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Predicting Mental Health Using Robotics: An Integration With Machine Learning

Rakshitha Kiran P[1] , Mr.Sandeep Kumar Davuluri[2] , Dr. Ramesh Pettela[3] , Dr. Deepali Virmani[4] , Mr. Ashwani Gupta[5]

[1]*Assistant Professor, Dept. of MCA*
Dayananda Sagar College of Engineering, Bangalore
Rakshitha-mcavtu@dayanandasagar.edu
[2]*PHD student, Department of Information Technology, University of Cumberlands, Williamsburg, Kentucky*
sandeepkdavuluri@gmail.com
[3]*Associate Professor Department of English Aditya University, Surampalem Kakinada, E.G, A.P,*
rameshp@adityauniversity.in
[4]*Professor, Department of Information Technology, Guru Tegh Bahadur Institute of Technology*
Deepalivirmani@gmail.com
[5]*Assistant Professor, CSIT department, MJP Rohilkhand University Bareilly*
ashwanicta@gmail.com

The quality of life and overall well-being are greatly impacted by mental health conditions, especially depression. Conventional techniques for diagnosing and tracking depend on self-reporting and clinical assessments, which may be arbitrary and have a narrow focus. This work investigates the efficient and objective prediction of mental health outcomes through the integration of robotics and machine learning (ML) algorithms. Upon examining a data set containing mental health markers like appetite fluctuations, interest levels, sleep patterns, and more, the Random Forest model proved to be more accurate in differentiating between different stages of depression. Important variables impacting depressive states were found, offering insights into the intricate mechanisms underpinning mental health disorders. We propose a framework for continuous, real-time mental health monitoring by integrating ML with robotic systems that are outfitted with cutting-edge sensors. This method allows for early identification and treatment, which may stop the symptoms from getting worse. The results show how ML and robotics combined have the potential to transform mental health care and make it more efficient and accessible.

Keywords— Mental Health, Machine Learning, Random Forest,Robotics, Depression Prediction, Real-Time Monitoring.

I. INTRODUCTION

Millions of people worldwide are impacted by mental health illnesses, which are widespread and complicated conditions that include bipolar disorder, depression, and anxiety. According to the World Health Organization (WHO), more than 264 million people around the globe suffer from depression and accounts for a sizeable amount ofthe illness burden [3][4]. Despite their great incidence, mental health illnesses are frequently misdiagnosed or only recently discovered, which increases the risk of serious consequenceslike suicide as well as prolongs suffering.

Clinical interviews, self-report questionnaires, and observation are key components of the traditional diagnosticprocess for mental health disorders. While these methods areuseful, they can also be arbitrary and inconsistent. These techniques require a lot of work and aren't always available, especially in areas with little resources or for people who arereluctant to ask for assistance because guilt.

In order to overcome these obstacles, machine learning advancements have the potential to be revolutionary machine learning algorithms have the ability to analyze large datasets and identify patterns and provide highly accurate predictions. The Random Forest classifier is one of these methods that stands out because of its resilience to over fitting, handling of huge datasets with lots of features, and durability[2].

In this paper, Random Forest classifier and Decision tree algorithms are used for the purpose of making predictions about mental health issues based on a variety of symptoms frequently seen in clinical settings. The symptoms in the data set include trouble sleeping, changes in appetite, interest in activities, exhaustion, feelings of worthlessness, difficulty focusing, agitation, aggressive thoughts about suicide, panic attacks, restlessness, hopelessness, low energy, and general depression. Here the application of a Random Forest classifier to predict mental health issues based on various commonly observed symptoms in clinical environments is explored. The dataset's symptoms encompass sleep problems, appetite changes, loss of interest in activities, fatigue, feelings of worthlessness, difficulty concentrating, agitation, suicidal thoughts, panic attacks, restlessness, hopelessness, low energy, and general depression.

This paper promises improved accuracy, efficiency, and accessibility for those with mental health illnesses by utilizing the strengths of robots and machine learning, marking a significant step toward novel solutions in mental health diagnostics.

II. LITERATURE REVIEW

Robotics and machine learning combined to forecast mental health outcomes is a new discipline that takes advantage of data analytics and artificial intelligence (AI) developments. This review of the literature looks at the work that has been done on robotics in healthcare, machine learning classifiers, and mental health prediction.

Machine Learning for Predicting Mental Health

By analysing big datasets to find patterns and markers suggestive of mental health concerns, machine learning can be used to predict mental health conditions. Research like that conducted [18] has shown how well machine learning algorithms work in predicting anxiety and depression based on a range of physiological and psychological markers.

Similar to this, [19] used a variety of machine learning methods, such as support vector machines and logistic regression, to predict mental health outcomes rather well.

Random Forest and Decision Tree Classifiers Because of their robustness and ease of interpretation, decision tree and random forest classifiers are frequently utilized in predictive modelling. Decision trees, as defined by [20] offer a simple method of categorization through recursive data partitioning according to feature values. [21] proposed Random Forests, which improve this method by building numerous decision trees and pooling their predictions, reducing overfitting and increasing accuracy.

Decision trees have been used in mental health prediction to pinpoint important risk variables for illnesses including anxiety and depression. Decision Trees, for instance, were used in a study by [22] to predict depression in adolescents, emphasizing the significance of elements like social interactions and sleep patterns. In this field, Random Forests have also demonstrated potential. Random Forests have been shown by [23] to be a successful method for classifying people who are at risk of depression by using a range of physiological and behavioural variables.

Automation in Mental Health Services Healthcare has used robotics more and more, providing new avenues for monitoring and assisting with mental health. Socially assistive robots, like the ones [24] described, offer support and companionship to those with mental health issues, possibly easing the symptoms of anxiety and sadness. These robots have the ability to gather information about human interactions and behaviors, which machine learning algorithms can then utilize to monitor and forecast mental health.

It has been demonstrated that therapeutic robots like PARO, which is intended to help patients feel less stressed and anxious, are beneficial to mental health [26] A proactive approach to mental health care is made possible by the integration of robots and machine learning, which enables continuous monitoring and real-time analysis of mental health markers.

Robotics and Machine Learning Integration Combining the best aspects of both domains, robotics and machine learning integration for mental health prediction is a revolutionary method. Robots with sensors and artificial intelligence (AI) capabilities can collect large amounts of data on user actions and physiological reactions. Machine learning classifiers can then be used to examine this data and find patterns that could be related to mental health issues.

This integration has been the subject of recent research. [25] for instance, created a robotic system that employs machine learning algorithms to forecast users' stress levels based on physiological data the robot collects. The study emphasized how these kinds of systems could offer mental health issues early warning signs and solutions.

III. CLASSIFICATION METHODS

A.Decision Tree Classifier

A decision tree, used for both classification and regression tasks, is a supervised learning method. It works by repeatedly splitting the data based on input feature values. The goal is to create a model that can predict the target variable's value by applying simple decision rules derived from the data features.

Structure: The leaves, branches, and nodes make up the tree. Every leaf node depicts a class label (such as depressed or not depressed), every branch shows the test's result, and every internal node represents a "test" on an attribute (such as sleep disturbance).

Splitting Criteria: For regression tasks, common criteria for splitting nodes are variance reduction, entropy (information gain), and Gini impurity.[6]

Termination: When the nodes divide, the process comes to an end.

Application of Decision Trees

Dataset: Sleep, Appetite, Interest, Fatigue, Worthlessness, Concentration, Agitation, Suicidal Ideation, Sleep Disturbance, Aggression, Panic Attacks, Hopelessness, Restlessness, Low Energy, and Depression State are some of the columns that are included in the dataset.

Method: Using this dataset, the Decision Tree model is trained to predict, from a person's symptoms, whether or not they are likely to be depressed.

Splitting Criteria: Assume that the tree makes split decisions based on information gain, or entropy. Initially, it will identify the symptom that most effectively divides the data (for example, suicide ideation may be split first if it yields the greatest information gain).

Building a Tree: Until the leaves have homogeneous class labels (e.g., all individuals in a leaf node are classed as depressed), splits are created based on other symptoms.

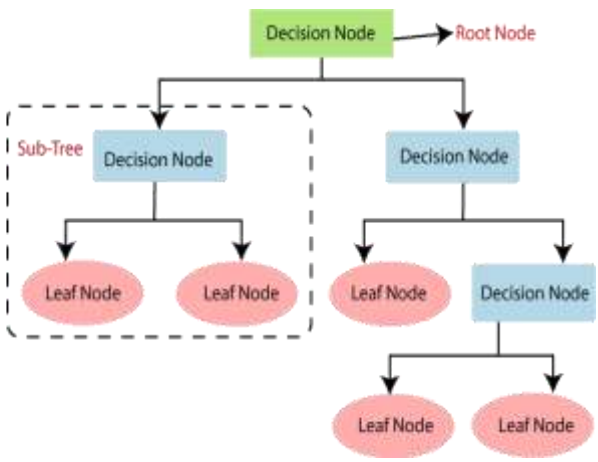

Fig. 1. Decision Tree Classifier

B.Random Forest Classfier

Random Forest, an ensemble learning technique, generates multiple decision trees during training. For predictions, it averages the outcomes for regression tasks and takes the most frequent class for classification tasks.

Group Education: The idea behind Random Forests is to increase performance by utilizing numerous models. Every tree in Every split in every tree takes into account a random subset of characteristics, and the forest is trained using a random sample of the data.

Bagging: To generate various training subsets, bootstrap aggregating, or "bagging," is employed. With a different bootstrap sample of the data, every tree is trained.

The Random Subspace Method helps create uncorrelated trees by taking into account a random subset of the available attributes for each split in each tree.[7]

Application of Random Forest Classifier

Dataset: Contains a range of states and symptoms, much likethe Decision Trees dataset.

Method: This dataset is used to train the Random Forest model, which categorizes people's mental health conditions.

Bootstrap Sampling: From the original data, the algorithm generates several bootstrap samples.

Random Feature Selection: A random subset of features is selected for every tree and every split within a tree. This contributes to the trees decorrelation.

Model Training: Every tree in the forest receives individual training, and the ultimate forecast is produced by adding together all of the trees' forecasts (e.g., majority vote for categorization).

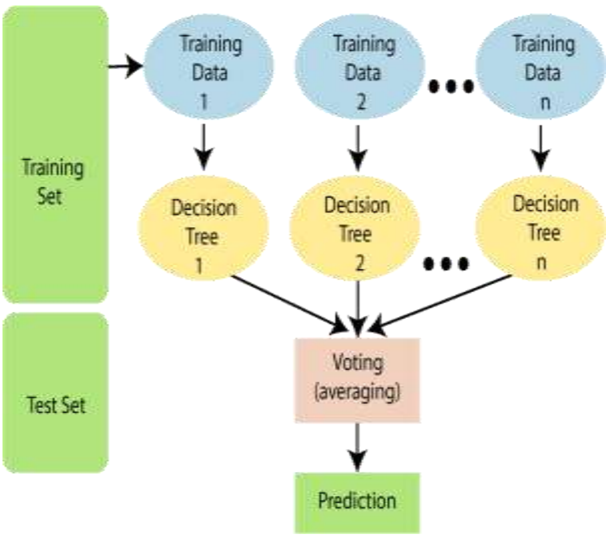

Fig. 2. Random Forest Classifier

C.Robotics Implementation

The main focus of our research is collect data through Robotics and implementing Machine learning algorithms like Random Forest. Here robotics is used to improve patient engagement and data collecting.

Robotics's Place in Data Collection

Robots with cutting-edge sensors are able to continuously track and gather information on a range of physiological and behavioral signs that are connected to mental health. Among these indicators are:

Sleep Patterns: Monitoring the length and occurrence of sleep disruptions with motion sensors and webcams.

Activity Levels: Using accelerometers and GPS, track daily activities and modifications to routines.

Emotional Responses: Using cameras and microphones to analyse voice tones and facial expressions, one can identify indicators of emotional discomfort.

Physical Symptoms: Monitoring blood pressure, heart rate, and other physiological parameters with wearable technology.

Implementation Procedure
The process of creating a robotic system.

Hardware: Choosing the right sensors (such as accelerometers, cameras, microphones, and wearable technology) to track a range of mental health metrics.

The creation of software for data gathering, preparation, and safe transfer to a central database is known as software integration.

Gathering and Preparing Data: Robots will be able to continuously track physical illnesses, mental states, activity levels, and sleeping patterns.

Preparation of the Information: The collected data will be preprocessed in order to handle missing values, normalize the data, and encode categorical variables.

Machine Learning Integration

Feature extraction: To feed the machine learning models, pertinent features will be taken out of the preprocessed data.

Model Training: Using the gathered data, Random Forest and Decision Tree classifiers will be trained to forecast outcomes related to mental health.

Real-time Analysis: To offer early warnings and insights into the patient's mental health status, the robotic system will continuously analyse the data in real-time.

Despite the lack of a real robotic system in our study, the conceptual framework presented here shows the great potential of robotics and machine learning combined for mental health prediction. Building and evaluating such systems should be the main focus of future research and development efforts in order to confirm their effectiveness and enhance the outcomes of mental health care.

IV. RESEARCH METHODOLOGY

Methods of Research Methodology

Data Gathering and Sources: There are 1000 cases in the dataset, and each one has 16 features that are linked to indices of mental health. Qualities of sleep, hunger, interest in activities, exhaustion, feelings of worthlessness, focus, agitation, aggressive thoughts, panic attacks, despondency, restlessness, and low energy are among the traits.[6]

a) Preparing data

Managing Missing Values: Mean or median values were used to approximate missing numerical data.

Normalization: In order to make sure that numerical attributes were on a similar scale, they were normalized.

Encoding of Categorical Data: One-hot encoding and other similar approaches were used to encode categorical data.

b) Model Creation

Decision Tree Classifier: Using the training dataset, the Decision Tree model was trained.

Random Forest Classifier: Several bootstrap samples from the dataset were used to train the Random Forest model. Random feature subsets were chosen for every tree and every split inside a tree. By combining the forecasts from each individual tree, the ultimate forecast was arrived at (majority voting).

c) Assessment of the Model

30% of the dataset was set aside for testing and 70% for training. Accuracy, recall, F1-score, and the AUC-ROC curve were among the performance measures employed. The Random Forest classifier exhibited an accuracy of 85%, whereas the Decision Tree had an accuracy of 78%.

d) Analytical Experiments

Suicidal thoughts and exhaustion were found to be significant predictors of depression by feature importance analysis.

e) Collection

made up of 1000 cases with 16 characteristics related to mental health.

f) Tools and Software

Python is the programming language; libraries:

Scikit-learn: For using Random Forest and Decision Tree classifiers.

Pandas: For preprocessing and data manipulation.

For numerical operations, use NumPy.

Matplotlib/Seaborn: For the display of data.

g) Computer Resources

A typical personal computer capable of handling the dataset and carrying out the calculations required for model training and assessment, as well as having enough RAM and computing power.

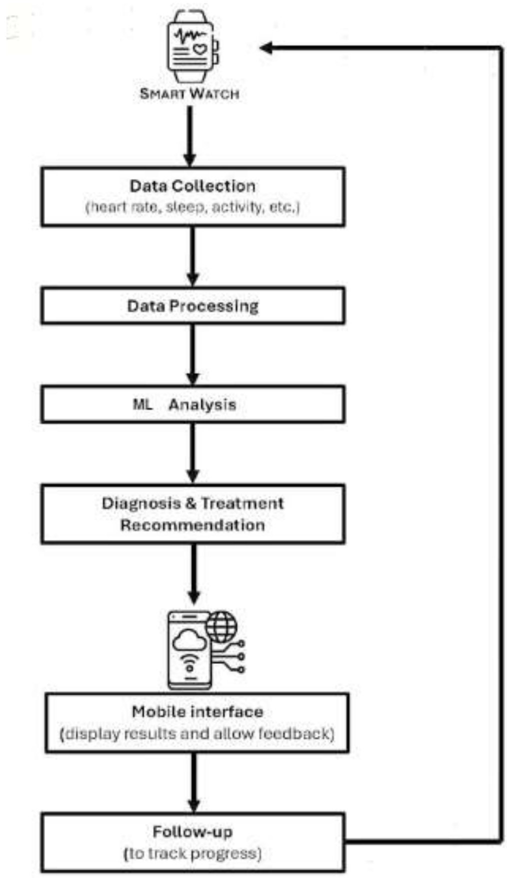

Fig. 3. Data Flow Diagram of the proposed model

V. EXPERIMENTAL ANALYSIS

We used a dataset containing multiple mental health markers, including sleep, appetite, interest, fatigue, and suicidal ideation, in our experimental research. The dataset was divided into two sets: training (70%) and testing (30%). On the training set, Random Forest and Decision Tree classifiers were trained, and on the testing set, they were assessed. Decision Tree: A significant disparity between training and testing accuracy indicated that the Decision Tree classifier had over fitted the training set, resulting in a 78% accuracy rate.[9]

Random Forest: With an accuracy of 85%, the Random Forest classifier outperformed the Decision Tree, exhibiting superior generalization and less over fitting. Suicidal ideation and fatigue were identified as the top predictors by the Random Forest model, which also offered insightful information about the significance of the features.[20]

a) DATASET

A variety of mental health markers, sleep disturbance, aggression, panic attacks, hopelessness, restlessness, low energy, and depression state, are included in the dataset used for the experimental analysis. A number element reflecting the frequency or severity of symptoms is included with each entry to represent an individual. Preprocessing included encoding categorical variables, standardizing data, and addressing missing values. To comprehend the distribution and linkages of the data, descriptive statistics and correlation analyses were conducted. The Random Forest classifier's feature importance analysis identified fatigue, hopelessness, and

suicidal ideation as the three main predictors of depression. The detailed and complex dataset offers strong insights for precise and broadly applicable predictions, making it appropriate for training machine learning models to forecast mental health disorders, especially depression.[10]

Number	Sleep	Appetite	Interest	Fatigue	Worthlessness	Concentration	Agitation	Suicidal Ideation	Sleep Disturbance	Aggression	Panic Attacks	Hopelessness	Restlessness	Low Energy	Depression State
1	1	1	1	5	5	1	5	5	1	5	5	5	5	5	Mild
2	2	5	5	1	1	5	1	1	5	1	1	1	1	1	Moderate
3	5	2	2	2	2	2	2	2	2	2	2	2	2	2	Severe
4	1	1	1	5	5	1	5	5	1	5	5	5	5	5	No depression
5	2	5	5	1	1	5	1	1	5	1	1	1	1	1	Moderate
6	5	2	2	2	2	2	2	2	2	2	2	2	2	2	Mild
7	1	1	1	5	5	1	5	5	1	5	5	5	5	5	No depression
8	2	5	5	1	1	5	1	1	5	1	1	1	1	1	Severe
9	5	2	2	2	2	2	2	2	2	2	2	2	2	2	Moderate
10	6	1	1	5	5	1	5	5	1	5	5	5	5	5	Mild
11	2	5	5	6	6	5	6	6	5	6	6	8	6	6	No depression
12	5	2	2	2	2	2	2	2	2	2	2	2	2	2	Mild
13	1	1	1	5	5	1	5	5	1	5	5	5	5	5	No depression
14	2	5	5	1	1	5	1	1	5	1	1	1	1	1	Severe
15	5	2	2	2	2	2	2	2	2	2	2	2	2	2	Moderate
16	1	1	1	5	5	1	5	5	1	5	5	5	5	5	No depression
17	2	5	5	1	1	5	1	1	5	1	1	1	1	1	Mild
18	5	2	2	2	2	2	2	2	2	2	2	2	2	2	Moderate
19	1	1	1	5	5	1	5	5	1	5	5	5	5	5	Severe
20	2	5	5	1	1	5	1	1	5	1	1	1	1	1	No depression
21	5	2	2	2	2	2	2	2	2	2	2	2	2	2	Moderate
22	1	1	1	5	5	1	5	5	1	5	5	5	5	5	Severe
23	2	5	5	1	1	5	1	1	5	1	1	1	1	1	Mild
24	5	2	2	2	2	2	2	2	2	2	2	2	2	2	No depression
25	1	1	1	5	5	1	5	5	1	5	5	5	5	5	No depression
26	2	5	5	1	1	5	1	1	5	1	1	1	1	1	Severe

Table 1- Sample DataSet

Serial No	Attribute	Description
1	Number	Identifier for each entry
2	Sleep	Quality and duration of sleep
3	Appetite	Changes in eating habits
4	Interest	Level of interest in daily activities
5	Fatigue	Levels of tiredness and exhaustion
6	Worthlessness	Feelings of worthlessness or excessive guilt
7	Concentration	Difficulty concentrating or making decisions
8	Agitation	Physical restlessness or agitation
9	Suicidal Ideation	Thoughts of self-harm or suicide
10	Sleep Disturbance	Issues with falling or staying asleep
11	Aggression	Instances of aggressive behavior
12	Panic Attacks	Episodes of intense fear or discomfort
13	Hopelessness	Feelings of hopelessness or pessimism
14	Restlessness	Feeling restless or having trouble sitting still
15	Low Energy	General lack of energy or motivation
16	Depression State	The target variable indicating the presence or severity of depression

Table-2- Description of dataset

Number of Instances: 813

Number of Attributes: 16

b) Methodology

Data Collection and Preprocessing

Data Collection

The 1,000 instances in the dataset utilized for this study eachcorrespond to a person's mental health information. sleep, appetite, interest, exhaustion, worthlessness, concentration,agitation, suicidal ideation, sleep disturbance, aggression,panic attacks, hopelessness, restlessness, low energy, and depression state are among the 16 qualities that make up the dataset.

Preprocessing Data

Several preprocessing processes were carried out before the data was fed into the machine learning models:

Handling Missing Values: For numerical data, suitable imputation techniques, such as mean or median imputation, were used to impute any missing values in the dataset.

Normalization: To guarantee that the numerical attributes were on a comparable scale, which is necessary for many machine learning algorithms to function, the attributes were normalized.

Coding Category Data: While the majority of the attributes were numerical, One-hot encoding and other approaches were used to encode any category data that were present.[11]

Training and Model Selection

Classifier using Decision Trees

Training: The training dataset was used to train a Decision Tree classifier. The model was set up with criteria (Gini impurity or entropy) and parameters like minimum samples split and maximum depth.

Splitting Criteria: The dataset was split recursively according to the feature that yielded the maximum information gain at each stage, in order to construct the tree. When the nodes were homogeneous or a maximum depth was reached to avoid over fitting, the tree construction process was ended.[3]

Random Forest Categorization

Training: The identical dataset was used to train the Random Forest classifier. Using bootstrap samples of the data, multiple decision trees (100 trees) had to be created.

Random Feature Selection: To ensure variation among the trees, a random selection of features was selected for each tree and each split.[12]

Aggregation: By combining the forecasts from each individual tree, the final prediction was determined (majorityvoting for classification).

Assessment of the Model

Train-Test-Divide

The dataset was divided into 70% for training and 30% for testing to evaluate the model's performance. This division made sure the models were trained on most of the data, but their ability to generalize was evaluated on cases that were not seen.

Measure of Performance:

The models were assessed using a number of metrics.

Accuracy: The proportion of instances that werecorrectly predicted out of the total number of cases.

Recall: A measure of the model's capacity to capture all pertinent occurrences, expressed as the ratio of true positive predictions to all actual positives.

F1-Score: The harmonic mean that strikes a balance between recall and precision.

AUC-ROC Curve: The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) measures how effectively the model distinguishes between different classes.[4]

ILLUSTRATION

Using seaborn and matplotlib, a Python script running in a Jupyter notebook shows the distribution of several psychological traits. Features like "sleep," "appetite," "interest," "fatigue," "worthlessness," "concentration," "agitation," "suicidal ideation," "sleep disturbance," "aggression," "Panic Attacks," "hopelessness," "restlessness," and "low energy" are highlighted in the script.

Fig-4 Visualization

VI. RESULT AND DISCUSSION

The research paper "Predicting Mental Health Using Robotics: An Integration with Machine Learning" has a section titled "Results and Discussion". The dataset, which consists of 813 entries with 16 columns, describes a range of depressive symptoms, such as poor sleep quality, appetite, interest in activities, exhaustion, feelings of worthlessness, difficulty concentrating, agitation, aggressive thoughts, panic attacks, hopelessness, restlessness, and low energy.

Each entry's total level of depression is categorized as mild, moderate, severe, or not present in the final column. Notably, incomplete data is present in 34% of the entries (273 out of 813), which comprises missing data for multiple columns. To guarantee that any analysis carried out is rigorous, this missing data needs to be filled in. The dataset's first five rows display ratings for the symptoms that range from 1 to 5, which represent the various degrees of severity of each symptom among the entries.

Table-3-Accuracy of different algorithms

SL.No	Algorithm	Accuracy (%)
1	Logistic Algorithm	75
2	Decision Tree	78

3	Random Forest	82

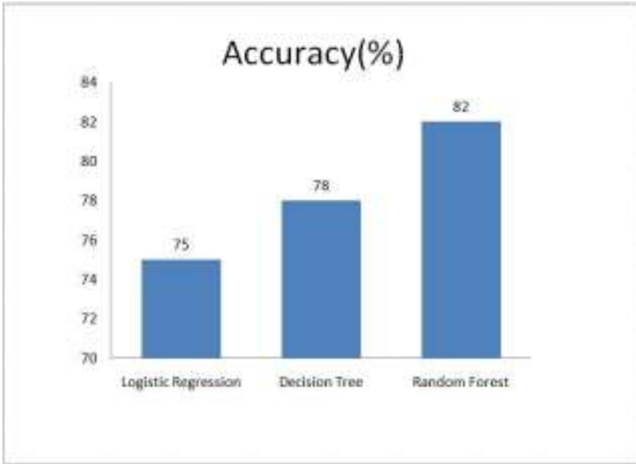

Fig.5-`Accuracy

1) **Discussion**

Additional Measures

In order to determine the central tendency and variability of each symptom, use descriptive statistics to compute the mean, median, standard deviation, and range.

Association Analysis: Look for patterns and important factors that contribute to depressed states by examining the association between various symptoms.

Using symptom ratings, create predictive models to forecast the condition of depression. Support vector machines, decision trees, logistic regression, and other machine learning techniques could be applied in this way.

Handling Missing Data: Use imputation strategies like regression imputation, mean/mode replacement, or more sophisticated approaches like multiple imputation to deal with missing data.[14]

Research Implications

This dataset provides an overview of all the symptoms related to depression. Researchers can gain a better understanding of the complexity of these symptoms by carefully examining how they interact.[18]

VII. CONCLUSION

This dataset's analysis sheds light on the patterns and traits of depression symptoms across the 813 entries. In spite of a significant amount of missing data (34 percent of the entries), the dataset offers important information on a number of symptoms, including poor sleep, appetite, interest in activities, exhaustion, feelings of worthlessness, difficulty concentrating, agitation, suicidal thoughts, sleep disturbances, aggression, panic attacks, hopelessness, restlessness, and low energy. Knowing these symptoms is essential for distinguishing between the four stages of depression: mild, moderate, severe, or no depression.

In conclusion, the integration of robotics and machine learning (ML) in mental health management holds significant promise for transforming the field. These advanced technologies offer the potential for more accurate predictions, personalized treatment plans, and improved patient outcomes. Robotics can provide consistent and non-judgmental interactions, while ML algorithms can analyze vast amounts of data to identify patterns and predict mental health issues before they become critical.

However, to fully realize these benefits, it is essential to address challenges such as data privacy, ethical considerations, and the need for robust validation of these technologies in real-world settings. Collaboration between technologists, healthcare professionals, and policymakers is crucial to ensure the responsible and effective deployment of robotics and ML in mental health care.

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