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Presenting a Real Time Method for Automatic Detection of Diabetes Based on Fuzzy Reward-Penalty System

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Abstract

Nowadays diabetes disease is one of the main problems of health domain and it's known as the fourth factor of death in the world. The main problem with this dangerous disease is the late or weak diagnosis. The reason of weak diagnosis is because sometimes doctors aren't able to select the right patterns or they can't use the standard patterns very well, so the outcome is that the disease will be diagnosed by the patients when it has become late for controlling or curing it. Therefore, implementing a method which can help each person to have an authentic diagnosis of being or not being affected to this disease; can be an important step for prevention and controlling this special disease at the beginning of it. In this paper, a new method is presented for diagnosing diabetes disease which is able to extract the proper knowledge by helping to cluster and analyze the training patterns, after that in recognition phase it can diagnose diabetes disease precisely and fast via a fuzzy reward-penalty mechanism. For evaluating the proposed method, PIMA dataset has been used. The experimental results show that the proposed method has a better performance compared to other existing methods.

Keywords: *Diabetes Diagnosis, Machine Learning, Clustering, Classification*

1. Introduction

Diabetes disease is one of the most widespread diseases known in the world. Although this disease is spreading more & more, there's still no way to eliminate it. Also, there are different methods which are being used for controlling and identifying this disease. Some of the symptoms that show up after someone gets this disease are coronary heart disease, and in an advance mode, blindness, kidney disease, nerve damage, mental disorders and amputations. Diabetes disease is divided into two kinds: insulin dependent diabetes mellitus, which in this kind the ill person's pancreas isn't able to sprinkle insulin, and non-insulin dependent diabetes mellitus which in this kind the ill person's pancreas is able to sprinkle insulin but the absorption amount of it is very low in the body. The main problem of diabetes disease is late or weak diagnosis. The reason of weak diagnosing is because sometimes doctors aren't able to choose the right patterns or they can't use the standard patterns very well. Therefore, implementing a method which can help each person to have an authentic diagnosis of being or not being affected to this disease can be an important step to prevent and control this special disease at the beginning of it. Researches show that more than 80% of the effects of the

second kind of diabetes can be delayed by early identification and recognition. In the field of diagnosis and preventing from diabetes disease, lots of methods have been presented that rely on machine learning techniques, which we will discuss them[1].

Artificial Neural Networks (ANN) are among the tools which have shown their performance in many fields such as pattern recognition and data mining[2]. Mr. Smith et al used an ADAP neural network model for diabetes diagnosis[3]. They can obtain an accuracy rate of 76% on PIMA dataset. K. Kayaerand T.Yildirim applied General Regression Neural Networks (GRNN) for diabetes diagnosis. The best result which was achieved was reported about 80.21% on PIMA dataset[4]. Mr.Temurtas et al used a Multi-Layer Neural Network(MLNN), which was trained by Levenberg-Marquardet (LM) algorithm, and a Probabilistic Neural Network(PNN) structure for this purpose[5]. They achieved to an accuracy rate of 79% on PIMA dataset. In 2010, a Complex-Valued Neural Networks (CVNN) and Real-Valued Neural Network (RVNN) was suggested for forecasting diabetes by A.Aibinu and et al[6]. A.A. Abusnaina and R. Abdullah used an Artificial Neural Network(ANN) which the network training was done by Mussels Wandering Optimizations(MWO)algorithm[7]. They obtained an accuracy rate of 75.1% on PIMA dataset. The very low training time is countered as the boldest feature of the mentioned method.

Support Vector Machine (SVM), is another useful tool for data classification operations which has recently become so popular [8]. Up to now, several SVM-based automatic diabetes diagnosis systems have been presented. R.Stoean et al have used a special SVM which its bind function parameters are optimized by the evolutionary algorithms[9]. Their suggested system was able to classify 78.43% of PIMA dataset. K. Polat et al applied Generalized Discernment Analysis (GDA) technique in preprocessing and Least Square SVM(LSSVM) in the classification phase in order to diagnose diabetes [10]. They achieved to an accuracy rate of 79.16%. In 2014, a Fuzzy SVM (FSVM) was presented by X. Gu, et al.[11].

Fuzzy logic has been used successfully in many scientific and engineering problems[12]. Fuzzy systems are indeed knowledge based or rules-based systems. The heart of a fuzzy system is its knowledge base that consists of fuzzy if-then rules. In 2008, A. Sharifi et al used a Takagi-Sugene fuzzy system which named it as ANFIS-GMDH to diagnose diabetes disease[13]. Their proposed method's accuracy was about 75.52%. In 2008, a new procedure was presented for the automated creation of fuzzy models based on decision trees. The presented procedure involves three stages: a preliminary crisp model based on a decision tree, turning model into fuzzy and optimizing income parameters[14]. M. Fathi Ganj and M. Saniee Abadeh were able to extract an optimum fuzzy if-then set of rules using the techniques of Ants Colony Optimization (ACO) to diagnose diabetes disease[15]. They achieved to an accuracy rate of 79.48%. In 2010, an evolving fuzzy rule-based classifier was presented for this purpose[16]. This method had an accuracy rate of 79.37%.

In 2010, M. Waqar Aslam and A. Kumar Nandi presented a classifier for diagnosing diabetes based on Genetic Programming[17]. The proposed system was able to achieve to an accuracy of 78.5%. An ensemble method based on human emotional processing system was presented to diagnose diabetes disease [18]. In another effort a new procedure based on class-wise K-NN was used for grouping diabetes data of input test pattern [19]. This system had an accuracy rate of 78.16%. In 2014, M.R Bozkurt et al applied six different neural networks (including PNN, LVQ, Feed Forward Networks, Cascade-Forward Networks, Distributed Time Delay Networks and Time Delay

Networks), Artificial Immune System and Gini algorithm from Decision Trees[20]. In the best case, they achieved an accuracy rate of 76% via Distributed Time Delay Network (DTDN).

As it was observed, until now, several methods have been presented to diagnose diabetes. Among essential problems of the mentioned methods are some very high time complexities of training and testing phases which leads us not to be able to use in real-time applications. In this paper, a new real-time methodology is suggested for diagnosing diabetes disease which is able to extract the existing hidden knowledge in the training patterns by synergic clustering and analyzing methods, after that in testing phase, it can diagnose diabetes precisely and fast via the structure of fuzzy reward-penalty vectors by the help of the extracted knowledge.

This paper is organized as follows. The proposed method is presented in Section 2. Experimental results are expressed in section 3. Finally the paper ends with the conclusion.

2. The Proposed Method

In this section a new method will be presented for diabetes disease diagnosis which is able to recognize this disease with a proper accuracy and speed. The proposed method contains two phases: knowledge extraction and testing, which each one will be described completely.

2.1 Knowledge Extraction Phase

The purpose of this phase is to extract the existing hidden knowledge from the training patterns which are used in this test's phase. Therefore in this section we will try to extract the required information by clustering and analyzing features of training patterns. The block diagram of the suggested knowledge extraction phase has been shown in Figure (1). Details of how the proposed method is fully described in the following.

Step 1. Because in many applications, range of the features' variations may be so different, therefore normalization will be necessary. As a result, the normalization operation is performed in range [0-1] by Eq. (1) [15]:

$$Normalize(X) = \frac{(X - X_{min})}{(X_{max} - X_{min})} \quad (1)$$

Step 2. Because of the different values of the pattern features, feature weighting can be caused improved classification rate. Therefore, feature weighting based on Laplacian criteria is done.

Step 3. In order to find gravity centers of training patterns, clustering based on Kmeans algorithm is performed. The obtained gravity centers are stored in a code book form. Also, repetitive and non-repetitive cluster centers which belong to normal and diabetic classes are determined.

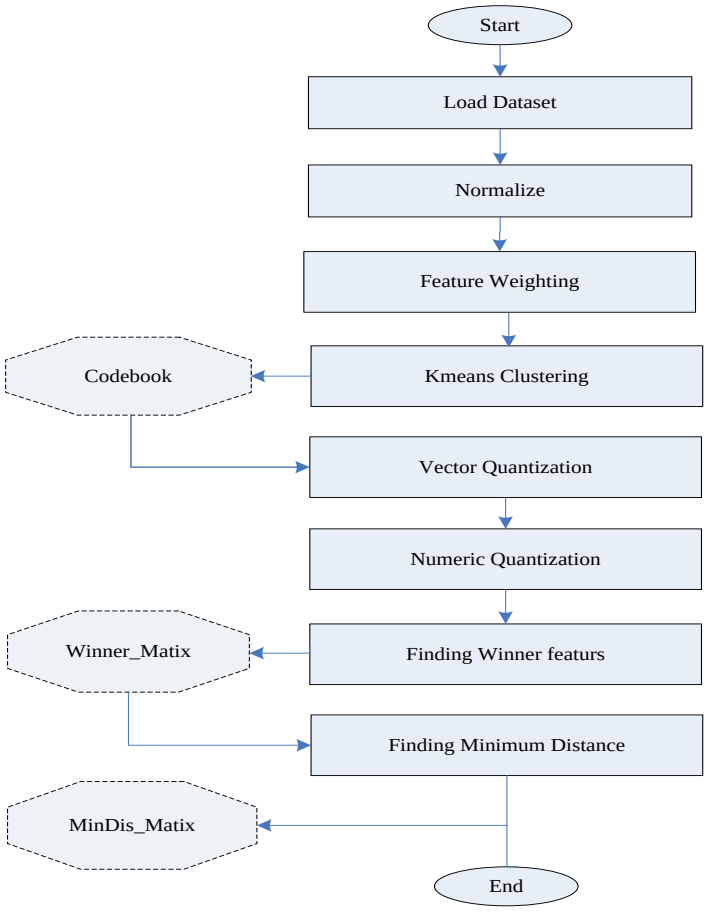

Figure (1): Block diagram of the proposed knowledge extraction method

Step 4. Vector Quantization (VQ) of training patterns by using the stored code book in step 3 via Eq.(2) and then producing new training patterns

$$D_{Pattern\_Codebook} = \sum_{i=1}^{N-1} \left[(Codebook(i,k) - Pattern(i)) \right]^2 , \quad 1 \le k \le K \tag{2}$$

where N indicates pattern length and K represents the number of clusters.

It should be mentioned that the purpose of applying VQ technique is lossy data compression.

Step 5. In order to generate training sequences, the new training patterns are quantized in range [0-255] with hop count 1.

Step 6. In order to find the winner features matrix, first, both the normal and diabetic's training sequences would be separated. Then, a winner matrix for each group would be formed where its *j-th* column equals to L observations which has had the most repeats in the sequences related to *j-th* feature. Its pseudo code is shown in Figure (2):

```
the numberof Classes : C = 2 classes(Diabetic and Normal)
the numberof pattern featurs : N = 8 features
the numberof the maximumfrequency: L = 4
for i = 1 to C do
  for n = 1 to N do
    for l = 1 to L do
      Winner_Class(i,l,n) = Maxfreq(Set_Patterns(i,:,n));
    end;
  end;
end;
```

Figure (2): Pseudo code that shows how to generate winner matrixes of each class in the proposed method.

Step 7. For generating least-distance matrixes, corresponding to each set of winner matrix, a least-distance matrix would be created which its elements have the least distance with the winner matrix's elements. The pseudo code is shown in Figure (3).

```
the numberof Classes : C = 2 classes(Diabetic and Normal)
the numberof pattern featurs : N = 8 features
the numberof the maximumfrequency: L = 4
numberof patterns in patterns set of class i : P(i)
for i = 1 to C do
  for n = 1 to N do
    for l = 1 to L do
      for cnt = 1 to P(i) do
        MinDis_Mat(i,n,l) = Min(|Winner_Class(i,l,n) - Set_Pattems(i,cnt,n)|)
      end;
    end;
  end;
end;
```

Figure (3): Pseudo code that shows how to generate each of the least-distance matrixes in the suggested method.

2.2. Testing Phase

In this section, process of classifying the proposed method will be discussed. This method is based on a fuzzy reward-penalty mechanism and uses achieved information in the knowledge extraction phase. Block diagram of the suggested classification method is shown in Figure (4).

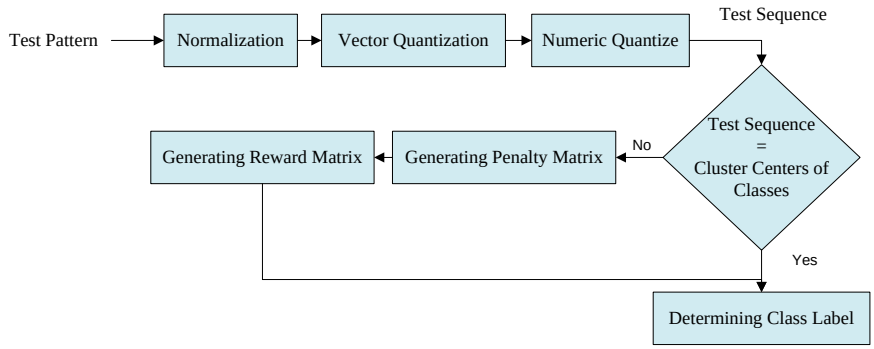

Figure (4): Block diagram of the proposed classification method

Steps of classifying test patterns using the suggested method are as follows:
Step 1. Preprocessing test's input pattern:
Preprocessing operations involve normalization between 0 and 1, vector quantization and finally quantizing a number between the ranges of [0-255].

Stage 2. Studying the preprocessed patte rn with the non-repetitive clusters of classes (diabetic and normal). In this stage, the preprocessed input pattern is being compared to all cluster centers which belong to the two existing classes. If it's equal to each one of the cluster centers, the specified test pattern's label and the classification operation would be ended. Otherwise, the classification process would be followed.

Step 3. Creating penalty matrix:
For this purpose, first, the preprocessed input pattern is subtracted from both diabetic and normal winner matrixes and the distance-difference matrixes are formed as an outcome. Then distance-difference matrixes would be compared to least-distance matrixes, and penalty matrixes that belong to each class would be created. Because selecting a feature has an important influence on classification's outcome, therefore the penalty matrix multiplies into features weight vector of training process to obtain a more realistic penalty vector.

Step 4. Creating reward matrix:
In order to calculate the value of input test pattern's matching with both diabetic and normal, uses a fuzzy triangular membership function. This membership function is designed somehow that the 0's penalty has the most and the 1's penalty has the least compatibility.

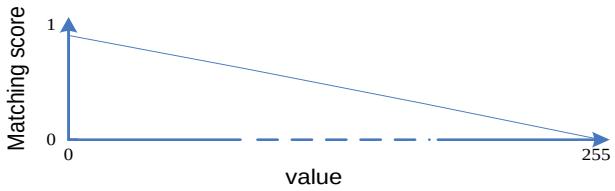

Figure (3) -The being used triangular membership function in the proposed method to determine the quantity of compatibility.

Step 5. Determining input test pattern's class label:

To calculate the input test pattern's class label, the average and the standard deviation of reward matrixes that belong to both diabetic and healthy would be calculated. The ones that have the highest value would be determined as the recognized ones.

3. Experimental Results

In this section, the obtained results of applying the proposed method on PIMA data set are presented. To do the simulations MATLAB software is used. Before presenting the results, at first PIMA diabetes dataset and performance evaluation criteria will be introduced.

3.1. PIMA Data Set

The PIMA data set is one of the standard datasets of training machine and intelligent UCI systems which consists of 768 ill women with at least 21 years old. 500 of this number are suffering from diabetes and 268 of them are healthy[21]. To identify diabetes, 8 characteristics are used which contain: frequent childbirth, plasma glucose concentration, blood pressure, thickness of triceps, serum insulin, BMI, history of diabetes and age. Statistics of the datasets are shown in Table (1).

Table 1: PIMA dataset statistics

Features	Mean	Standard Deviation	Min/Max
Number of times pregnant	3.8	3.4	0/17
Plasma glucose concentration a 2h in an oral glucose tolerance test	120.9	32	0/199
Diastolic blood pressure (mm Hg)	69.1	19.4	0/122
Triceps skin fold thickness (mm)	20.4	16	0/99
2-hour serum insulin (mu U/ml)	79.8	115.2	0/846
Body mass index (kg/m^2)	32	7.9	0/67.1
Diabetes pedigree function	0.5	0.3	0.078/2.42
Age(years)	33.2	11.8	21/81

3.2. Performance evaluation criteria

In order to assess the performance of the proposed method, at first introducing a matrix named the confusion matrix, is needed:

		Actual Class	
		Diabetes	**Normal**
Predicted Class	**Diabetes**	True Positive(TP)	False Positive(FP)
	Normal	False Negative(FN)	True Negative(TN)

True Positive (TP): This parameter indicates the number of individuals which should have been recognized as diabetics and the system truly recognized them.

False Positive (FP): This parameter indicates the number of individuals which should have been recognized as healthy but the system mistakenly recognized them as diabetics.
***False Negative (FN)*:** This parameter indicates the number of individuals which should have been recognized as diabetics and the system falsely recognized them as healthy.
True Negative (TN): This parameter indicates the number of individuals which should have been recognized as healthy and the system truly recognized them.

In the following *Sensitivity, Specificity, False Positive Rate (FPR) and False Negative Rate (FNR) as well as Accuracy* measures can be introduced [20]:

$$Sensitivity = \frac{TP}{TP + FN}(\%) \quad (3)$$

$$Specificity = \frac{TN}{TN + FP}(\%) \quad (4)$$

$$FPR = \frac{FP}{FP + TN}(\%) \quad (5)$$

$$FNR = \frac{FN}{FN + TP}(\%) \quad (6)$$

$$Accuracy = \frac{TN + TP}{TP + FP + TN + FN}(\%) \quad (7)$$

It's necessary to say that the suggested method applied the 2-Fold, 4-Fold and 10-Fold cross validations. K-Fold cross validation means that all data is partitioned into *K* segments and then K-1 segments will be held for training and one segment will be held for testing. This operation has been repeated *K* times and each time one of the *K* sets has been held as the test set. The results of comprehensive evaluation of the proposed method on PIMA dataset are shown in Table 2 for each of 2-Fold, 4-Fold and 10-Fold cases.

Table 2: The results of the performance evaluation of the proposed method on a PIMA dataset

Evaluation Measures	2-Fold	4-Fold	10-Fold
Sensitivity	71.26	71.64	74.32
Specificity	83.76	85.24	85.45
FPR	16.23	14.75	14.54
FNR	28.73	28.35	25.67
Accuracy	79.54	80.50	81.51

As it can be seen in Table 2, the best classification accuracy is obtained in 10-Fold case because the system becomes trained with more data (90% of data) at this condition.

The results of the evaluation of the proposed method in terms of classification accuracy in 10-Fold case are shown in Table 3 with the other existing methods.

Table 3: Evaluation of the proposed method compared to previous methods in 10-Fold case

Method	Accuracy	Study
Bayes Net	74.34	WEKA software
Naïve Bays	76.30	WEKA software
LibSVM	76.95	WEKA software
Multilayer Perceptron (MLP)	75.39	WEKA software
RBF Network	75.39	WEKA software
Logistic	77.21	WEKA software
Decision Table	71.21	WEKA software
J.48	83.82	WEKA software
LMT	77.47	WEKA software
Bagging	77.47	WEKA software
AdaBoost	77.21	WEKA software
Random Forest	73.56	WEKA software
RepTree	75.13	WEKA software
PART	75.26	WEKA software
NNge	73.56	WEKA software
ESOM	78.40	D. Deng et al, 2001[22]
GRNN	80.21	K. Kayaer et al, 2003[23]
Attribute Weighted AIS	75.87	S. Sahan et al, 2005[24]
Evolutionary SVM	78.43	R.Stoean et al, 2006[9]
Fuzzy integral-based Perceptron	74.81	Y.C. Hu, 2007[25]
LS-SVM	78.21	K. Polat et al 2008[10]
GDA-LS-SVM	79.16	K. Polat et al, 2008[10]
Fuzzy modeling	77.56	N.Sean et al , 2008[14]
Adaptive Neurofuzzy System	75.52	A. Sharifi et all, 2008[13]
MLNN with LM	79.62	H. Temurtaset al, 2009[5]
Data Gravitation	76.56	L. Peng et al, 2009[26]
Genetic Programming	78.50	M. W Aslam and A. K Nandi, 2010[27]
Fuzzy-ACO	79.48	M. F Ganji and M.S. Abadeh, 2010[15]
eClass	79.37	S. Lekkas, L. Mikhailov,2010[16]
ANN based MWO	75.10	A. A. Abusnain and R.Abdullah, 2013[7]
CKNN	78.16	Y. A Christobel, P.Sivaprakasam,2013[19]
Fuzzy SVM	-	Xiaoqing Gu et al,2014[11]
Distributer Time Delay Network	76.00	M.R Bozkurt et al,2014[20]
Fuzzy Penalty-Reward	81.51	The Proposed Method

As it can be seen in Table (3), the performance of the proposed method is much better than the other method. The reason behind this can be considered as synergic clustering and analyzing techniques which is able to model training patterns of the normal and diabetic classes only by two small feature winner matrices and least-distance.

Table (4) shows the results of time evaluation of the proposed method in two phases: knowledge extraction and testing on PIMA dataset.

Table 4: Results of the proposed method's time evaluation in PIMA dataset

Phase	Time(ms)		
	2-Fold	4-Fold	10-Fold
Knowledge Extraction	200	370	490
Test	870	400	160

As shown in Tables (3) and (4), the proposed method not only has a very good classification accuracy compared to other existing methods, but also, has a low time

complexity. The result is that the proposed method is very suitable for real-time applications.

4. Conclusion

In this paper, a new method has been presented to diagnose diabetes disease based on a fuzzy reward-penalty system. The proposed method in the first phase has gained a proper knowledge with clustering pattern and analyzing their characteristics which would be used in diagnostic process. Recognizing process, is a two-stages process which in the first stage, the system tries to determine the test input pattern's class using vector quantization, if wasn't able to determine it, it would determine the class's (normal or diabetic) label by creating a reward-penalty matrix based on a triangular fuzzy membership function. In order to evaluate the proposed method, PIMA diabetes dataset is used. The results of testing shows 10-Fold's validation with 81.5 % of accuracy and knowledge extraction time and recognizing less than 0.5 second which has a better usage compared to other methods. Because the proposed method has a simple nature and a high usage, it's suitable for hardware implementation on programmable FPGA chipsets and can be used in real-time usages.

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