An Automatic Adaptive Case-based Reasoning System for Depression Remedy Recommendation

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***Abstract*—Social media data represents the fuel for advanced analytics concerning people's behaviors, physiological and health status. These analytics include identifying users' depression levels via Twitter and then recommend remedies. Remedies come in the form of suggesting some accounts to follow, displaying motivational quotes, or even recommending a visit to a psychiatrist. This paper proposes a remedy recommendation system which exploits case-based reasoning (CBR) with random forest. The system recommends the appropriate remedy for a person. The main contribution of this work is the creation of an automated, data-driven, and scalable adaptation module without human interference. The results of every stage of the system were verified by certified psychiatrist. Another contribution of this work is setting the weights in case similarity measurement by the features' importance, extracted from the depression identification system. CBR retrieval accuracy (exact hit) reached 82% while the automatic adaptation accuracy (exact remedy) reached 88%. The adaptation presented an error-tolerance advantage which enhances the overall accuracy.**

Keywords*—*Case-based reasoning (CBR); depression; remedy; adaptation; similarity; twitter

I. Introduction

Depression is among the most critical mental illness that put more than 300 million people lives on risk, and affect patient and his family quality of life. Depression is highly common nowadays and recorded an increased number of cases due to economic factors, global pandemics, and social isolation. Early detection, with an appropriate remedy recommendation is the key to minimize the emotional and financial burden of the depression. However, the increased usage of social network platforms has brought up the essential need to modern analysis techniques on the enormous amount of data available. Twitter, as one the most important and commonly used social network platforms, has a great impact around the world in seconds. More than 500 million tweets are shared per day, bringing up more information and emotions to be diffused among the large number of users. Negative emotion spreads through the network, raising mental illness, especially depression. As a result, techniques from different fields have been used to analyze and process social network data to diagnose and suggest the appropriate treatments to mitigate such situations [1, 2]. This work exploits Case bases reasoning approach to detect depression in Twitter users. As a result, this study proposes an automatic adaptive case-based reasoning system for early depression detection on social network and automatic remedy recommendation.

Case-based reasoning (CBR) retrieves, analyzes, and stores new knowledge, making it available for solving problems [3]. CBR were used in medical assistant systems for diagnosing and treatment formulation [4 - 9]. Similarly, machine learning is a significant technique for classifying and predicting illnesses through patterns found in the training dataset [10].

This work extends the previous work in the identification of depression levels (tended to be depressed, depressed, deeply depressed) [11, 12] by adding a remedy recommendation system. It uses a hybrid system of CBR and the Random Forest algorithm (RF-CBR), where Random Forest (RF) outcomes feed the CBR to find treatment for users who are depressed. This study aims to recommend the best remedy to depressed Twitter users, when they are in their early stages of illness, or else recommend the visit to a psychiatrist. The most critical stage in the CBR system is the similarity calculation to find the best fit for the new case from the knowledge base. Researchers have used various techniques to reach for the best similarities the match in the CBR model. For example, [13] and [14] used correlations, while [13] used fuzzy logic to calculate the similarity of users to diagnose depression. On the other hand, [14] showed that a combination of RF with the CBR had the best results and highest accuracy among other techniques. As a result, this study used feature importance measurements for calculating similarity through the integration of RF and CBR (RFCBR).

The main challenge of CBR is the adaptation task, which depends on the domain and application characteristics [7]. Most CBR systems are built as retrieval-only systems, especially CBR in the medical and healthcare domain, as they leave it to human experts [15, 16]. The adaptation task is often left out due to the complexity of the domain or the difficulty in acquiring the knowledge needed [7, 17]. Some studies have attempted to adopt and explore automatic and semi-automatic adaptation strategies, such as [16, 18-22], but they have all required human interference to complete and/or assess a system's performance. The integration of CBR with other methodologies has been used to overcome the adaptation problem [11]. For this, most CBR systems use either human experts or are rule-based for the adaptation task, while this study is data-driven, which, to our knowledge, is novel and has not been introduced for depression treatment.

The proposed work enhanced the previous research by developing an automatic system called Remedy Recommender Model (RRM) entailing RF and CBR for detecting users' depression levels and in consequent of those outcomes recommends the best remedy. The experiments depend on ground truth data prepared by psychiatrists. They studied the cases in the knowledge base and gave recommendations of remedies accordingly. Three feature importance measurements are used each in a separate experiment to identify the features' weights, namely, overall, permutation, and tree interpreter feature importance measures. The results of this study correspond to [12], showing the best results from retrievals and adaptation using the tree interpreter feature importance measurement.

The rest of the article is organized as follows. Section II illustrates the previous work in both CBR and healthcare. Section III elaborates on the background, while Section IV drafts the proposed approach and solution. Section V discusses the experimental results in addition to comparative analysis with other authors. Finally, Section VI concludes and positions the findings and insights.

II. RELATED WORK

CBR has been used in healthcare for diagnostics and treatment. CASEY is one of the earliest medical expert systems that used CBR for heart failure diagnosis. The system searches for similar cases, finds the differences between a current and a similar case, and transfers the diagnosis of the similar case to the current case. The system uses rule-based domain theory if modification attempts fail or if no similar cases are found [7]. Additionally, Nasiri et al. [9] introduced the DePict CLASS, a cased-based learning assistant system that recommends information retrieved from dementia research based on the ICF framework of the WHO. The system detects and predicts the disease using image classification and text information. Caregivers and domain experts use and update the DePicT CLASS for dementia that is used by caregivers and patients' relatives to find answers in dealing with their problems [9]. Moreover, Mulyana et al. [23] developed a case-based reasoning system for diagnosing types of schizophrenic disorders and mood disorders with their treatment. Medical records of patients with mental disorders were obtained from a mental hospital in Yogyakarta and were used to construct the knowledge base of the system. The system selects the case with the highest similarity to the new problem and recommends its treatment to the new case [23].

To increase the accuracy of the similarity measurements in CBR, the authors in [24 - 26] introduced fuzzy logic with CBR. For example, Ahmed et al. [6] reached an accuracy of 88% in the diagnosis and treatment of stress. Houeland et al. [27] also introduced the random decision tree (RDT), which proved that the hybrid combination outperformed the base algorithms in similarity measures. Similarity was calculated using proximities that were computed using an RF algorithm.

Furthermore, Asim et al. [15] compared the nearest-neighbor and artificial neural network to RF and found that RF contributed to the efficiency of the CBR system they used to identify influential bloggers. They reached an accuracy of 89% when using Gini impurity as weights in the similarity measure of the CBR system. Hseih et al. [28] also compared different classifiers and ensemble classifiers as the best for use with CBR to find Internet-addicted users and were able to reach 89.9% accuracy. In addition, Gu et al. [29] used CBR with a genetic algorithm to diagnose breast cancer, achieving 0.927 accuracy.

In the mental illness sector, several studies used CBR to help diagnose or treat mental illnesses. Mulyana et al. [30] used CBR to diagnose mood disorders, achieving 89.3% accuracy using Modified Tcersky to increase similarity retrieval accuracy. On the other hand, other studies used CBR with different techniques. Kwon et al. [31] used crowd knowledge with CBR to diagnose depression and stress. Furthermore, Rahim et al. [32] used the help of specialists and built an expert system with CBR to diagnose physiological disorders. Table I summarizes some CBR systems in different domains.

TABLE I. COMPARISON OF CBR SYSTEMS IN DIVERSE DOMAINS

Author/ Domain	**Techniques**	**Results**	**Similarity**	**Adaptation**
Asim [15] (blogger influence)	RF + ANN + C4.0 + NN	f-measure (85% before adaptation, 91% after adaptation)	Gini entropy	Yes
Mulyana [23] (mental disorder)	CBR	Accuracy: 99%	NA	No
Hsieh [28] (internet addiction)	Ensemble classifier + CBR	Accuracy: 89.9%	Weight of classifier	No
Gu [29] (breast cancer)	CBR	Accuracy: 0.927	Genetic algorithms for weights	No
Mulyana [30] (mood disorder)	CBR	Accuracy: 89.3%	Modifies Tversky Similarity	No
Kwon [31] (depression & stress)	Crowd knowledge + CBR	Accuracy: 92.5%	NA	No
Rahim [32] (phycological disorder)	CBR + expert system	Accuracy: 75%	NA	No

As previously mentioned, most studies have used human experts for adaptation tasks or ignored them. Eknog et al. [14] and Nasisri et al. [9] used experts to perform the adaptation task. On the other hand, Asim et al.'s [15] adaptation was automatic in its use of similarity equations but with no change in the results.

The present study reveals the gap in the treatment of depression and other mental illnesses is that most of the studies did not utilize adaptation or created adaptation with human assistance.

III. Background

A. Case-based Reasoning

CBR is found to be a good model because it assimilates problem solving, understand, and learn, and integrate all of them with memory processes. It also amends old solutions to meet new requirements [13]. Thus, in the past few decades, has befitted the medical domain as intelligent computer-aided decision support systems [6, 13]. CBR system depends on reusing previous knowledge to solve new problem through defining the similarities between them. Later, before applying the solution (remedy) CBR revises them then retains applicable solutions (remedies) for further reuses [33 - 36]. These steps of the 4R processes demonstrate the R4 model developed by Aamodt and Plaza [13, 37].

Based on the CBR cycle (Fig. 1), the RETRIEVE process in this article starts with identifying similar cases in the knowledge base using the features' importance and the score of each case. Similarity calculations help find the most similar case with the most similar treatment. A case that has the highest level of similarity will be suggested as the most alike treatment for the case, and this is called the REUSE process. Next, the case will enter the REVISE process, where an adaptation algorithm will be applied to identify if this is the most suitable treatment or if there is another case with better treatment. Finally, after finding the most similar case and recommending the most similar treatment, the RETAIN process can save the case in the knowledge base as a new case.

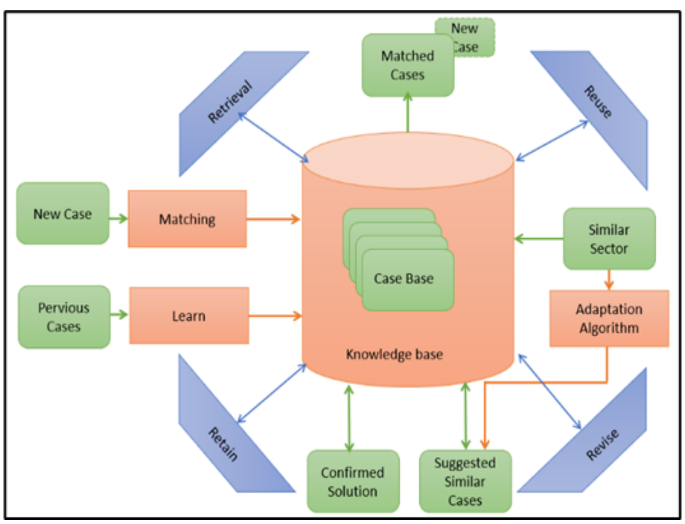

Fig. 1. The CBR Cycle.

B. CBR in Healthcare

CBR's ability to solve problems and its efficiency in the recommendation process has attracted researchers in the healthcare domain [4 - 9]. CBR systems are increasingly used in healthcare due to its utility for the thought process of a physician [13, 38]. Automatic establishment of a facility-adapted knowledge base is highly beneficial to CBR systems in healthcare [39], which is of great significance in medical decision making [13].

CBR has also been used for developing intellectual computer-aided decision support systems in the medical domain in the past few years because of the continuously changing nature of the medical knowledge base and the presence of more than one solution [6, 13, 40].

IV. Proposed System (RRM)

RRM used for depression detection starts with retrieval of similar cases in the knowledge base which is an important and critical phase to reach an optimal solution for the desired case. The similarity – as first step in the CBR cycle - depends on the features weights to get the most similar cases according features similarities of both cases. The most similar cases will be used to enter the CBR's REUSE stage. Later, adaptation phase is performed in the REVISE stage which is important to recommend the most suitable treatment for depression in its early stages. Finally, the recommended new case will be retained in the knowledge base. This study uses data from [11], data collected consisted of Twitter users who were depressed and non-depressed. A total of 500 users were collected with more than 1M tweets, and 334 users were classified as depressed. The data consisted of user accounts' information and tweets.

The data has been used for running RF to classify users as depressed and non-depressed users and find importance of each feature and the score of each case obtained from the RF probabilities [12]. Importance of features is used as weights for the similarity calculation to retrieve from the training set the most similar case to the case in the test set. Only depressed users' data is used in this study since they are targeted to recommend the best remedy for them. these results based on generating 10 random splits of data to 50% knowledge base and 50% unseen cases. The target is to neutralize the system to any cases temporal order to the system.

Data is trained using 10-fold cross validation to avoid over fitting and then tested on held-out test data. Fig. 2 summarizes the RRM phases. Novelty of this work appears in both retrieval and adaptation phase where the recommended solution for depressed users is proposed.

A. Retrieval Phase

Retrieval of similar cases utilizes Algorithm 1 using local and global similarity equations [33, 34]. The algorithm starts with calculating local similarity of features for the new case and old cases in the knowledge base:

$$sim\,(f_x, f_y) = 1 - \frac{|f_x - f_y|}{f_{max} - f_{min}} \tag{1}$$

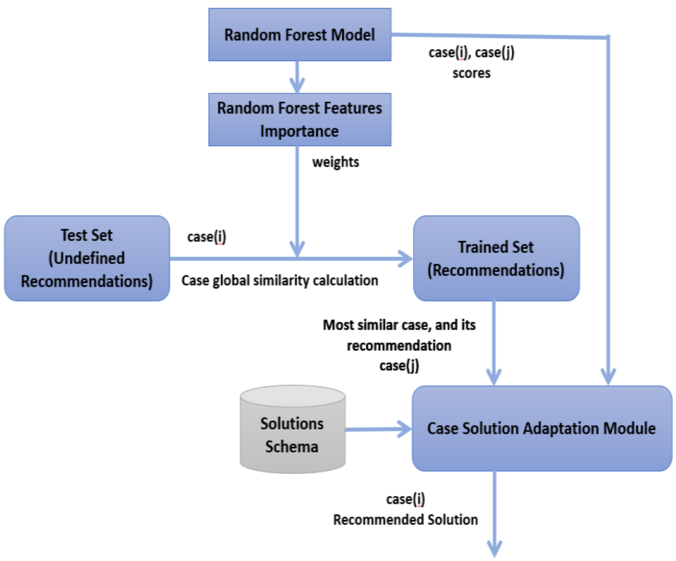

Fig. 2. The RRM System.

where f_x is the feature's value for the new case, f_y is the feature's value for the *y*-th old case, and $f_{max} - f_{min}$ includes the minimum and maximum values for all the old cases included in the database.

Next, the global similarity is calculated, which is the weighted sum of the local similarities of all features used in the analysis. Global similarity is calculated using the following equation:

$$similarity(x,y) = \frac{\sum_{f=1}^{n} w_f \times sim(x_f, y_f)}{\sum_{i=1}^{n} w_f} \quad (2)$$

Where w_f is the weight of the f-th feature, $similarity(x,y)$ is global similarity between the case x from the training set and the new case y, and $sim(x_f, y_f)$ is the local similarity for the f-th feature between case x and the new case y.

Importance of the features concluded from the RF is used as the weight for each feature. Finding the most similar case is important for the accuracy of the adaptation phase.

To illustrate how algorithm 1 is implemented, this study provides an example from the cases used in this study. This will use a new case and a small case base, containing just two cases and four features as shown in Table II. Importance, minimum, and maximum values of each feature are also shown in Table II. The new case Ci will be compared to the cases stores in the training case repository. The goal is to find the most similar case to the new case to be able to recommend the same remedy. In other words, the remedy used for the case in the repository will be recommended the same remedy. In other words, the remedy used for the case in the repository will be recommended to the new case. Similarity calculations aims to find cases that are analogous in a way their remedy can be reciprocally reused.

Algorithm 1 starts with calculating local similarity for the new case Ci and the two cases using equation (1). Local similarity between C1 and Ci for the (Retweets feature) is:

Algorithm 1: Get_Most_Similar_case (C_i, TC)

Input:
C_i: input case
***TC*: training cases in case repository**
Output: The most similar case

1: MaxSim=0
2: For all training cases *TC*:
3: For all features in features space:
4:
- Calculate Feature_Local_Sim (case of **C_i** and case of TC) //using equation (1)

End for
5:
- Calculate New_sim = GlobalSim (Feature_Local_Sim of **C_i**, Feature_Local_Sim of TC) //using equation (2)

End for
6: MaxSim=max (MaxSim, new_sim)
7: Return the most similar case with MaxSim

TABLE II. FEATURES' COMPARISON OF NEW CASE AND CASES IN REPOSITORY CORRESPONDING TO THEIR MAXIMUM AND MINIMUM VALUES

Features	**C_1**	**C_2**	**New case C_i**	**Importance of features**	**Maximum Value**	**Minimum Value**
Retweets	26	70	100	0.9	200	0
Hashtags	10	72	20	0.8	123	5
Depress	30	10	56	0.5	350	4
Hate	14	40	20	0.7	120	0

$$\mathrm{Sim}(C_i, C_1) = 1 - \frac{|26-100|}{200-0} = 0.63 \quad (3)$$

Similarly, local similarity for all features are calculated for the Ci with C1 and C2:

Sim (Ci, C1) = {retweets 0.63, hashtags 0.91, depress 0.92, hate 0.95}

Sim (Ci, C2) = {retweets 0.85, hashtags 0.56, depress 0.87, hate 0.83}

The second step in the retrieval phase is calculating global similarity. Equation 2 is applied to find similarity between cases and the new case. This is done by taking weighted sums of local similarities with the importance of features as weights. Global similarity is calculated as follows in Eq. 4 and 5:

$$Similarity(C_{i,} C_1) = \frac{1}{2.9} \times (0.9 \times 0.63 + 0.8 \times 0.91 + 0.5 \times 0.92 + 0.7 \times 0.95) = 0.834 \quad (4)$$

$$Similarity(C_{i,} C_2) = \frac{1}{2.9} \times (0.9 \times 0.85 + 0.8 \times 0.56 + 0.5 \times 0.87 + 0.7 \times 0.83) = 0.769 \quad (5)$$

Therefore, C1 were chosen to reuse and continue to adaptation phase. C_i is more similar to C_1 than C_2.

B. Adaptation Phase

Adaptation phase depends on the knowledge base which has three sectors of remedies for different depression levels. Levels of depression are for users who tend to be depressed, depressed users, and users with advanced depression where a doctor consultation is a must. Cases' scores, Sc = {Sc1, Sc2,…Scn} are calculated and retrieved for RF model and saved in the knowledge base with appropriate recommended remedies R = {R1, R2,…Rn}, for each case.

Algorithm 2 illustrates the adaptation phase. For each new case Ci, score Sci, and remedy Ri, first, similarity is calculated with the cases in the training set to find the most similar case, Cj. Later, all mean score for remedies in the same sector are calculated. KNN is applied to find the nearest mean score which determines the nearest remedy appropriate for Ci.

In order to illustrate Algorithm 2, this study introduced an example from the study cases. Cases used were introduced in illustrating algorithm 1 above. After applying Algorithm 1, C1 was found to be closer to Ci. As a result, case C1 remedy will be first recommended for new case Ci but adaptation phase will try to reach a better remedy for Ci.

Algorithm 2: RRM Adaptation Pseudo code

Input:

TC: training cases in case repository (knowledge base)

C_i: input case

Sc_i: Depression classification score of case C_i

CSR: table with columns case, score and remedy

Output: remedy R_i

1: Case C_j = Get_Most_Similar_Case (C_i, TC) // ***using Algorithm 1***
2: RemedySector rs of C_i is the RemedySector of C_j
3: For every remedy r from rs:
4: - Obtain Sc(score) from CSR where remedy is r
5: - ScoreMean[r,m] where m is the mean of scores of table Sc
6: closeScore = minimum distance between input Sc_i and Scores in ScoreMean
7: R_i is a remedy r obtained from ScoreMean[r, m] where m is closeScore
8: Return remedy R_i

For Algorithm 2, score of new case Ci - derived from the RF result- is used as an input for the algorithm implementation where score Sci is equal to 0.74. Also, CSR containing scores and remedies for repository cases is given in Table III. Since C1 is most similar to new case Ci, remedy of C1 will be used to define the sector. Using classification of sectors in Fig. 3 remedy of C1 is R8 meaning that C1 and R8 is in depressed sector. For each remedy in the depressed case sector, the cases will be retrieved, and the mean score will be calculated. In other words, mean score for cases with remedy in [R6, R7, R8, R9, R10] will be calculated. From Table III, Mean scores of R6= (Sc2 +Sc7)/2= 0.69+0.75/2=0.72. Mean score of R8= (Sc1 +Sc3)/2= 0.785, mean scores of R9 = 0.82, and for R10 = 0.88.

To find best remedy for Ci, Algorithm 2 will apply KNN and find closest mean score to Sci and choose the corresponding remedy for Ci. Since mean score of R6 is the nearest neighbor to score Sci = 0.74 of input case Ci. Sci, Algorithm 2 will return R6 as a better remedy recommended for input case Ci.

TABLE III. CSR CONTAINS SCORES AND REMEDIES FOR EACH CASE

Cases	Score	Remedy
1	0.85	R8
2	0.69	R6
3	0.72	R8
4	0.74	R1
5	0.32	R2
6	0.88	R10
7	0.75	R6
8	0.41	R3
9	0.82	R9

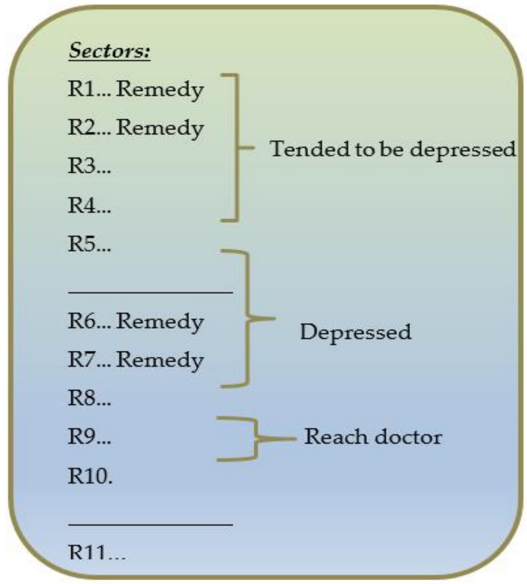

Fig. 3. Classification of Depression Sectors.

V. EXPERIMENTS AND RESULTS

Data used for this experiment has 133 depressed users and 66 not depressed. In an attempt to have ground reality, data for validation of the RRM system results, for each depressed user best recommended solution is assigned with the help of psychologists. This helped to identify how many correct retrievals of similar cases and number of successful adaptations of best solution to each depressed user.

Depending on the score of each case obtained from classification step using RF, the system categorizes the cases to one of the following sectors: tend to be depressed cases, depressed, and deeply depressed as shown in Table IV. Results proved that depression has the exponential distribution of contagious diseases shown in Fig. 4.

TABLE IV. PERCENTAGE OF EACH DEPRESSION LEVEL ACCORDING TO THE SCORES OF CASES

Level	Percentage to data
Tend to be depressed	62%
Depressed	30%
Deeply depressed	8%

A. Retrieval Phase Results

The implementation of CBR starts with applying the similarity equation to find the similarity of the new case to cases in the training set. As explained in the proposed system section retrieval phase is applied to find the most similar cases to the desired case. The results of the implementation showed the accuracy of retrieving similar cases from the knowledge base.

Retrieval experiments employ three different importance feature measures to determine the feature weights used in the similarity equation namely overall, permutation, and tree interpreter feature importance measures. Evaluation measures are applied independently for each experiment. Applying tree interpreter feature importance was able to retrieve successfully 54 users which revealed highest accuracy, 82% as shown in Table V. Precision, recall, and the f-measure revealed tree interpreter is the highest among the other importance criteria reaching 0.766, 0.349, and 0.480, respectively. Overall and permutation feature importance criteria had a smaller number of correct retrievals where the accuracy was 73% and 67%, respectively. Also, precision, recall, and the f-measure indicated that overall and the permutation are less accurate than tree interpreter. Overall results were 0.62, 0.343, and 0.442, respectively while the permutation results were 0.706, 0.343, and 0.472, respectively. Results of retrieval are summarized in Fig. 5.

B. Adaptation Phase Results

Completing the CBR cycle for the experiment, the adaptation phase results are conducted for each cycle and results are recorded according to the type of feature importance measurement used. Tree interpreter feature importance measurement has outperformed other feature importance measurements resulting accuracy of 88% with 58 successful user adaptations as shown in Table VI. Overall and Permutation feature importance criteria had lower result, 76% and 71% were their accuracy results, respectively. Precision, recall, and the f-measure indicated that tree interpreter had higher results than the other measures, reaching 0.762, 0.358, and 0.511, respectively, while overall and permutation reached precision of 0.671 and 0.7401, recall 0.456 and 0.3128, and f-measure 0.543 and 0.439 respectively. Fig. 6 illustrates the adaptation results.

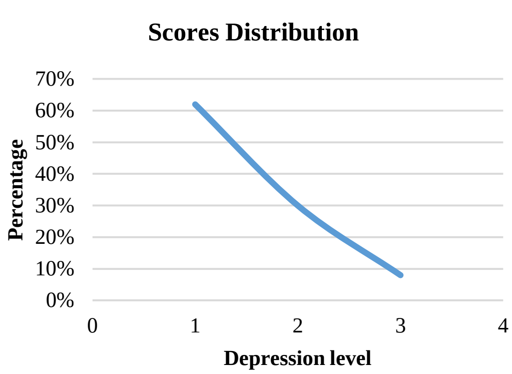

Fig. 4. Exponential Distribution of Depression Levels.

TABLE V. RETRIEVAL PHASE RESULT FOR DIFFERENT IMPORTANCE CRITERIA

Feature Importance Criteria	Retrieval Accuracy	Precision	Recall	F Measure
Overall	67%	0.61189	0.328456	0.427457
Permutation	73%	0.71192	0.30867	0.43063
Tree Interpreter	82%	0.76611	0.34986	0.480356

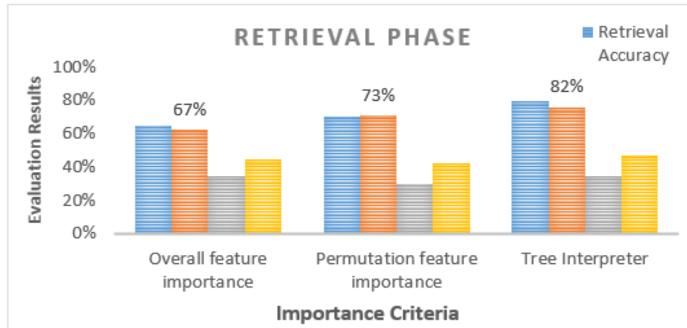

Fig. 5. Statistical Illustration of Retrieval Phase Results.

TABLE VI. ADAPTATION PHASE RESULTS FOR DIFFERENT IMPORTANCE CRITERIA

Feature Importance Criteria	Retrieval Accuracy	Precision	Recall	F Measure
Overall	71%	0.6713	0.4561	0.543161
Permutation	76%	0.7401	0.3128	0.439744
Tree Interpreter	88%	0.7624	0.38519	0.511801

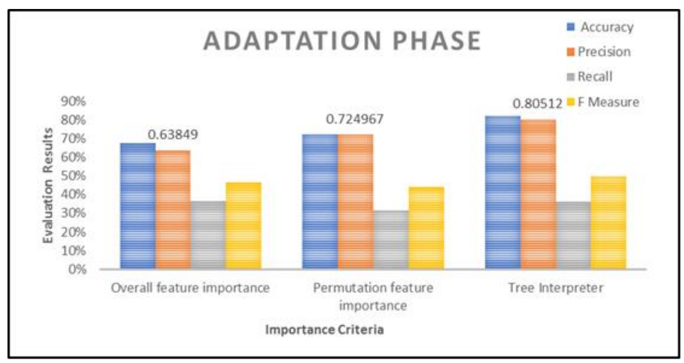

Fig. 6. Statistical Illustration of Adaptation Phase Results.

Results of retrieval and adaptation showed that tree interpreter feature importance results outcomes correspond to the results of [12].

VI. COMPARATIVE STUDY

This comparison has been considered to guarantee the effectiveness of the proposed RRM. Other studies used different data sets and labels and aim to propose objective and non-biased results and analysis, this comparative study will apply the same data to different techniques. As mentioned earlier, different studies have used correlations [14 - 15] and fuzzy logic [16] to find similarities between cases in the retrieval phase. As a result, those techniques were implemented on this research's data and proved that tree interpreter is best used for feature weights in the similarity equation and the adaptation task.

As shown in Fig. 7 and Fig. 8, this tree interpreter in this study (TI) reached accuracy of 88% while the accuracy of fuzzy logic (Fl) and correlation (Cr) are 71% and 68%, respectively. Also, the precision, recall, and f-measure results in Table VII and Table VIII proved that tree interpreter outperforms fuzzy logic and correlation assessments.

TABLE VII. COMPARISON OF RETRIEVAL STUDY RESULTS

Importance Criteria	**Retrieval Accuracy**	**Precision**	**Recall**	***f*-Measure**
Tree Interpreter	82%	0.76611	0.34986	0.480356
Correlation	68%	0.5124	0.367341	0.427911
Fuzzy Logic	72%	0.691529	0.30156	0.419977

TABLE VIII. COMPARISON OF ADAPTATION STUDY RESULTS

Importance Criteria	**Adaptation Accuracy**	**Precision**	**Recall**	***f*-Measure**
Tree Interpreter	88%	0.7624	0.38519	0.511801
Correlation	77%	0.5841	0.38911	0.467071
Fuzzy Logic	78%	0.7518	0.3671	0.493316

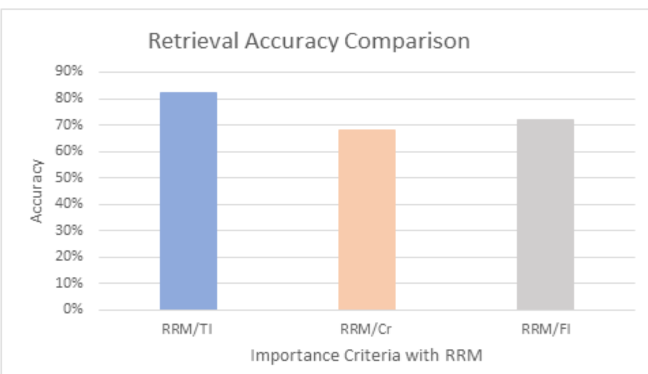

Fig. 7. Comparison of Retrieval Phase Study Accuracy Results.

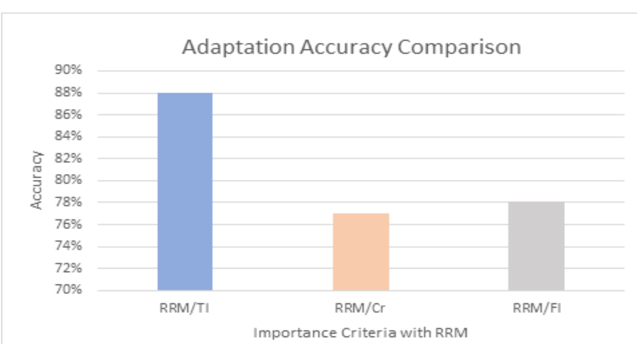

Fig. 8. Comparison of Adaptation Phase Study Accuracy Results.

TABLE IX. DEPRESSION DETECTION FOR TWITTER USERS USING ARTIFICIAL INTELLIGENCE TECHNIQUES

Reference	**Accuracy (%)**				
	SVM	**Random Forest**	**KNN**	**multimodal analysis**	**CBR**
Bohang Chen et al. [42]	74.18	-	-		
Gonzalo A Ruz et al. [43]	81.2	72.5	-		
Priyanka Arora et al. [44]	79.7	84.6	-		
Akshi Kumara et al. [45]	-	81.04	-		
Shakeel Ahmed et al. [46]	-	-	72.0		
Safa, R., et al [47]	-	-	-	83%	
Proposed hybrid RF and CBR system	-	-	-	-	82

The proposed hybrid random forest and Case-based reasoning model showed comparable retrieval accuracy compared to other studies [40 - 47] aimed to depression detection using artificial intelligence and machine learning techniques as shown in Table IX.

VII. CONCLUSION

This research concludes the best techniques and results for introducing a more accurate retrieved criteria and remedy recommender for depressed user of Twitter. The hybrid system of RF and CBR is a good technique for memory processing, but there were challenges found by previous studies in various fields that CBR system is built as a system for the retrieval of data only. The adaptation task in CBR system is left out, therefore, human interference is needed to complete system performance. To overthrow this dilemma, an automatic system – Remedy Recommendation using (RRM) was developed. This system detects the level of depression for each user and recommends the best solution. As explained in this study, the proposed system is applied to find the most similar cases and recommend remedies accordingly through applying adaptation phase to find best remedy recommended for each user. The system's successful hits exceeded 85% in its optimal hyper parameters configuration. RRM has proven that remedy recommendation done without the interference of human is possible. The main novelty of this work derives from introducing an adaptation task for depression treatment. RRM can be generalized to any type of illness to recommend the best solution using data from different social media platforms. In future work, this study aims to enrich the dataset with raw data collected from other social media platforms, such as Facebook or Snapchat.

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