Prediction of Obesity Disorder using Rough Set Theory based Prediction Model

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Abstract

Prediction of any disorder in the medical field has attracted the attention of many scientists all over the world to provide better medical service to people. The main challenge in the medical field is to diagnose a disorder rather than a disease. In this paper, a rough set theory based prediction model is designed for identification or diagnosis of obesity disorder. An investigation of the prediction of the obesity disorder using the Data mining technique in the Rough set based Prediction Model (RPM) is reported. The problematic symptoms are gathered from a set of every individual and the related linguistic inputs are converted into an obesity dataset which is in turn given as input to naïve Bayes rough set based prediction model. The three different types of input attributes were taken based on eating habits(FAVC ,FCVC,NCP,CAEC,CH2O,CALC) ,physical conditioning (SCC,FAF,TUE),and characteristics of responders(Gender, Age,Height,Weight,Family_history_with_overweight) and the target attribute is NObeyesdad. The obesity dataset consisted of 2,111samples. The Rough Set based Attribute Selection (RAS) method is used to select relevant attributes from the obesity dataset with 99% accuracy. The results showed that the prediction of obesity disorder obtained by using the aforesaid model was found to yield 98.6% accurate results, sensitivity as 0.95 and specificity as 0.96 and compared favorably with the experimental ones.

Keywords: *Data mining, Prediction model, Rough set, Obesity dataset.*

1. Introduction

Obesity creates lot of health problems like heart related issues. Obesity leads to high cholesterol and blood pressure which leads to heart related issues. It is very important to take into account the obesity disorder for health care purposes. Normally obesity increases ideal body weight. Changes in diagnosis will harm the people having obesity and spoil the reputation of the medical organization. Clinical based prediction models are important for the medical field. There are two types of prediction models are available such as diagnostic and prognostic. Diagnostic prediction models depend on the likelihood of an individual health issue and prognostic prediction models depend on individual experiencing a specific issue at a particular future duration. Generally the clinical prediction models are based on regression models and machine-learning techniques.

2. Related Work

Prediction models are helpful to predict different variety of health related issues as heart and infertility related issues [1]. There are number of prediction models are available for specific outcomes especially for heart disease [2]. But, only limited studies have conducted on the prediction of obesity disorder [3][4], which is the main work of this review. DeGregory et al., 2018 reviewed the application of machine learning in obesity [5]. The study of Dunstan et al., 2020 found a technique to predict obesity issues based on food intake. They found that the list of relevant food intake to predict obesity as baked foods mainly with cheese. They identified the main predictor of obesity as body mass index [6]. Jindal et al., 2018 used the ensemble prediction approaches to predict health attributes and also they recommend solutions based on obesity values [7]. Machine learning based prediction of childhood and adolescent obesity also discussed by Colmenarejo, G 2020 [8]. In this research paper, a rough set theory based prediction model is used to predict obesity disorder.

3. Experimental

For this study, data were taken from the UCI (University of California Irvine) Machine Learning Repository. This obesity dataset includes data for obesity levels in individuals and supported their eating habits and bodily health. This dataset is created via survey. The dataset contains 2,111 sample values with 17 columns. The summary of the dataset is given in Table 1. It should be mentioned that all the samples considered are details of the survey. They were fully valid information. Out of 2,111 sample values of the dataset, one group consisted of 1478 sample values of the dataset using for the learning (training purpose) and another group consisted of 633 sample values of the dataset for testing purposes. A list of attributes used for training and testing is given in Tables 2 and 3. The training dataset showed in Table 2 is used for development of prediction model and testing dataset showed in Table 3 is used for verification of the prediction model.

Table 1. Summary of attributes of entire dataset (for 2,111 samples)

S.No.	Attributes	Mean	Standard deviation	Max. value	Min. value
1.	Gender	2	0.5	2	1
2.	Age	24	6.36	61	14
3.	Height	2	0.09	1.98	1.45
4.	Weight	87	26.19	173	39
5.	Family_history_with_overweight	2	0.39	2	1
6.	FAVC (Frequent consumption of high caloric food)	2	0.32	2	1
7.	FCVC(Frequency of consumption of vegetables)	2	0.53	3	1
8.	NCP (Number of main meals)	3	0.78	4	1
9.	CAEC(Consumption of food between meals)	2	0.47	4	1
10.	SMOKE (Smokes Yes or No)	1	0.14	2	1
11.	CH2O (Consumption of water daily)	2	0.61	3	1
12.	SCC(Calories consumption monitoring)	1	0.21	2	1
13.	FAF(Physical activity frequency)	1	0.85	3	0
14.	TUE(Time using technology devices)	1	0.61	2	0
15.	CALC(Consumption of alcohol)	2	0.52	4	1
16.	MTRANS (Transportation used)	1	0.86	4	1
17.	NObeyesdad	4	1.96	7	1

Table 2. Summary of attributes used for training dataset (for 1,478samples)

Attributes	Mean	Standard deviation	Max. value	Min. value
NCP (Number of main meals)	3	0.74	4	1
CAEC(Consumption of food between meals)	2	0.41	4	1
Age	24	6	55	14
CH2O (Consumption of water daily)	2	0.61	3	1
NObeyesdad	4	1.93	2	1

Table 3. Summary of attributes used for testing dataset (for 633 samples)

Attributes	Mean	Standard deviation	Max. value	Min. value
NCP (Number of main meals)	3	0.86	4	1
CAEC(Consumption of food between meals)	2	0.59	4	1
Age	25	7.07	61	15
CH2O (Consumption of water daily)	2	0.62	3	1
NObeyesdad	3	1.61	7	17

3.1 Rough set based Prediction Model (RPM)

Data science is a process used to discover unknown patterns from data using machine learning approaches. The proposed idea is to predict the obesity disorder based on the relevant attributes of the obesity dataset using a rough set based prediction model (RPM). A naive Bayesian method is one of the important data science classification methods which are used to develop the proposed prediction model. Figure 1 depicts the entire flow work of the proposed framework. The data preprocessing is applied on the obesity dataset to improve the quality of the dataset. Then the relevant attributes are selected using Rough set Attribute Selection (RAS) method from the completed dataset.

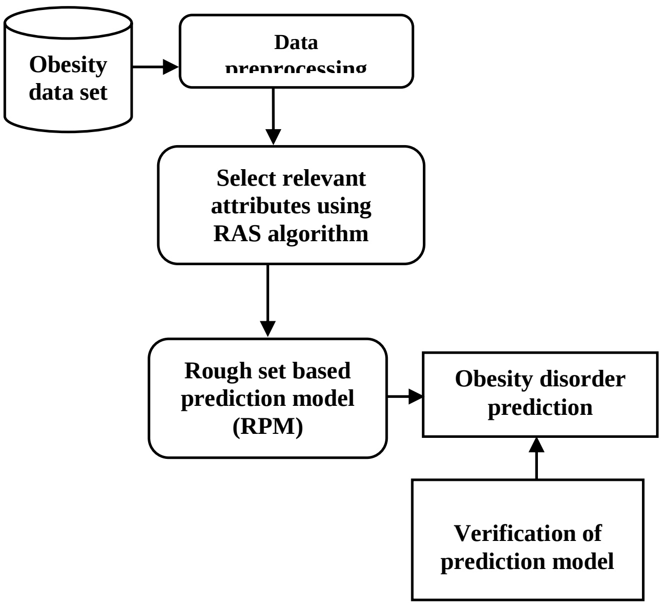

Figure 1. Flow Work of Rough Set based Prediction Model

Based on the selected attributes, Rough set based prediction model is developed with training dataset to predict the obesity disorder of the patient. Finally the RPM model's performance is verified with testing dataset.

3.2 Data preprocessing

Data preprocessing is an important process in data analysis. There are several problems related to the data set. The first problem is the presence of incomplete, missing values and noisy data. To prepare the quality data set, data cleaning is the initial step to identify noisy and missing values and remove or smoothen the noisy data and replace the missing values using standard procedures. Mostly the missing values are filled by the mean of the attribute or most frequent attribute value in case of continuous data and mode in the case of categorical data [9]. The most important problem in the dataset is irrelevant attributes which is determined by applying the attribute subset selection method. Attribute subset selection is employed to identify the set of attributes [10]. In this paper Rough set based Attribute Selection (RAS) method explain to find relevant attributes from the obesity dataset.

3.3 Attribute selection using rough set

The aim of the attribute selection is to find the relevant attribute, remove the irrelevant attribute and build a novel prediction model based on the relevant attributes. Many attribute selection methods are available to reduce the number of attributes from original dataset before data analysis to increase the accuracy of the prediction models. Some of the classical attribute selection methods used is PCA [11], LDA [12] and fuzzy [13] approaches. In this research paper, rough set theory based attribute selection method is developed and compares favorably with the classical attribute selection methods.

3.3.1 Rough set attribute dependency:

Today the world is driven by data. The presence of vagueness, incompleteness, and granularity in the generated data set gives an unreliable solution in the data analysis. Traditional approaches handled most of the problems in a crisp, deterministic and precise manner. But the real-world problems cannot be crisp and precise. Various methods have been developed by experts to address this issue. Fuzzy set [13][14] and rough set theory [15] are the two important models to handle vague, uncertain, imprecise, and imperfect data. The rough set theory doesn't need any initial and extra information about data and it allows evaluating the significance of data.

A rough set is depicted by a pair of lower and upper approximations of the set. Novotny and Pawlak introduced three different types of approximate equalities [16]. The principal concept in rough set theory are approximation space, lower and upper approximations of a set. The approximation space provides a formal classification of knowledge about the data. The representation of the rough set is depicted in Figure 2.The diagram represents the overall data space and approximation space.

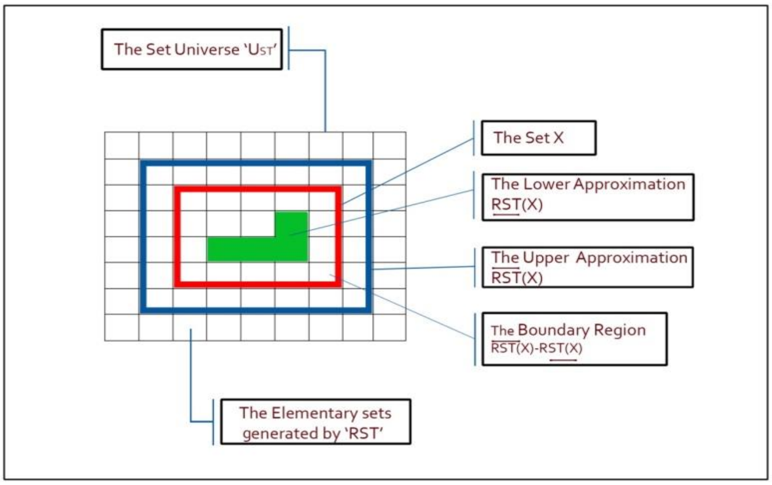

Figure 2. Representation of rough set

Let $'U'$ be the universe and let $RS = U \times U$ be an equivalence relation on $'U'$, called an indiscernibility relation. The pair $AS = (U, RS)$ is called an approximation space. The approximations are very important in the rough set which represents granules of knowledge. Mainly, there are two types of approximations available in the rough set. Lower approximation defines the certainty of the object for the relation surely belonging to the set considered and upper approximation defines the possibility of the objects for the relation that may belong to the set considered. The lower and upper approximation of set $'X'$ with respect to $'RS'$ can be written as [18]:

$$\underline{RS}(X) = \cup \{ x \in U : [x]_{RS} \subseteq X \} \quad (1)$$
$$\overline{RS}(X) = \cup \{ x \in U : [x]_{RS} \cap X \neq \emptyset \} \quad (2)$$

The lower and upper approximation of $X \subseteq U$, partition the universe $'U'$ into three regions such as: ([19], [20])

- Positive region in which objects certainly belonging to a member of a set.
- Negative region in which objects certainly belonging to a non-member of a set.
- Boundary region which defines the entire set of objects possibility with or without the relation which can be classified neither as member of set nor as a non-member of set considered.

The positive, negative and boundary region of set $'X'$ with respect to $'RST'$ can be written as [21]:

$$POS(X) = \underline{RS}(X) \quad (3)$$
$$NEG(X) = U - \overline{RS}(X) \quad (4)$$
$$BND(X) = \overline{RS}(X) - \underline{RS}(X) \quad (5)$$

3.3.2 Rough set based relevant attributes:

The relevant attributes are determined using the concept of reducts and core in rough set theory. Let the decision table $DT = (U, S, A, B)$is independent if all $'a'$ in $'A'$ are indispensable [22]. A set of attributes $R \subseteq A$ is called the reduct of $'A'$ which satisfies $POS_{R}(B) = POS_{A}(B)$. Furthermore, there is no $T \subseteq R$ such that $POS_{T}(B) = POS_{A}(B)$. There could be several set approximation subsets of condition attributes which exists in minimal are termed as reducts. There may be several subsets of attributes available in $'DT'$ similar to $'R'$. Core is the intersection of all the reducts to a set or a system considered as follows,

$$CORE\ (A) = \cap\ RED\ (A) \tag{6}$$

where $CORE(A)$ defines all the indispensable condition attributes and $RED(A)$ defines all the set of reducts of attribute $'A'$ [15].

3.3.3 Significance of Attributes:

The concept of relevant attributes selection can be given as identification of relevant attributes and removal of irrelevant from the data set by maintaining the integrity of the original data set. The identification of relevant and irrelevant attributes is generalized by the significance of attributes. Initially, all the attributes of the data set need to be evaluated based on the dispensable and indispensable concept of attributes to discover the significance of attribute. The significance values of attributes can be given by a very closed interval [0,1]. The process of obtaining relevant attributes in a decision table is processed by eliminating the irrelevant attributes from the attribute set. For a set considered as $'\gamma(A, B)'$, let the attribute be $'a'$ in a set. And when the attribute $'a'$ is removed from the set $'\gamma(A, B)'$then it can be given as,

$$\gamma((A - \{a\}), B) \tag{7}$$

From the above conditions and processes the significance of attributes can be given as by normalizing the basic difference between the coefficients of the set and the set obtained after removing the attribute $'a'$ i.e., $'\gamma(A, B)'$and $'\gamma\big((A - \{a\}), B\big)'$is given below:

$$\sigma_{(A,B)}(a) = \gamma(A, B) \Leftrightarrow (\ \gamma(A - \{a\}, B)/\gamma(A, B)\ ) = 1 \tag{8}$$

$$\sigma_{(A,B)}(a) = (\ \gamma(A - \{a\}, B)/\gamma(A, B)\ ) \tag{9}$$

Thus, the coefficient $'\sigma(a)'$is termed as error of classification. This error of classification in general occurs when the attribute is removed from the set considered. And so the significance of the attributes can be protracted by the other remaining attributes $'R'$ of a set and can be given as,

$$\sigma_{(A,B)}(R) = \gamma(A, B) \Leftrightarrow (\ \gamma(A \Leftrightarrow R, B)/\gamma(A, B)) = 1 \tag{10}$$

$$\sigma_{(A,B)}(R) = (\ \gamma(A \Leftrightarrow R, B)/\gamma(A, B)) \tag{11}$$

Here, $'\sigma(R)'$is given as the coefficient obtained from the extension of attribute significance. Also $'R'$ is considered as subset of $'A'$ i.e., $'R'$ is reduct of the set of attributes in$'A'$. The attribute of any subsets $'R'$ and $'A'$ is deliberated as the reduct of $'A'$ and so after removing the attribute this can be given as,

$$\sigma_{(A,B)}(R) = \gamma(A,B) \Leftrightarrow (\gamma(R,B)/\gamma(A,B)) = 1 \quad (12)$$
$$\sigma_{(A,B)}(R) = (\gamma(R,B)/\gamma(A,B)) \quad (13)$$

Thus, $'\sigma_{(A,B)}'$ with respect to $'R'$ is defined as the reduct approximation or error of reduct approximation which depicts the significance of attributes of $'R'$ relatively in the set $'A'$. The minimum error of approximation results in the increase of accuracy in a set through a classification approach. The equations from (1) to (19) are used to identify the relevant attributes and to compute the attribute significance approximation values.

3.4 Naïve Bayes Classifier

A naive Bayesian classifier is a probabilistic classifier based on Bayes' theorem with the "naive" assumption of independence between each pair of attributes. The rough set based prediction model (RPM) algorithm is developed based on naïve Bayes classifier given below.

3.4.1 Proposed RPM Algorithm:

Input *: Obesity Dataset, n: number of attributes*
Output *: RPM Model*

Step 1: *Missing value analysis*
Step2: *Identify the relevant attributes from the obesity dataset*
  2.1 *Compute significance values of every attribute*
  2.2*Compare the significance values of every attribute,*
  2.3 *If attributes are highly related then eliminate the less significance value attribute(s).*
Step 3: *For each k = m+1 to n Do*
  3.1 *Compute a value for all class labels using naïve bayes classifier,*
  3.2 *Compare the class labels value and predict the obesity disorder.*
  next k

In this work, a novel RPM algorithm is reported. RPM algorithm has two set of works: the first work is used to select relevant attributes using rough set based attribute selection (RAS) method and the second work is used to develop RPM prediction model. The obesity dataset may have missing values and these values are replaced by using missing value analysis. This process helps to increase the classification ability of the prediction model. Then the completed dataset is given as input to the RAS algorithm to find the relevant attribute(s) and the output of the RAS algorithm is supplied to the RPM algorithm to predict obesity disorder. The RPM performance is compared with various prediction models.

4. Results and Discussion

The obesity dataset consists of totally 17 attributes and its detailed summary is shown in Table 1. Out of 17 attributes, first 16are conditional attributes and NObeyesdad is a decision attribute. The data pre-processing procedures such as missing value analysis is applied to the obesity dataset.The RPM algorithm is developed using Matlab codes for finding the relevant attribute(s) and predicting a model to predict the obesity disorder of a person. The first work of the proposed algorithm is to find relevant attributes among the various conditional attributes using rough set techniques. Through the computational program, the attribute significant values of all the attributes are found. Then those attributes are classified based on their attribute significance value.

From the Table 4, It should be observed clearly that the conditional attributes such as MTRANS, FAF, gender, height, FAVC, SCC, and FCVC are not taken during relevant attribute selection process because of their less importance and also viewed that Weight, Family_history_with_overweight and SMOKE have less attribute significant score. So these set of irrelevant attributes are removed from the input dataset based on core and reduct concept of rough set theory. The relevant attributes obtained from RAS algorithm through computation are NCP, CAEC, Age, CH2O, and TUE. The position of each attribute is shown in Figure 2 based on their attribute significance value. Then the selected relevant attributes are supplied to the RPM prediction model to predict the value of obesity disorder.

Table 4. Significance approximation values of attributes

S.No.	Name of The attributes	Attribute significance approximation values
1	Gender	0.172
2	Age	0.789
3	Height	0.172
4	Weight	0.225
5	Family_history_with_overweight	0.226
6	FAVC (Frequent consumption of high caloric food)	0.174
7	FCVC(Frequency of consumption of vegetables)	0.184
8	NCP (Number of main meals)	0.973
9	CAEC(Consumption of food between meals)	0.852
10	SMOKE (Smokes Yes or No)	0.321
11	CH2O (Consumption of water daily)	0.775
12	SCC(Calories consumption monitoring)	0.183
13	FAF(Physical activity frequency)	0.132
14	TUE(Time using technology devices)	0.763
15	CALC(Consumption of alcohol)	0.163
16	MTRANS (Transportation used)	0.124

The researchers select acquainted attribute selection methods in different applications like Principal Component Analysis (PCA) [14], Linear Discriminant Analysis (LDA) [15], and Fuzzy based analysis [16]. The performance of the proposed RAS method is compared with the above-said methods. From Figure 3, it clearly shows that the proposed method is performed better than other attribute selection methods.

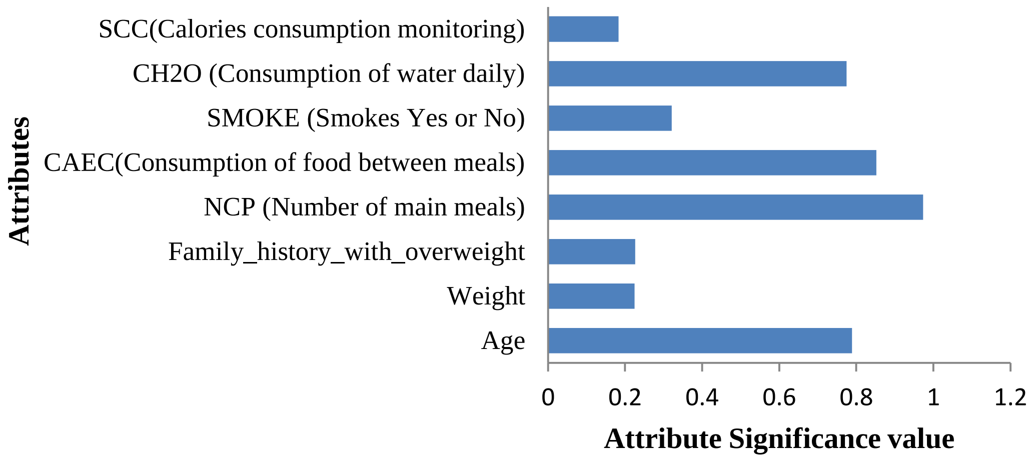

Figure 3. Attributes Vs Attribute Significance Values

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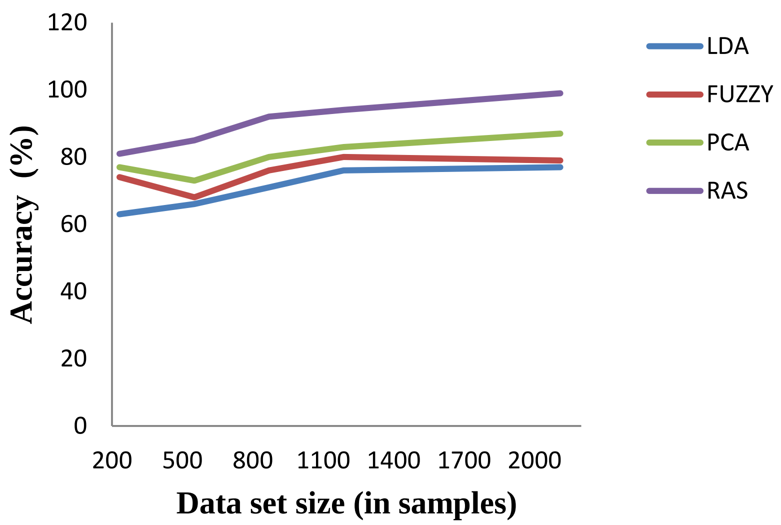

Figure 4. Performance of Various Attribute Selection Methods

The prediction model was developed as the second work of the RPM algorithm with selected relevant attributes. The performance of RPM algorithm is compared with ANN (Artificial Neural Network) Model [19] and ANN with PSO [20] (Artificial Neural Network with Particle Swarm Optimization). The cross k-validation method is used to split the obesity dataset into training and testing datasets to overcome the unbalanced dataset problem. All the above three prediction models are developed with 1,478 training samples and tested with 633 testing samples.

4.1 Performance Analysis

The proposed prediction model is analyzed using three metrics, namely classification accuracy, sensitivity, and specificity.

4.1.1 Classification accuracy:

The accuracy of the classifier is the percentage of total correct predictions made divided by the total number of predictions made.

$$Classification\ accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{14}$$

Where TP, FP, TN, and FN are True Positive, False Positive, True Negative, and False Negative respectively.

4.1.2 Sensitivity:

Sensitivity or True Positive Rate is the metric that evaluates a model's ability to predict actual positives.

$$True\ Positive\ Rate\ (TPR) = \frac{TP}{TP + FN} \tag{15}$$

4.1.3 Specificity:

Specificity or True Negative Rate is the ratio between how much were correctly classified as negative to how much was actually negative.

$$True\ Negative\ Rate\ (TNR) = \frac{TN}{TN + FP} \tag{16}$$

Table 5. Comparison of RPM with other prediction models

Performance metrics	ANN	ANN with PSO	RPM
Classification accuracy (%)	97.5	98.2	98.7
Sensitivity	0.65	0.84	0.95
Specificity	0.63	0.86	0.96

Table 5 contains classification accuracy (%), sensitivity, and specificity of all the three prediction models. Thus, our proposed prediction model performance is evaluated and it is apparent that our proposed RPM compares favorably with experimental values which show its accuracy and reliability.

Figures 4(a),4(b) and 4(c) show the comparison of the performance of ANN, ANN with PSO, and RPM prediction models based on classification accuracy (%), sensitivity, and specificity respectively. The classification accuracy (%) is changed based on the prediction models. In the case of the ANN model, the classification accuracy (%) value is lower than the ANN model is optimized with PSO, where it is higher for our proposed RPM compared with the other two prediction models. The proposed RPM performance is also verified based on sensitivity and specificity. The proposed RPM has the highest sensitivity value and specificity value over the other two prediction models namely ANN and ANN with PSO. The comparison shows that the proposed RPM model outperforms both ANN and ANN with PSO prediction models.

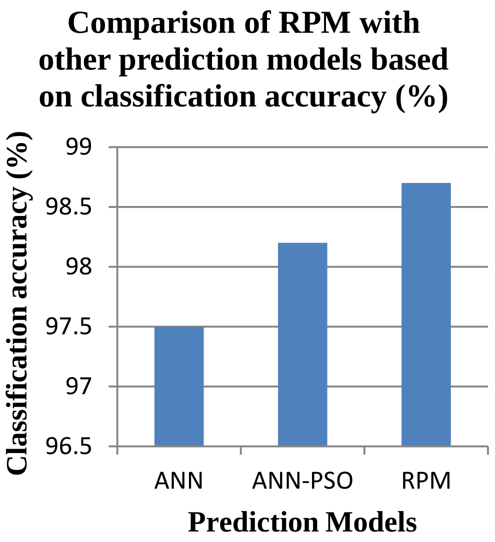

Figure 4(a)

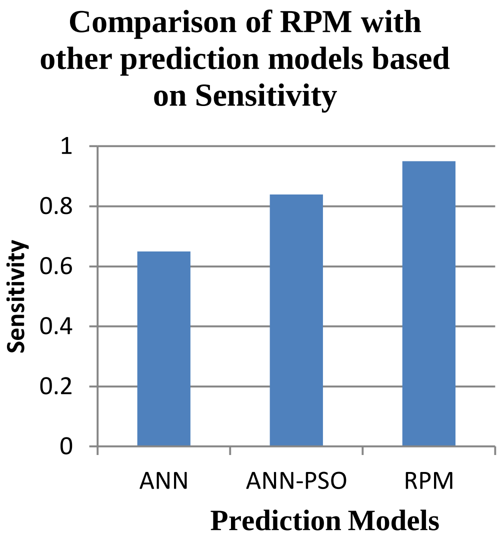

Figure 4(b)

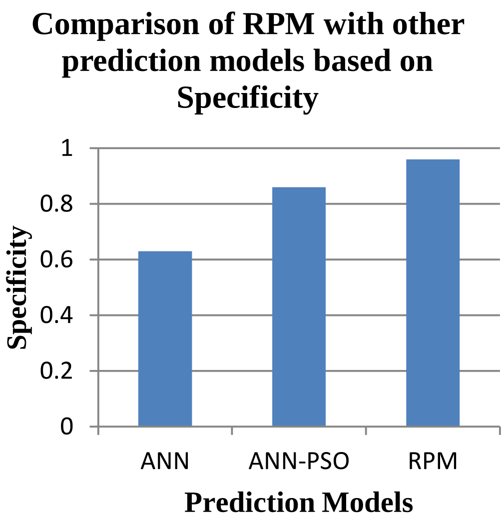

Figure 4(c)

Figure 4. Comparison of RPM with other prediction models based on (a) Classification accuracy(%), (b) Sensitivity, (c) Specificity

5. CONCLUSION

Obesity disorder is a major problem in our day-to-day life. The disease is easily identified by its symptoms but identification of disorder is not that much easy. During the various stages of diagnosing, a lot of problems are encountered. The most important problem is predicting obesity disorder during the diagnosing process. The medical field needs the model to predict the obesity disorder accurately to overcome unwanted medical issues and provide a smart environment in medical diagnosis. In this research work, one of the soft computing techniques namely the rough set approach was used for an attribute selection and developed rough set based relevant attribute selection (RAS)method to find relevant attributes from the obesity dataset, and its performance is found to be better than those of other existing attribute selection methods. Based on the selected relevant attributes, the rough set based prediction model (RPM) is developed with the help of the naïve Bayes algorithm. This proposed model with the inputs is used to predict obesity disorder in the medical diagnosing process in the medical domain. Attempts can be made to optimize the developed model further. The results show that the relationship between the predicted and the experimental value is good. The proposed algorithm is verified with obesity dataset and, doubtless, will be of use to all people in society. In real life, there are lot of obesity disorder patients available. The size of dataset would be grown larger. So there is a need of scalable algorithms to handle extensive data set. Our future work will be extended to propose a new scalable algorithm for handling extensive obesity dataset effectively using Hadoop Framework or Spark.

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