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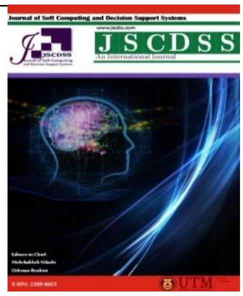

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Early Detection of Diabetic Retinopathy Using Ensemble Learning Approach

Mehrbakhsh Nilashi [a,*], Sarminah Samad [b], Elaheh Yadegaridehkordi [c], Azar Alizadeh [d], Elnaz Akbari [e], Othman Ibrahim [a]

[a] School of Computing, Faculty of Engineering, Universiti Teknologi Malaysia, 81310, UTM, Johor Bahru, Johor, Malaysia
[b] CBA Research Centre, Department of Business Administration, Collage of Business and Administration, Princess Nourah Bint Abdulrahman University, Saudi Arabia
[c] Department of Information Systems, Faculty of Computer Science & Information Technology, University of Malaya, 50603, Kuala Lumpur, Malaysia
[d] School of Engineering, University of California, Merced, USA
[e] Faculty of Electrical & Electronics Engineering, Ton Duc Thang University, Ho Chi Minh City, Viet Nam

*** Corresponding authors email addresses**: nilashidotnet@hotmail.com

Abstract

Diabetes has been one of the leading health problems in all over the world. Diabetic retinopathy is the most common retinal vascular disease. Supervised data mining techniques have been successful in detecting diabetic retinopathy through a set of datasets. However, the most methods developed by supervised methods do not support the ensemble learning of data. The aim of this paper is to take the advantages of ensemble learning and develop a new method for diabetic retinopathy using data mining techniques. We use Non-linear Iterative Partial Least Squares for data dimensionality reduction, Self-Organizing Map for clustering task and ANFIS ensemble to classify unlabeled retinal images with high accuracy. We evaluate our method on a publicly available Messidor dataset and present our results in comparison with the latest results of previous studies. For classification task, features of retinal images used for experimental analysis have been extracted by two algorithms, anatomical part recognition and lesion detection. The experimental analysis showed that the proposed method is robust in classifying the retinal images with Accuracy= 0.915, Sensitivity=0.946 and Specificity=0.917. The results of experimental analysis also demonstrated that our method performance is superior to Neural Network (NN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Decision Trees (DT), K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). The hybrid intelligent system has potential to assist medical practitioners in the healthcare practice for early detection of diabetic retinopathy.

Keywords: Healthcare, Early detection, Diabetic Retinopathy, NIPALS, SOM, Ensemble Learning

1. Introduction

Diabetes has been one of the leading health problems in all over the world. It has attained the dubious distinction of becoming the fifth leading cause of disease-related death (Hamburg et al., 1982). Diabetes is a chronic endocrine disorder affecting the body's metabolism and resulting in structural changes affecting the organs of the vascular system (Court, 1988; Egede, 2004). Generally, diabetes is characterized as existing in two major forms: (a) insulin-dependent (Type I) (Frandsen et al., 2016) and (b) noninsulin-dependent (Type II) (Kramer et al., 2013). The latter appears to be the more common, accounting for 80% of all cases (Hamburg et al., 1982). Diabetes mellitus will manifest The Pima are one of the most studied populations regarding diabetes, not only among American Indians, but in the world (Knowler et al., 1983). The most studied populations regarding diabetes is Pima, not only among American Indians, but in the world (Knowler et al., 1983). The samples of studied populations regarding diabetes refer to discrete Type-2 positive and negative instances.

The only way for the diabetes patient to live with this disease is to keep the blood sugar as normal as possible without serious high or low blood sugars this is achieved when the patient uses a correct management (therapy) which may include diet and exercising, taking oral diabetes medication or using some form of insulin (Hamburg et al., 1982). On the other hand, treating the diabetes disease is also a difficult, an expensive and a complex task for the medical staff (Egede and Miohel, 2001). There are number of important things to record about the patient and disease that help the doctors to make an optimal decision about the patient to make his/her life better.

As a micro vascular complication of diabetes, diabetic retinopathy has been one of the most common retinal vascular diseases (Zhang et al., 2001). Diabetic retinopathy is the leading cause of blindness in the working population in most industrialized countries (Spaide and Fisher, 2006).

Complications of proliferative diabetic retinopathy and macular edema have been the main causes of severe visual loss in diabetes. The pathophysiology of diabetic retinopathy is complex (Ulas et al., 2015).

The natural history of diabetic retinopathy has been classically divided into and a very early nonproliferative stage and a later, proliferative stage, including a spectrum of retinal vascular signs (Wang et al., 2013). Diabetic retinopathy can be diagnosed either through retinal photography or ophthalmoscopy (Abràmoff et al., 2008). In addition, the presence of diabetic retinopathy can be detected by examining the retina for its characteristic features.

Expert systems developed by machine learning techniques have been successful in disease diagnosis systems (Mardani et al., 2018; Nilashi, Ahmadi, Shahmoradi, Mardani, et al., 2017; Nilashi, Ahmadi, Shahmoradi, Salahshour, & Ibrahim, 2017; Nilashi, bin Ibrahim, Ahmadi, & Shahmoradi, **2**017; Nilashi, Ibrahim, Dalvi, Ahmadi, & Shahmoradi, 2017; Nilashi, Ibrahim, et al., 2019; Nilashi, Roudbaraki, & Farahmand, 2017). In this study, a hybrid method is proposed for diabetic retinopathy diagnosis using SOM, NIPALS and ANFIS ensemble.

- SOM is used for the clustering of data in diabetic retinopathy dataset.
- NIPALS (Nilashi, Ibrahim, Ahmadi, Shahmoradi, & Farahmand, 2018) is used for dimensionality reduction and dealing with the multi-collinearity problem in the dataset.
- We use ANFIS (Mardani et al., 2018; Nilashi, Cavallaro, et al., 2018; Yadegaridehkordi et al., 2018)Nilashi et al., 2016; Nilashi et al., 2014) to predict the disease. In addition, ANFIS ensemble (Nilashi, Ahmadi, Shahmoradi, Ibrahim, & Akbari, 2019)is used for retinal images classification task to detect diabetic retinopathy.

We evaluate the proposed method on a diabetic retinopathy dataset. The dataset, Messidor dataset, is taken from Data Mining Repository of the University of California, Irvine (UCI) (Newman et al., 1998). Overall, in comparison with research efforts found in the literature, our work has the following contributions. In this research:

Our study at hand is orgnized as follows: In Section 2 reseach method is presented. Section 3 presents the results of experimenal analysis of SOM and NIPALS. Section 4 presents ANFIS ensemble results and method comparision. Finally, conclusions and future work is provided in the Section 5.

2. Methodology

This paper aims to develop a hybrid intelligence method for diabetic retinopathy diagnosis using a set of real data. We use Non-linear Iterative Partial Least Squares (NIPALS) for data dimensionality reduction, Self-Organizing Map (SOM) (Ahani, Nilashi, Ibrahim, Sanzogni, & Weaven, 2019; Nilashi, Ahani, et al., 2019; Nilashi, Bagherifard, Rahmani, & Rafe, 2017; Nilashi, Ibrahim, Yadegaridehkordi, et al., 2018) for clustering the data and ANFIS ensemble for classifying the retinal images to detect diabetic retinopathy. In the first step of our method, data is clustered using SOM (1). In this step, similar observations of patients are categorized in clusters generated by SOM. Then, we use NIPALS for data dimensionality reduction (2). Using NIPALS, the latent variables of Principal Component Analysis (PCA) are obtained without correlation matrix diagonalization. In the last step, we use ANFIS ensemble for for classifying the retinal images to detect diabetic retinopathy (3).

We test our method on Messidor dataset dataset which is available in the machine learning repository in UCI, University of California, Irvine. The dataset includes 1151 instances which are presented by 19 condition attributes and one decision attribute (see Table 1).

Table 1
Image features of Messidor dataset.

Attribute	Description of attribute
(0)	The binary result of quality assessment. 0: bad quality; 1: sufficient quality.
(1)	The binary result of prescreening, where 1 indicates severe retinal abnormality and 0 its lack.
(2-7)	The results of MA detection. Each feature value stands for the number ofMAs found at the confidence levels alpha = 0.5…1, respectively.
(8-15)	Contain the same information as (2–7) for exudates. However, as exudates are represented by a set of points rather than the number of pixels constructing the lesions, these features are normalized by dividing the number of lesions with the diameter of the ROI to compensate different image sizes.
(16)	The Euclidean distance of the center of the macula and the center of the optic disc to provide important information regarding the patient’s condition.This feature is also normalized with the diameter of the ROI.
(17)	The diameter of the optic disc.
(18)	The binary result of the AM/FM-based classification.
(19)	Class label. 1: containing signs of diabetic retinopathy (accumulative label for the Messidor classes 1, 2, and 3); 0: no signs of diabetic retinopathy .

3. Results and Discussion

The results of experimental analysis of the proposed method for the prediction of diabetic retinopathy are explained in this section. Here, the results of applying all incorporated methods in the proposed system are discussed.

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3.1 Step 1: Clustering Using SOM

As we discussed in the methodology section, SOM technique for clustering is applied on PD dataset. We selected different clustering size for SOM. For SOM, SOM 2×3 (6 clusters), SOM 3×3 (9 clusters), SOM 3×4 (12 clusters) and SOM 4×4 (16 clusters) were considered. In Tables 2-5, the number of instances in PD dataset along with the Map quality are presented in each cluster of SOM 2×3 (6 clusters), SOM 3×3 (9 clusters), SOM 3×4 (12 clusters) and SOM 4×4 (16 clusters). As the Map quality of SOM 4×4 was higher than other SOM Map qualities, we selected 16 clusters for further experimental analysis.

Table 2
MAP Topology for SOM 2×3

Map Quality=0.8104	1	2
1	84	196
2	255	127
3	218	271

Table 3
MAP Topology for SOM 3×3

Map Quality=0.8256	1	2	3
1	49	186	160
2	70	83	120
3	145	164	174

Table 4
MAP Topology for SOM 3×4

Map Quality=0.8566	1	2	3	4
1	44	103	89	99
2	64	61	55	113
3	156	144	112	111

Table 5
MAP Topology for SOM 4×4

Map Quality=0.8894	1	2	3	4
1	101	85	76	69
2	111	51	62	84
3	78	44	55	100
4	93	49	38	55

3.1 Step 2: Dimensionality Reduction Using NIPALS

After a number of different SOM clusters are developed, we applied NIPALS on the clusters for data dimensionality reduction. We performed PCA with fully informative analyses using the NIPALS and accordingly computed PCs until above than 99% of variation was explained (Wold et al., 1987). In Table 6, it can be seen that for Cluster 1, 13 PCs provide the 99.27 % information of original data.

Table 6
NIPALS result of Cluster 1

Axis	Eigenvalue	Proportion (%)	Cumulative (%)
1	6.277032	34.87 %	34.87 %
2	3.660458	20.34 %	55.21 %
3	1.757528	9.76 %	64.97 %
4	1.250673	6.95 %	71.92 %
5	1.087071	6.04 %	77.96 %
6	1.038580	5.77 %	83.73 %
7	0.772195	4.29 %	88.02 %
8	0.688760	3.83 %	91.85 %
9	0.555777	3.09 %	94.93 %
10	0.250882	1.39 %	96.33 %
11	0.227715	1.27 %	97.59 %
12	0.206025	1.14 %	98.74 %
13	0.095784	0.53 %	99.27 %

4. ANFIS Ensemble Evaluation

The prediction models constructed by ANFIS were trained under a 4 GHz processor PC and Microsoft Windows 7 running MATLAB 7.10 (R2010a). For evaluating the ANFIS modles, we initially considered 20% of data in each cluster for test set, 20% of data for checking set and 60% for training set. To evaluate the classification models of ANFIS technique, sensitivity, specificity and classification accuracy. In the following equations, the sensitivity, specificity and classification accuracy are defined.

One of the main objectives of this research is also to make a consistent comparison between the classification accuracy achieved by our method and the classification accuracy achieved by other corresponding results of several supervised techniques. Hence, in this section, comparison experiments with other methods in the literature are performed on the same dataset.

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$$Sensitivity = \frac{\text{number of true positive decisions}}{\text{number of actually positive cases}} \quad (1)$$

$$Specificity = \frac{\text{number of true negative decisions}}{\text{number of actually negative cases}} \quad (2)$$

$$Total\ classification\ accuracy = \frac{\text{number of correct decisions}}{\text{total number of cases}} \quad (3)$$

In this research, totally 16 ANFIS ensemble classification models were developed as 16 clusters have been generated by SOM. In each cluster, different types of MFs were designed and considered for fuzzification task. The types of MFs were considered as: Triangular, Generalized Bell-Shaped, Gaussian and Π-Shaped. In addition, there linguistic variables (Low, Moderate and High) were used as MFs degree for each PC. Hence, we totally developed 16 ANFIS ensemble models using four types of MFs. For each ensemble ANFIS, we then applied integration by average approach for the final decision. It should be noted that after 200 epochs and using 10-cross validation the sensitivity, specificity and classification accuracy were calculated for ANFIS classification models.

To experimentally show the effectiveness of ANFIS ensemble, we conduct the experiments on the diabetic retinopathy dataset and compare with the other methods on classification accuracy of diabetic retinopathy. From the results we found the performance of ANFIS ensemble measured by sensitivity, specificity and classification accuracy are =0.946 and 0.917 and 0.915, respectively.

We also compare the results of our study with other supervised machine learning techniques, Neural Network (NN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Decision Trees (DT), K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). We apply these techniques on the same dataset without incorporating SOM and NIPALS for the prediction task. The results are provided in Table 7. The comparisons are made on the average classification accuracy of diabetic retinopathy. It can be seen from the results that the method which uses SOM, NIPALS and ANFIS ensemble (SOM-NIPALS-ANFIS ensemble) is more accurate compared with the other methods which use solely classification techniques.

Table 7
Results of classification accuracy for all classifiers

Method	Classification Accuracy
KNN	0.864
NN	0.878
ANFIS	0.892
SVM	0.894
DT	0.852
SOM- NIPALS-ANFIS ensemble	0.915

5. Conclusion and future work

In this paper, we proposed a new hybrid method for diabetic retinopathy diagnosis using machine learning techniques. The predictions have been made for diabetic retinopathy using ANFIS ensemble. SOM and NIPALS were respectively used for clustering and data dimensionality reduction. To evaluate proposed method, several experimental analyses were conducted on a real-world diabetic retinopathy dataset taken from UCI. The results indicated that the method which combines SOM, NIPALS, and ANFIS ensemble techniques obtain good classification accuracy in relation to the methods which solely use prediction data mining techniques. The results showed that the average classification accuracy of all clusters was 0.915 with average Sensitivity=0.946 and Specificity=0.917.

Our method proposed in this study has been evaluated by a public dataset from UCI (Messidor dataset) which has input and output parameters for diabetic retinopathy disease diagnosis. However, compared to the big healthcare data, the nature of the data in this datasets is not complex. In addition, in case of big healthcare data which can be complex datasets with unique characteristics, the future studies need to consider this issue in the development of new methods in order to overcome the challenges of data processing time and take advantage of big data. Furthermore, as big healthcare data include multi-spectral, heterogeneous, imprecise and incomplete observations (e.g., diagnosis) which are derived from different sources, therefore new methods are needed and relying solely on conventional machine learning techniques may include some shortcomings in diagnosis the disease.

There is still plenty of work in conducting researches on clustering, dimensionality reduction and ensemble of classification techniques for diabetic retinopathy prediction in order to exploit all their potential and usefulness. In future study, we plan to evaluate the proposed method on additional diabetic retinopathy datasets and in particular on large datasets which includes other attributes for diabetic retinopathy diagnosis to show the effectiveness of the method for computation time of large data. In addition, our future work will investigate that how the proposed method can be extended to be applicable to the other types of datasets in medical domain.

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