correlation between the variables, thereby impeding its ability to offer precise predictions.

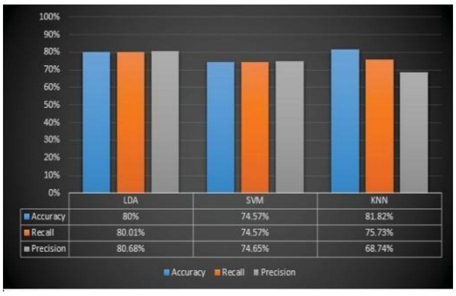

Fig. 2. Comparative Analysis of Accuracy, Precision, and Recall for Depression

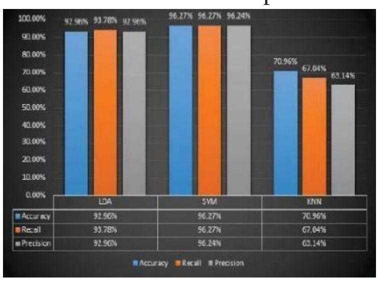

Fig. 3. Comparative Evaluation of Accuracy, Precision, and Recall for Anxiety

Figures 2 and 3 present a comparison of accuracy, precision, and recall concerning depression and anxiety, respectively, employing three distinct algorithms: LDA, KNN, and SVM. Among these algorithms, SVM exhibited the highest precision and recall, whereas KNN demonstrated the lowest values for these metrics. We may conclude from the aforementioned results that all of the algorithms have relatively similar accuracy. However, CNN achieved the highest accuracy, registering 96.8% for sadness and 96% for anxiety. In contrast, KNN yielded the lowest accuracy, achieving a score of 81.82% for both anxiety and depression.

The CNN was set to 45 epochs, while the usual default value for anxiety and depression is commonly 100. As overfitting was noticed prior to reaching 100 epochs, the choice was made to decrease the epochs to 45 to enhance the model's performance.Therefore, extending the period might improve accuracy, but there might be modifications that lead to an overfitting of the model. An epoch represents the iteration count that the program executes to minimize errors while training the model.Higher precision is associated with higher epochs. Upon completion of each epoch, a comparison is made between the initial outcome and the past finding result.Consequently, the process aims to diminish errors by adjusting the function within the layers.Figures 4 through 9 demonstrate the consistency and effectiveness of training, testing, and validation regarding anxiety and depression.

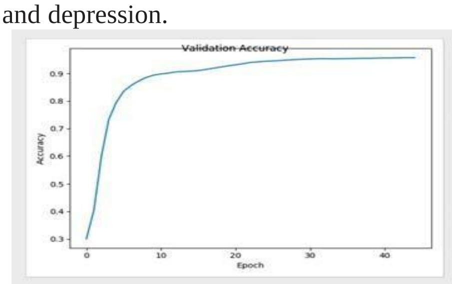

Fig. 4. Validation Accuracy Analysis for Anxiety

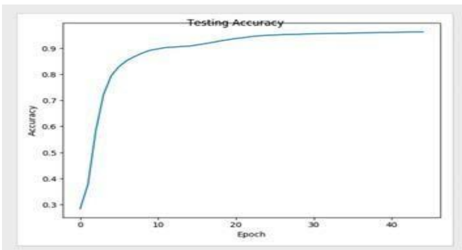

Fig. 5. Testing Accuracy Assessment for Anxiety

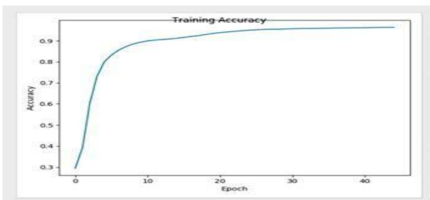

Fig. 6. Training Accuracy Evaluation forAnxiety.

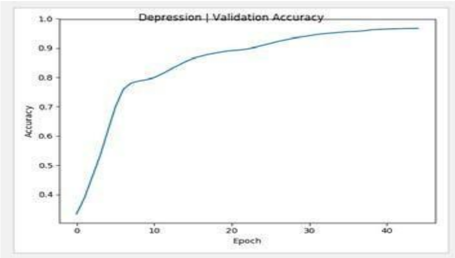

Fig. 7. Validation Accuracy Analysis for Depression

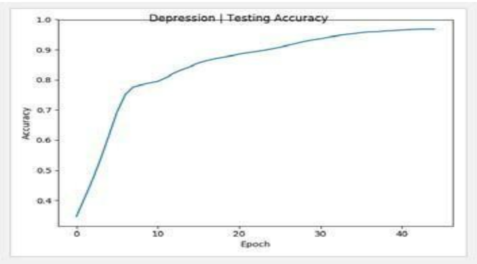

Fig. 8.Testing Accuracy Assessment for Depression

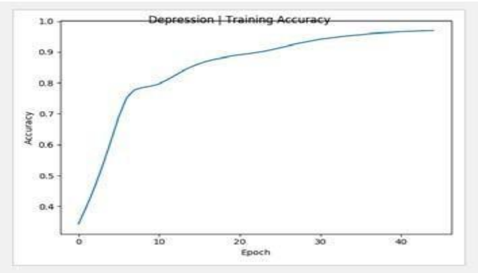

Fig. 9.Training Accuracy Evaluation for Depression

```
Anxiety::TotalRow- 35000
Anxiety::Mild- 14877 Percentage- 42.505714285714284 %
Anxiety::Moderate- 9109 Percentage- 26.025714285714287 %
Anxiety::Severe- 8419 Percentage- 24.054285714285715 %
Anxiety::Profound- 2595 Percentage- 7.414285714285715 %
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Fig. 10. CNN Performance Evaluation for Anxiety

```
Depression::TotalRow- 35000
Depression::Minimum- 22583 Percentage- 64.52285714285715 %
Depression::Mild- 4494 Percentage- 12.84 %
Depression::Moderate- 2457 Percentage- 7.02 %
Depression::Severe- 5466 Percentage- 15.617142857142857 %
```

Fig. 11. CNN percentage for Depression.

Confusion Matrix: Anxiety (CNN)

Mild	423	4	0	0
Moderate	4	251	0	0
Profound	0	2	232	3
Severe	0	0	20	61
⬆ True Label Predicted Label ➡	Mild	Moderate	Profound	Severe

Fig. 12. Confusion Matrix for Anxiety dataset.

Mild	2030	0	22	0
Moderate	0	515	0	25
Profound	9	0	399	32
Severe	0	5	8	230
⬆ True Label Predicted Label ➡	Mild	Moderate	Profound	Severe

Fig. 13. Confusion Matrix Analysis: Depression Dataset

Furthermore, the early stop parameter was set to 3. The default value for the early stop parameter is set to 5.Early stopping in machine learning refers to the technique of ceasing the training process prior to the weights achieving convergence, with the goal of mitigating overfitting issues within models. The remaining parameters in our dataset were set to their default configurations..A confusion matrix is displayed in Fig. 12 and is used to assess how well our trained model performs with CNN on the anxiety dataset. The diagonal elements represent the instances where the model's prediction matches the actual class, while the off-diagonal elements indicate misclassifications made by our model. Figure 13 exhibits a comparative confusion matrix specifically for the depression dataset employing CNN.

V. CONCLUSION

Within the medical domain, mental or psychological disorders are widespread, yet they are often undertreated or receive limited attention. Throughout life, people experience different levels of anxiety and depression at different times. Urban women experience these diseases at a rate twice that of males, but in this day of globalization, getting help—specifically, psychological treatment—is still frowned upon. The proposed methodology employs supervised learning algorithms to predict the levels of anxiety and depression, aiming to mitigate and address these conditions. We also have a ballpark estimate of the proportion of women who suffer from these diseases thanks to our analysis. We intend to introduce this method in the future to help psychologists track post-therapy progress and streamline the post-psychotherapy monitoring procedure. Considering the advancements made in our work so far, implementing this system in the future appears to be quite feasible.

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