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A Novel Hybrid Approach for Diagnosis of Mental Health Condition Applying Intelligent Data Analysis

Dr. Sandip Roy[1], Dr. P. S. Aithal[2], Dr. Rajesh Bose[3]

[1] Post-Doctoral Research Fellow, Srinivas University, Mangalore 574146, India, sandiproy86@gmail.com

[2] Srinivas University, Mangalore 574146, India, psaithal@gmail.com

[3] Brainware University, Kolkata, West Bengal 700125, bose.raj00028@gmail.com

ABSTRACT

When a man is depressed, he is so due to getting hemmed in several issues. Consequently, it takes the shape of a relentless, reiterating disorgaized state. Physicians suggest that the setback of the reiteration of depression should be hindered. So, researchers have initiated some steps to get acquainted with the possibilities of the reiteration issues of depression. Now, problem-solving time patient information diagnosis can make a solution of a few exotic facts in the field of medical analysis. It is a fact that occasionally, physicians also face hazards in using even proper drugs for a certain disease. The research concentrates on the necessity of resourceful investigation of information in medical diagnosis and scrutinizes various categorizations of the means of resourceful investigation of information on almost three thousand specimens of the information of patients, anticipated from the information of the National Institute of Health Organization (NH). From this research, we deduce the aptness of used resourceful investigation of information techniques and their pertinence in medical studies.

Key words: Depression Relapse, Decision Tree, Smart Data Analysis, Judging Medicine, Medical Diagnosis, Machine Learning.

1. INTRODUCTION

Depression is a customary mental hazard. Above 264 million all over the globe are suffering from this problem. When a person suffers from it, utter melancholy and devoid of keenness or joy are observed in him in his past achievements or cheerful pursuits [1]. Depression also causes insomnia, weariness, and a lack of concentration on everything. It is a prime factor of afflictions all over the globe. It is profoundly responsible for the universal hazards of ailments. The consequence of depression is resilient or chronic and gravely harms one's potentiality to work and lead a gratifying life [2].

Depression is such a ubiquitous mental disturbance which augments the probability of committing suicide of 10% to 20%. People of all ages from a young age to old age, this is assumed to set second-grader as estimated by Disability Adjusted Life Years [DALY]. It has the fourth rank in the universal hazards of ailments [3]. If we look at the scenario of India, we will find that almost 3%-4% of folks get affected by severe depression and almost 7%-10% folks get affected by slight depressions [4][5]. Almost one man in six and four women in so, suffer from severe despondent disturbance. In this way, the possibility of committing suicide of a woman is twice more than that of a man [6] [7].

People say that the reason behind depression and disturbance of restlessness is most of the time adverse, with persistent [8], [9]. The way of depressed mood and worry hazards is most of the time adverse, with persistent [8] [9] or sporadic occurrences of worry and depression [10] on a great danger of setback. It is observed that (22-58)% due to worry [11] [12] and (27-77)% due to depression [13] [14] have turned up as setback rate with greater rates in longer pursued researches [14].

Besides, most of the time, victims obtain respite for a certain period instead of complete respite. He also gets lingering symptoms [17]. As worry and depression are most of the time-periodic and victims of them get endangered, these hazards ought to be stated as persistent ailments.

Persistent concern prototypes formerly built up for other persistent ailments like diabetes [18], were used. The mind setup of self-help management is a significant means of persistent concern prototype. [19]. The Recovery of the repetition of the similar symptoms of depression is one of the biggest challenges in such control of anxiety and depression [20].

Reappearance is ubiquitous in severe depression. Generally, half of the total number of victims suffering from depression, recovers from the case of depression, experiencing five to nine different cases in their total lifetime [6]-[21]. This has also been observed that for the first time when the first case occurred, there is a probability of repetition of another case within five years of the first case [22] [23]. If we keep an eye at the statistics regarding such cases in the USA, we will observe that every year almost 20% of grown-ups face cogent psychological disorder, and almost 17% of children from 6 years to 7 years of age group face psychological health ailments. Now, those who are doing researches on such issues, require assessing what are the main issues for which folks of the age group of 10 to 34 years are dying by committing suicide [24].

In this modern time, depression is gradually known as a persistent and repetitive ailment. There were several long-lasting pursuits of researches of psychiatric outpatients and from those researches, customarily same results have been generated [25]-[27]. From research, it is observed when depressed patients are there under the treatment of psychiatrists, almost 50% of them do not come round within 6 months and 10% of them expose a persistent behavior, not coming round from the indication periods more than 5 years. They who come round, almost 40% of them again tend to fall in the same after 2 years and it may increase to 80% after 15 years. Adequate information from those populations expresses ample risk of consistent ailment whereas insignificant data is obtainable about a long period of forecast of depression in initial supervision or community specimens [28].

2. BACKGROUND STUDY

Several online podiums exist in the web-world, which can save information for presenting conditions of patients [29]. They assist physicians too for coming to a concrete point to their objectives. Currently, several researchers have found out some ways for getting rid of chronic depression [30][31]. As depression does not show any substantial symptoms, it is very difficult to detect depression with other physical problems such as stomach ache, chickenpox, etc. At present medical experts apply the PHQ-9 and PHQ-2 elements of the Patient Health Questionnaire to detect depression [32] [33]. There are so many online platforms that can store data for screening patient information [29]. It also helps doctors for decision-making purposes. Recently different researches have been done for preventing the recurrence of depression [30]-[31]. Due to the absence of physical symptoms, depression can be harder to identify along with other medical conditions like Chest pain, Measles, etc. Nowadays medical professionals use the PHQ-9 and PHQ-2 components of the Patient Health Questionnaire for diagnosing depression [32], [33].

The purpose of the research [34] lies in the record and dissimilarities of the application types and medical outputs all over the United States among three distinct auto-regulated mobile applications for depression. Which means they suggested, that says that contestants were appointed via web-dependent ads and social media? Besides, those were arbitrarily allocated to 1 of 3 mood applications. The procedure of the control of therapy and analysis was executed casually on all contestants' smartphones or tabs with nominal attachments with researchers.

In this procedure, the authors registered 626 youths (≥18 years old) who can make verbal communication in English, with slight to limited depression as specified by a 9 item Patient Health Questionnaire (PHQ-9) score ≥5 or whether their score on item 10 was ≥2 or not. These applications were i) Project EVO which is a perceptive training application hypothesized for lessening indications of depression with the development of perceptive command. ii) iPST is an application that acts based on a psycho treatment on the proof for depression, and iii) Health Tips, an authority on therapy. The results were points on the PHQ-9 and the Sheehan Disability Scale [32][33]. Attachment to therapy was calculated with the number of times the contestants opened and applied the features as per guidelines. The purpose of this research is to resolve the conscientious connotations of therapy for depression based on significant applications [35].

The authors stated that the insertions of applications for the therapy of depression can be fruitful for patients till (i) the utility of a therapy based on application, is evaluated for every single patient. (ii) In such cases, applications are opted to conform to the sternness of symptoms and attributes such as the grade of self-dependence of the patients, what extent of knowledge they have, for surfing the internet, and their receptiveness vis-à-vis applications. (iii) Creators of the applications develop their confidentiality strategies and the standard of applications. Most of the time, depression commences in juvenile states and makes it a perfect time to intercede. The author created a customary subjective evident treatment based on the program (MEMO CBT) that was conveyed through multimedia cell phone texts for adolescents [36]. There is a growing eagerness in the implementation of smartphone apps and other customer mechanization in the concern of psychological health for several years [37] [38] [39]. For the assumption of the detection sternness of depression and feedback to therapy, the authors improved and assessed computation prototypes which apply electronic health record [EHF] information towards the target of incorporating therapy for depression [40] Toward the goal of personalizing treatment for depression, the authors developed and evaluated computational models that use electronic health record (EHR) data for predicting the diagnosis and severity of depression, and response to treatment [40]. Their suggested prototypes can speculate a prospective detection of depression till 1 year ahead of time [area under the receiver operating characteristic curve (AUC) (0.70-0.80)].

In [41], the research has two goals linked with improving comprehension of mechanization's dormant worth in psychological health: i) improving a predicting method which can be applied to detect youth being in danger of accounting a depression detection on adults based on a series of input variables and (2) comprehending the improvement routes of depression for juveniles. The detection of psychological illness is based on systemized patient interviews with illustrated series of queries and ranks that seem a time killing and expensive method. The goal refers to the use of a machine learning prototype and the assessment to observe whether there is an anticipating power of patient information to make the betterment of depression issues [7] [42] [43].

We make a target of creating a podium that can categorize the series of information into reappearance and no reappearance based on age, sex, and drug and therapy time before and after providing drugs. Besides, our objective is to assume the application of the drug if the repetition of the symptoms of depression is observed even after recuperation from the psychological ailments. Based on the reappearance issue, our suggested algorithm advises the use of drugs based on the coordination of forms filled up by patients while in an appointment.

2.1 Formation of Database

From the specimen of around 109 folks in the National Institute of Health Organization which is named as the CLINICAL group, a group of three thousand data has been processed, and it has been applied in this research that vastly envelopes Reappearance and Non-Reappearance results within the treatment offered to the victim (Lithium, Imipramine or Placebo). This therapy is scrutinized in comparison with customary therapy methods. While doing so, we keep an eye at Time, Acute T, age, and sex procedures exemplified in the motive of Queries and their responses. Initially, universal analytical trials and machine learning algorithms are implemented in avid research [7]. This kind of data can be obtained imperceptibly and the algorithm offered by us secure confidentiality suitably.

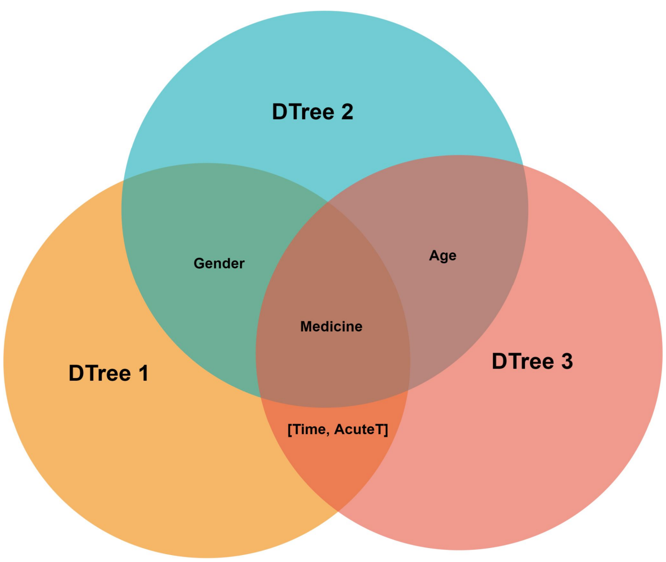

Figure 1: Venn-figure of our prototype with the application of on the basis of decision tree method

The dataset offers the particulars below:

- Hospt: The whereabouts of the hospital which the victim was taken to, symbolized by a numeral among 1, 2,3,4,5 or 6 among five hospitals.
- Treat: The treatment that is offered to the victim (Lithium, Imipramine, or Placebo)
- Outcome: A reappearance that occurred in the time of treatment or devoid of treatment (Reappearance/Non -Reappearance)
- Time: If reappearance is visible, the time or number of days is noted down till the happening of it and in which case, non-reappearance is perceived, the victim's participation span or its number of days is counted in the research.
- AcuteT: The total span of the patient's depressed mood before initiating the research.
- Age: It refers to victim's age in years in the time of his approach to the study.
- Gender: It refers to which sex the victim/patient belongs to. (If female, then 1, if male, then 2)

In figure no. 1 it is illustrated how to categorize the dataset for the assumption of the application of the drug of the setback depression victim depicting the Venn-figure below. The segments Figure 2 – Figure 4) as follows are clarified the block figure to outline our suggested decision tree algorithms (Algorithm 5 – Algorithm 7) applied for the assessment of possible result (Reappearance / Non-reappearance) based on our input dataset. Based on the result (Reappearance / Non-appearance) of figure 5 and figure 6 are coherently illustrated the block figure of the arbitrary forest algorithm and k-nearest neighbor algorithm to propose the possible therapy provided to the patient. The subsequent segment shows the logical illustration of our suggested algorithm.

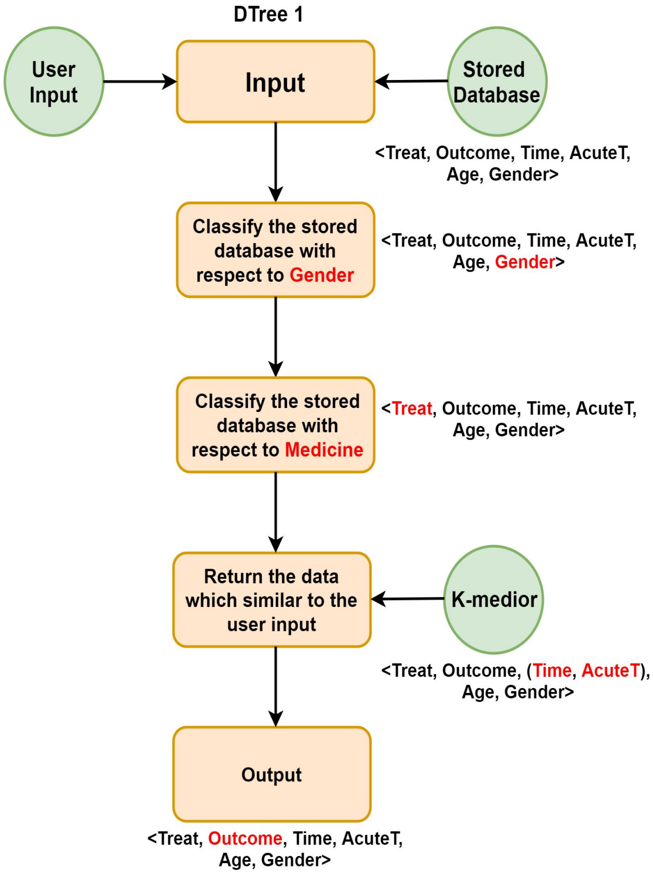

Figure 2: Block figure of Decision Tree 1 (DTree 1) algorithm for our proposed model

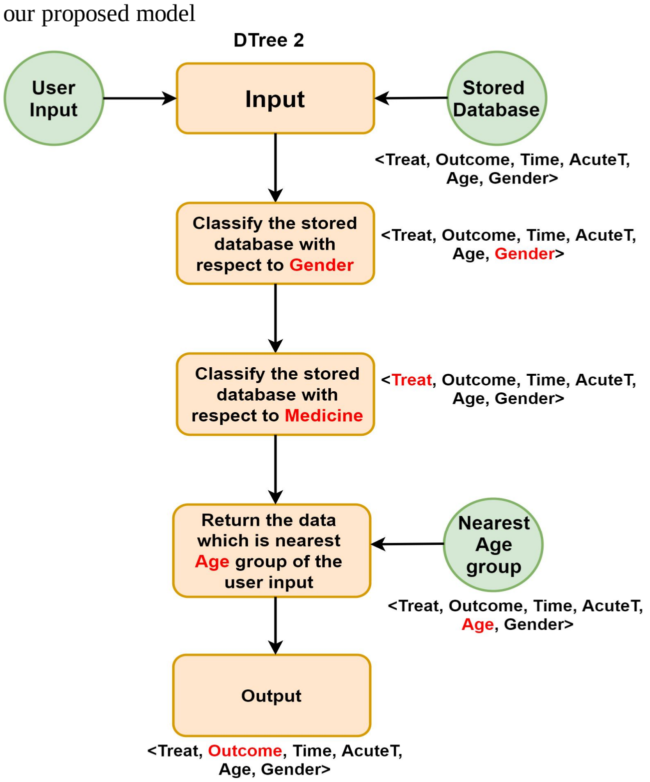

Figure 3: Block figure of Decision Tree 2 (DTree 2) algorithm for our proposed model

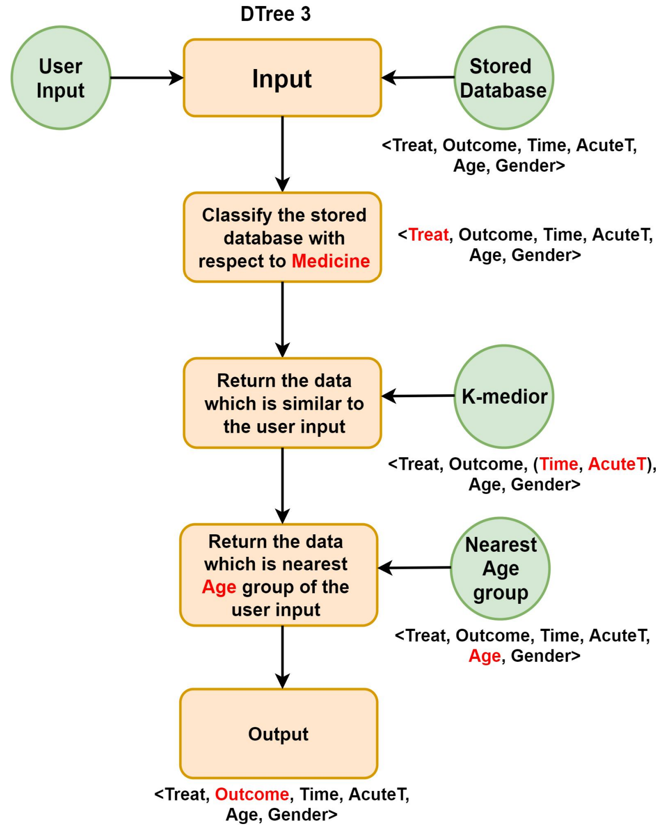

Figure 4: Block figure of Decision Tree 3 (DTree 3) algorithm for our proposed model

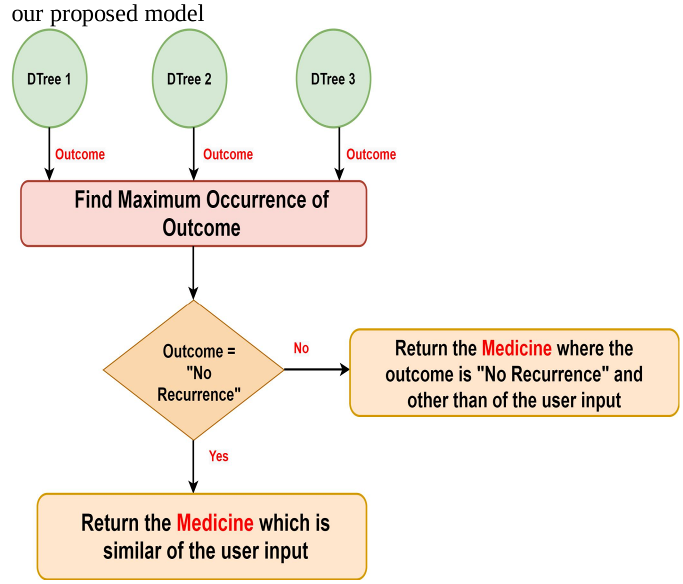

Figure 5: Block figure of Random Forest algorithm for our proposed model

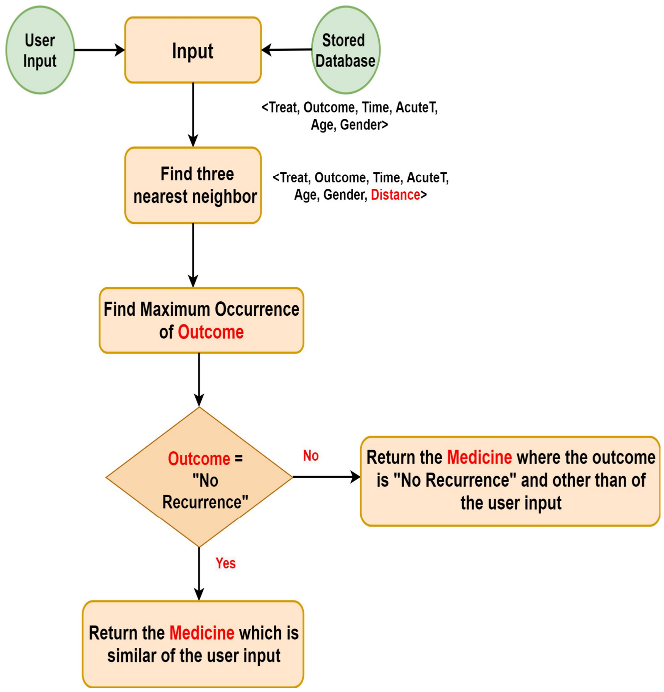

Figure 6: Block figure of K-Nearest Neighbor algorithm for our proposed model

3. PROPOSED ALGORITHM

This part offers clarification of the algorithms which have given a suggestion of making an outline of the study. The algorithm was outlined for accepting insertion from the user and it assumes that fetches the result whether it is Reappearance or non-Reappearance. Then we have to look for the majority of the event. Now, if the majority of events of the result is “Non-Reappearance”, then it fetches drug that is analogous to user insertion and if it is not so, then it fetches the drug in which the result is “Non-Reappearance” that is something else but user insertion. Here k-nearest neighbor algorithms which are algorithm 2 and 3 have been applied for the assumption of the application of the drug concerning location (You can notice it in figure 6) [44] [45]. In this paper, we suggested our random tree algorithm too in algorithm 4 [46] [47] [48] [49] [50]. This algorithm output works out with the support three decision trees that have been depicted in figure 1, figure 2, figure 3, and figure 4.

Algorithm 1: Input

Step 1: Start
Step 2: take information as input from user and create a list = [medicine, output [], time, acuteT, age, sex] as element
Step 3: extract data from the database as dataSet
Step 4: call the function predictMed (dataSet, element) from RandomForest and pass the parameters dataSet and element and store it in element [1]
Step 5: if element [1] = "Recurrence"
  Step 5.1: call the function predictMed (dataSet, element) from RandomForest and pass the parameters dataSet and element and store it in element [1]
Step 6: else
  Step 6.1: print element [1]
Step 7: End

Algorithm 2: K-Nearest Neighbors

Sep 1: import Classifier, KNN
Step 2: defined a function named predict and the pass the parameters (dataSet, elements)
  Step 2.1: declared neighborSet = []
  Step 2.2: call the getNeighbors (dataSet, element, k) function from KNN and pass the parameters dataSet, element, and k
  Step 2.3: find the max occurred value in neighborSet list and return it
Step 3: defined a function named predictMed (dataSet, elements, k) and the pass the parameters dataSet, elements, and k
  Step 3.1: classify the dataSet with respect to Outcome and store it in dataSet
  Step 3.2: if dataSet [0] [0] [1] = 'Recurrence' then
    Step 3.2.1: dataSet = dataSet [1]
  Step 3.3: else
    Step 3.3.1 dataSet = dataSet [0]
  Step 3.4: declared neighborSet = []
  Step 3.5: call the getNeighbors (dataSet, element, k) function from KNN and pass the parameters dataSet, element, and k
  Step 3.6: find the max occurred value in neighborSet list and return it
Step 4: defined a function named Accuracy (predictionSet, dataSet, element) and pass the parameters predictionSet, dataSet, and element
  Step 4.1: call the beyondAccuracy (predictionSet, dataSet, element) function from modules and pass the parameters predictionSet, dataSet, and element and store the return value in a variable named beyondAccuracy
  Step 4.2: call the normAccuracy (predictionSet, dataSet, element) function from modules and pass the parameters predictionSet, dataSet, and element and store the return value in a variable named normAccuracy
  Step 4.3: return beyondAccuracy

Algorithm 3: KNN

Step 1: defined a function named getNeighbors (trainSet, testInformation, k) and the pass the parameters trainSet, testInformation, and k
  Step 1.1: declared Neighbors = [] and getNeighbor = []

Step 1.2: for loop with variable element in range of length trainSet
Step 1.2.1: find the distance of trainSet [element] and testInformation and store it in a local variable named 'distance'
Step 1.2.2: append [trainSet [element], distance] in Neighbors
Step 1.3: sort the list Neighbors from greater to lesser value using 'Neighbors.sort (key = operator.itemgetter (1))'
Step 1.4: for loop with variable i in range of k
Step 1.4.1: append Neighbors [i] [0] in getNeighbor
Step 1.5: return getNeighbor

Algorithm 4: RandomForest

Step 1: import DTree1, DTree2, DTree3, K-Nearest Neighbors
Step 2: defined a function named prediction (dataSet, element) and pass the parameters dataSet, and element
Step 2.1: declared a list named prediction = []
Step 2.2: call the function predict (dataSet, element) from DTree1, DTree2, and DTree3 with the parameters dataSet, and element and store the returned value in prediction
Step 2.3: find the max occurred element in prediction and return the value
Step 3: defined a function named predictionMed (dataSet, element) and pass the parameters dataSet, and element
Step 3.1: declared a list named predictionMed = []
Step 3.2: call the function predictMed (dataSet, element) from DTree1, DTree2 and DTree3 with the parameters dataSet and element and also call the function predictMed (dataSet, element, 4) from KNN with the parameters dataSet, element, and 4 store the returned value in prediction
Step 3.3: find the max occurred element in prediction and return the value
Step 4: defined a function named Accuracy (predictionSet, dataSet, element) and pass the parameters predictionSet, dataSet, and element
Step 4.1: call the function beyondAccuracy (predictionSet, dataSet, element) from modules and pass the parameters predictionSet, dataSet, and element and store the return value in a variable named beyondAccuracy
Step 4.2: call the function normAccuracy (predictionSet, dataSet, element) from modules and pass the parameters predictionSet, dataSet, and element and store the return value in a variable named normAccuracy
Step 4.3: return beyondAccuracy

Algorithm 5: DTree1

Step 1: import Classifier, KMedior
Step 2: defined function named predict (dataSet, elements) and the pass the parameters dataSet, and elements
Step 2.1: append the element in the list dataSet
Step 2.2: classify the dataSet with respect to Medicine
Step 2.3: for loop with the data in dataSet
Step 2.4: if data [0] [0] = element [0] then go to next step otherwise go to Step 2.3
Step 2.5: dataSet = data
Step 2.6: classify the dataSet with respect to gender
Step 2.7: check dataSet [0] [0] [5] = element [5] if yes then dataSet = dataSet [0] else dataSet = dataSet [1]
Step 2.8: declared dataSet1 = [], medSet = [], predict = []
Step 2.9: for loop with the data in dataSet and append [data [2], data [3]] in dataSet1
Step 2.10: call the KMedior (dataSet1, 3) with the parameters dataSet1, and 3 from the module KMedior and store the returned value in dataSet1
Step 2.11: for loop with the data in dataSet and check if [element [2], element [3]] in data then dataSet1 =data
Step 2.12: for loop with data1 in dataSet1
Step 2.12.1: for loop with data in dataSet
Step 2.12.2: if data1 = [data [2], data [3]] then append data [1] in predict list else continue
Step 2.13: find the max occurrence element from predict list using findMaxOccurrence function and return it
Step 3: defined a function named predictMed (dataSet, elements) and the pass the parameters dataSet, and elements
Step 3.1: declared a list named element1 = [], a string named predict
Step 3.2: element1 = element
Step 3.3: defined medList = ['Lithium', 'Imipramine', 'Placebo']
Step 3.4: for loop with i in list medList
Step 3.4.1: element1 [0] = i
Step 3.4.2: predict = predict (dataSet, element1)
Step 3.4.3: if predict = 'No Recurrence' return i else continue
Step 3.5: return 0 position data of element

Algorithm 6: DTree2

Step 1: import Classifier
Step 2: defined function named predict (dataSet, elements) and the pass the parameters dataSet, and elements
  Step 2.1: classify the dataSet with respect to Medicine
  Step 2.2: for loop with the data in dataSet
  Step 2.3: if data [0] [0] = element [0] then go to next step otherwise go to Step 2.3
  Step 2.4: dataSet = data
  Step 2.5: classify the dataSet with respect to gender
  Step 2.6: check dataSet [0] [0] [5] = element [5] if yes then dataSet = dataSet [0] else dataSet = dataSet [1]
  Step 2.7: classify the dataSet with respect to age and store it in dataSet
  Step 2.8: declared s = []
  Step 2.9: for loop with the data in dataset
    Step 2.9.1: find the difference of data [0] [4] and element [4] and append the difference in list s
  Step 2.10: find the index of the minimum term in list s and store it in s
  Step 2.11: dataSet = dataSet [s]
  Step 2.12: declared predict = []
  Step 2.13: for loop with data in dataSet
    Step 2.13.1: append data [1] in predict
  Step 2.14: find the max occurrence element from predict and return it
Step 3: defined a function named predictMed (dataSet, elements) and the pass the parameters dataSet, and elements
  Step 3.1: classify the dataSet with respect to Outcome and store it in dataSet
  Step 3.2: if dataSet [0] [0] [1] = 'Recurrence' then dataSet = dataSet [1] else dataSet = dataSet [0]
  Step 3.3: classify the dataSet with respect to gender
  Step 3.4: check dataSet [0] [0] [5] = element [5] if yes then dataSet = dataSet [0] else dataSet = dataSet [1]
  Step 3.5: classify the dataSet with respect to age and store it in dataSet
  Step 3.6: declared s = []
  Step 3.7: for loop with the data in dataset
  Step 3.7.1: find the difference of data [0] [4] and element [4] and append the difference in list s
  Step 3.8: find the index of the minimum term in list s and store it in s
  Step 3.9: dataSet = dataSet [s]
  Step 3.10: declared predict = []
  Step 3.11: for loop with data in dataSet
    Step 3.11.1: append data [0] in predict
  Step 3.12: find the max occurrence element from predict and return it

Algorithm 7: DTree3

Step 1: import Classifier, KMedior
Step 2: defined function named predict (dataSet, elements) and the pass the parameters dataSet, and elements
  Step 2.1: append the element in the list dataSet
  Step 2.2: classify the dataSet with respect to Medicine
  Step 2.3: for loop with the data in dataSet
  Step 2.4: if data [0] [0] = element [0] then go to next step otherwise go to Step 2.3
  Step 2.5: dataSet = data
  Step 2.6: declared dataSet1 = [], medSet = [], predict = []
  Step 2.7: for loop with data in dataSet and append [data [2], data [3]] in dataSet1
  Step 2.8: dataSet1 = KMedior.KMedior (dataSet1, 3)
  Step 2.9: for loop with data in dataSet1
    Step 2.9.1: check if [element [2], element [3]] in data then dataSet = data
  Step 2.10: for loop with data1 in dataSet1
    Step 2.10.1: for loop with data in dataSet
    Step 2.10.1.1: if data1 = [data [2], data [3]] then append data in midSet
  Step 2.11: declared dataSet1 = [], s = []
  Step 2.12: for loop with data in midSet
    Step 2.12.1: check if data is not in dataSet1 then append data in dataSet1
  Step 2.13: delete the element from dataSet1
  Step 2.14: for loop with data in dataSet1
    Step 2.14.1: find the difference between data [4] and element [4] and store it in a local variable c
    Step 2.14.2: append [data, c] in s
  Step 2.15: sort the list s from greater to lesser value using 's.sort (key = operator.itemgetter (1))'
  Step 2.16: take first three elements from list s
  Step 2.17: for loop with i in s
    Step 2.17.1: append I [0] [1] in predict
  Step 2.18: return the max occurred element in predict
Step 3: defined a function named predictMed (dataSet, elements) and the pass the parameters dataSet, and elements
  Step 3.1: declared a list named element1 = [], a string named predict
  Step 3.2: element1 = element
  Step 3.3: defined medList = ['Lithium', 'Imipramine', 'Placebo']
  Step 3.4: for loop with i in list medList
    Step 3.4.1: element1 [0] = i
    Step 3.4.2: predict = predict (dataSet, element1)
    Step 3.4.3: check if predict = 'No Recurrence' return i else continue
  Step 3.5: return 0 position data of element

4. END-USERS WEB APPLICATION

In this research [7], the authors had supplied significant data about the attributes and blemishes of all machine learning algorithms used to forecast of mental states. A great many machine learning methods regarding persistent and sporadic choice and categorization were analyzed for depression. Machine learning algorithms were used to create prototypes for having assumptions. For this K-nearest Neighbors (KNN), Support Vector Machine (SVM) and Random Forest were applied. The outcomes of the execution focuses on the power of depression conclusion from three puzzling matrix. Among these algorithms, the K-Nearest Neighbors worked most suitably assuming 83% aptly quickly pursued by the inconsistent forest with 78%. Puzzling Matrix of K-nearest Neighbors has obtained the greatest aptness [7]. Nevertheless, the little specimen volume range has been confronted in this study.

For the betterment of the work of departing linguistic, we designed three decision trees that have been logically clarified in figure 2, figure 3, and figure 4. We categorized applying sex, drug and <Time, Acute T> in the first decision tree. Analogously, we classified applying sex, drug and age in the second decision tree. Third decision tree was also used to categorize age, drug and <Time, Acute T>. Concerning the output from these decision trees, we had a result from the group <Reappearance, Non-Reappearance>.When it is perceived that the possible result is "Non-Reappearance", the anticipated drug should not be changed and patient should carry on the same. If it is not so, the anticipated drug would be the drug in which the possible result is "Non-Reappearance" that is other than the consumer's insertion. In this research, a web application end-user interface on the basis of the control of python has been illustrated. This is shown in figure 7 and figure 8. From the users, specimen trial instances have been systematized in the Table 1. Table 2 shows the Accuracy of Our Suggested Random Forest (ACC_{RF}) and k-nearest neighbor (ACC_{KNN}), and it gives an evidence of the development of execution of the linguistic that remains.

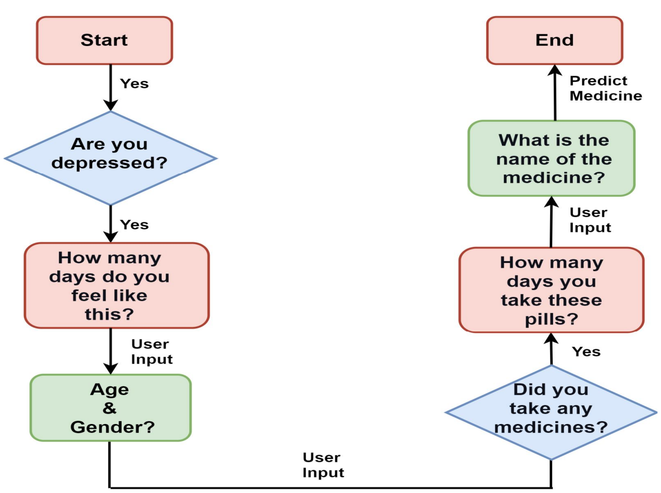

Figure 7: Procedure flow chart of the web application on the basis of control of python

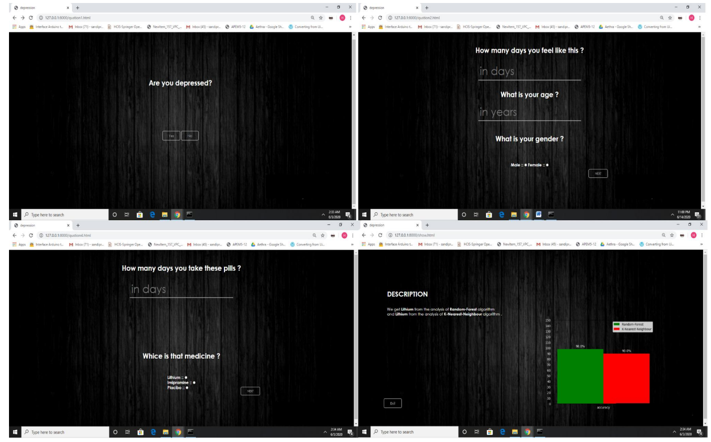

Figure 8: Python-driven web application end-user interfaces

Table 1: User input dataset

Time	Age	Gender	AcuteT	Treat
45	33	Male	15	Lithium
105	18	Female	30	Imipramine
90	25	Female	30	Imipramine
300	40	Male	60	Lithium
50	25	Female	30	Imipramine
150	47	Female	100	Lithium
90	38	Male	50	Imipramine
60	50	Female	30	Lithium
365	55	Male	45	Imipramine
200	70	Female	75	Lithium

Table 2: Accuracy between Random Forest and K-Nearest Neighbor

Random Forest	K-Nearest Neighbor	ACC_{RF}	ACC_{KNN}
Lithium	Lithium	93%	93%
Placebo	Placebo	92%	89%
Lithium	Lithium	96%	95%
Imipramine	Imipramine	98%	96%
Lithium	Imipramine	98%	95%
Lithium	Lithium	97%	95%
Lithium	Placebo	99%	95%
Lithium	Lithium	96%	96%
Imipramine	Imipramine	100%	99%
Imipramine	Imipramine	98%	95%

5. CONCLUSION

To come to the assessment, here we at first distinguished the results of three changeable personal decision tree clarifiers for verifying the link between apparent result and the presentation of clarifiers. Then we noticed that our suggested three clarifiers' presentation was significant on the basis of the on hand linguistic. After that, we disclosed a collection tactic on the basis of three suggested decision trees and assumed the drug on the basis of our suggested arbitrary forest methodology. Among those algorithms, the arbitrary forest algorithm worked most suitably assuming almost 98% aptly abruptly pursued by the k-nearest neighbor with 95%.

Nevertheless, the little model volume extent has been dealt with by this study. In addition, whereas the tentative results are hopeful, a probable restriction of this study is that expected drug will probably possess supplementary attributes which are related to depression. A prospective route of this research conveys examining developments in unequivocal derivation and choice policy.

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