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Development of a Diabetes Mellitus Diagnostic System Using Self-Organizing Map Algorithm: A Machine Learning Approach

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ABSTRACT

Delivery of Health care services in developing nations has posed a huge problem to the world at large. The United Nations and the World Health Organization have been on the front burner sorting for ways of improving these problems to abate the yearly mortality rates which are caused largely by inadequate health facilities, poor technical know-how, and poor health care administration. One disease that has a high number of patients is diabetes. In Nigeria, out of a population of 200 million, diabetes kills over 2% yearly. To reduce this menace, early diagnosis and awareness are important. And automation of the medical diagnostic system is one of the sure ways of achieving these feet. This paper explores the potential of a self-organizing map algorithm; a machine learning technique in the development of a diabetes mellitus diagnostic system (DMDS). Data collected from 120 patients from the University of Port Harcourt Teaching Hospital (UPTH) was used in the training and validation of the model. The confusion matrix formula was used in testing the sensitivity and accuracy of the model which yielded 75.63% and 87.2% respectively which are within the accepted range, predefined by expert physicians.

Keywords Artificial Intelligence, self-organizing map, diagnosis, neural networks, diabetes mellitus

INTRODUCTION

Healthcare delivery in developing nations has been a huge problem for the world at large. The United Nations and the World Health Organization has been on the front burner seeking ways these problems can be alleviated to minimize the yearly mortality rate due to poor health facilities, insufficiency of medical specialist, and inadequate health care administration. One disease that has a high number of patients is diabetes. In Nigeria, of the 200 million population, diabetes kills over 2% of them yearly. Thus, it is a serious problem that requires prompt attention. To reduce this menace, early diagnosis and awareness are key. Automation of the system of medical diagnosis is one sure way of achieving these feet. In most developing countries of the world, the insufficiency of medical expert physicians is a common challenge that has increased the mortality rate of patients who suffer from various diseases. Due to poor motivation in the area of remuneration, this insufficiency of medical professionals may not be overcome within a short period. Current practice for medical treatment requires patients to consult specialists for further diagnosis and treatment. Other medical practitioners may not have enough expertise or experience to deal with certain high-risk diseases. However, the waiting time for treatments normally takes a few days, weeks, or even months. By the time the patients see the specialist, the disease may have already spread out, as most the high-risk diseases could only be cured at the early stage. Consequently, computer-aided technology has been developed to detect and diagnose diabetes mellitus in patients, thus reducing mortality and reducing the waiting time to see a specialist. In recent times, an increasing computer-aided method utilized in the detection and diagnosis of diseases is the machine learning (ML) technique. ML is an algorithm that allows a system to learn from experience. Some of such commonly used ML algorithms for solving real-world problems include artificial neural networks, decision trees, random forests, fuzzy neural networks, support vector machine learning, k-means algorithm, Bayesian algorithm, neuro-fuzzy classifier, etc. [1, 2]. This paper explores the possibility of the development of a diabetes mellitus diagnostic system using self-organizing map technique; an algorithm that could learn from experience. According to [3], self-organizing map (SOM) neural network, also called as the Kohonen network, is an example of the unsupervised learning network whose main feature is the ability to automatically seek the essential attributes and the intrinsic rules of the training samples and to change neuron structure and network variables through the characteristics of self-adaptation and self-organizing. In the network training process, the data only includes the input samples and there are no corresponding ideal output samples. Through the self-learning of the network, the connection weights between neurons can be changed by the self-organization strategy to find the inherent relations among the input samples and complete the self-learning and automatic classification of the network. In this paper, for meeting the real-time fault diagnosis and optimization monitoring requirements of the polymerization kettle, a real-time fault diagnosis strategy for the polymerization kettle based on SOM neural network is proposed. The improved PSO algorithm is adopted to optimize the structure parameters of the SOM neural network. The simulation results verify the efficiency of the proposed fault diagnosis strategy. SOM neural network is widely applied in the fault diagnosis field. The SOM neural network is established based on the adjustable kernel function method and the genetic algorithm (GA) is adopted to adjust the SOM neural network parameters to obtain better classification results than a single kernel function [3]. A fault diagnosis method combining the wavelet packet analysis with SOM neural network is put forward. Firstly, the gear model is established by using the virtual prototype technology to simulate all kinds of faults. Then the wavelet packet analysis is used to extract energy characteristics. Finally, the SOM neural network is used to classify the fault data [4]. For the difficult identification problem of rock volcanic, an identification method of rock nature combining the principal component analysis method with SOM neural network is proposed [5]. In this paper, for meeting the real-time fault diagnosis and optimization monitoring requirements of the polymerization kettle, a real-time fault diagnosis strategy for the polymerization kettle based on SOM neural network is proposed. The improved PSO algorithm is adopted to optimize the structure parameters of the SOM neural network. The simulation results verify the efficiency of the proposed fault diagnosis strategy.

Literature Review

Diabetes Mellitus and its effect

Diabetes mellitus (DM) is a chronic disease primarily defined by the high levels of blood glucose (hyperglycemia) that is associated with severe morbidity due to both microvascular and macrovascular complications [6]. DM has become one of the leading causes of death and the biggest global health emergency of the post-millennium era. This is because no country is immune from the diabetes epidemic as it is a common threat that does not respect the borders or social class. It leads to morbidity and mortality among the patients. According to the International Diabetes Federation, an estimated 4 million people between 20 and 79 years of age are estimated to die from diabetes in 2017, worldwide. In Africa, an estimated 0.23 million people died due to DM before the age of 60 years representing 77.0% of all death before 60 years [6]. Nigeria, the most populous country in Africa, has an estimated 1.7 million people living with the disease [6]. DM alone accounted for 2% of all mortality of all ages in Nigeria, with an estimated 27,500 deaths in both males and females attributable to the disease. High blood glucose among the age group of 30–69 years[7].

In the 1990s, little was known about diabetes in Nigeria. Today, the average household has a diabetes scare. Diabetes is the main cause of serious diseases like heart failure, cardiovascular diseases like stroke, sexual dysfunction, nephropathy, retinopathy, vascular dysfunction, and different forms of cancer. Most diabetic patients suffer from non-healing wounds, which leads to amputation of limbs, hands, and feet. Also, diabetes is the leading cause of chronic kidney disease. Nigeria has one of the worst healthcare facilities in the world and the poverty index is slow. Most of the mortality attributable to DM is a result of poor management practices leading to persistently high glucose levels, which often results in acute and chronic microvascular and macrovascular complications. The common complications associated with DM include cardiovascular disease (CVD), blindness, kidney failure, and lower-limb amputation. In Nigeria, the general management of DM both at the individual, facility, community, and governmental levels has been reported to be suboptimal [8, 9, 10]. Nigeria has no known countrywide survey data on DM comprising the morbidity and mortality rate attributable to DM [11]. However, few available studies have reported the morbidity and mortality rates attributable to DM in Nigeria. A review study in Nigeria reported the pooled mortality rate to be 30.2 (95% confidence interval [CI] 14.6–45.8)/100,000 population, with a case fatality rate of 22.0% (95% CI 8.0%–36.0%). In addition, common complications reported were Hyperglycemic emergencies, diabetic foot, and CVDs [11]. A hospital-based study in Makurdi, North Central Nigeria, reported mortality for males is 47%, while that of the females is 53%, with common causes of death attributable to hyperglycemic crises (38%), septicemia (18%), diabetic ulcers (15%), and a variety of other causes (29%) [12]. Due to the relatively limited epidemiological evidence on the burden of DM in Nigeria and as recommended by the World Health Organization, the need for more research on the burden of diabetes, including country-specific responses to diabetes treatment and management and anthropological and cultural perspectives on diabetes in Africa [11, 13]. This hospital-based study was designed to document the pattern of DM-related complications and mortality rate in a tertiary hospital in Warri, Delta State Nigeria, as this would contribute to the few already existing studies estimating the burden of DM-related complications and mortality in Nigeria. This would help in developing diabetes registers across facilities and implementing a national response to DM in Nigeria.

Self-Organizing Map Technique

Machine learning is a branch of artificial intelligence; Artificial intelligence (Al) is the science and technology whose goal is to develop computers that can think, see, perceive, hear, talk and feel, etc. like human beings [14]. The self-organizing map (SOM) or the Kohonen neural network is an unsupervised machine learning algorithm that is popular in the competitive neural network field [15]. Its main advantage is its capability of functioning as both clustering and projection methods together. The SOM is a class of unsupervised systems that is based on competitive learning, in which the output neurons compete amongst themselves to be activated, with the result that only one is activated at any one given time. This activated neuron is termed as a winner-takes-all neuron or simply the winning neuron. Such competition can be induced or implemented by having lateral inhibition connections (negative feedback paths) between the neurons. The result is that the neurons are forced to organize themselves, giving the network the name "self-organizing map (SOM)".

MATERIALS AND METHODS

This study is aimed at a binary classification of diabetes mellitus cases into "sick" and "healthy" classes. The problem is a partitioning task using a self-organizing map neural network which falls into the "unsupervised" machine learning paradigm (clustering) but can equally work as "supervised" learning paradigms (classification). To achieve the objectives of the research, the study method consists of several phases, which include: description of clinical data for diabetes mellitus and method of collection of data and attribute selection and preprocessing; description of the classification method based on a self-organizing map SOM) algorithms, its training, validation and testing methods; and evaluation criteria.

Diabetes Mellitus Data

The data used for the training of the Self-organizing map algorithm consists of 120 clinical data instances and 8 attributes collected from the University of Port Harcourt Teaching Hospital (UPTH), Rivers State, Nigeria. There were 54 male patients (45%) and 66 female patients (55%), aged between 20 to 87 years (with a mean age of 55 years old and standard deviation of). Out of the 120 total instances of clinical cases, 112 datasets were used and the remaining was excluded due to missing values of data. Table 1 shows the features of diabetes mellitus used in the research. In the development of the self-organizing map model, the 112 instances of the clinical datasets were randomly divided into a training dataset of 80 clinical datasets (69.6%), a validation dataset of 20 clinical datasets (17.4%), and a test dataset of 15 clinical datasets (13.0%).

Table 1: The 8 Attributes of diabetes mellitus and descriptions extracted were used in the development of the self-organizing map model

S/n	Features	Code	Data Type
1	Age	Age	Integer
2	Gender	Sex	Boolean
3	Blood (Hemoglobin) Sugar Level Test	A1C	Floating point
4	Body Mass Index	BMI	Floating point
5	Random Blood Sugar Test	RBS	Floating point
6	Fasting Blood Sugar	FBS	Floating point
7	Oral Glucose Test	OGT	Floating point
8	Diabetes Mellitus Diagnosis	DMD	Nominal

Self-organizing Map Algorithm and Architecture

The self-organizing map (SOM) is a data visualization technique invented by [15]. It works by reducing the dimensions of data through the use of self-organizing neural networks [15]. In the conventional self-organizing map (SOM), training samples are generated by transforming input data into normalized values using normalization methods. Then, the Best Match Unit (BMU) is identified as the neuron that holds the minimum distance value to the normalized input features. All neurons within the BMU neighborhood are then updated so that their values look like that of the input features. This process is the SOM learning, which involves the preservation of the mapping topology to train the weights to simulate the real features of the datasets. Data preprocessing is key to the success of the model.

Each node n has a weighted vector w with d dimension ($w = (w_{i1}, w_{i2}, \ldots, w_{id})$), where i is the number of neurons. The SOM algorithm is as follows [16 - 19].

1. Initialization of weights (w_{ij}), determination of the parameter distance, and learning rate (α)
2. Select from the input space, a random sample of input training vector x(t). this value serves as the input to all neurons.
3. Identify the winning neuron that has the weighted vector in the closest vicinity of the input vector. The best neuron is selected from the minimum value from
   $$c = arg\{\|w_i(f) - x(f)\|\} \quad (1)$$
   Where $w_i(t)$ and x(t) are the weights and input vector of neuron n at f iteration, respectively and c is the Euclidian distances.
4. The weight of the neurons is updated with
   $$w_i(f+1) = w_i(f) + h_{ci}(f)[x(f) - w_i(f)] \quad (2)$$
   Where $h_{ci}(f)$ is the Gaussian distribution to compute the neighborhood is denoted by equation (3) as follows:
   $$h_{ci}(f) = \vartheta(t) \times \exp\left(\frac{\|r_c - r_i\|}{2\sigma^2(t)}\right) \quad (3)$$
   Where $\vartheta(t)$ is the learning rate, r is the coordinate of a neuron on the grid, and $\sigma(t)$ is the width of the neighborhood radius.
5. Steps 2 to 4 are iterated until the feature map reaches the optimum value and stops changing.

Performance Evaluation method

According to [20], the most important measures of performance of algorithms used in the field of medical science include the sensitivity, specificity, precision, and accuracy measures. In this study, these measures will be employed to ascertain the performance of the algorithm. To measure the performance, the confusion matrix is used. [21], assert that a confusion matrix is a table that allows visualization of the performance of an algorithm. It is made up of a two-class problem (with classes C1 and C2), the matrix has two rows and two columns that specify the number of false positives (FP), false negatives (FN), and true positives (TP), and true negatives (TN). These measures are defined as follows: TN is the number of samples of class C1 which has been correctly classified. TN is the number of samples of class C2 which has been correctly classified. FN is the number of samples of class C1 which has been falsely classified as C2. FP is the number of samples of class C2 which has been falsely classified as C1. Table 2 shows the confusion matrix table.

Table 2: Confusion Matrix

	Actual Class C1	Actual Class C2
Predicted class C1	True positive (TP)	False positive (FP)
Predicted class C2	False negative (FN)	True negative (TN)

To evaluate the performance of the algorithm, the following formula of sensitivity, specificity, precision, and accuracy based on the confusion matrix will be used.

Table 3: Evaluation methods and Equations for the performance of the Self-Organizing Map Technique

Evaluation Methods	Equations
Sensitivity (Recall)	$Sensitivity = \frac{FP}{(TP + FN)}$
Specificity	$Specificity = \frac{TN}{(TN + FP)}$
Precision	$Precision = \frac{TP}{(TN + FP)}$
Accuracy	$Accuracy = \frac{(TN + TP)}{(TN + TP + FN + FP)}$

RESULTS AND DISCUSSION

The proposed SOM model has been trained, validated, and tested using diabetes mellitus datasets obtained from the University of Port Harcourt Teaching Hospital from October 2021 to February 2022. The experiment is conducted using the Matlab R2018a tool on a personal computer (PC) with a RAM size of 6GB and an Intel i5 processor speed of 2.5 GHz. The results and evaluations of the experimentations are reported in this section.

RESULTS

The result of the program has confirmed the automated process. The sample forms below show the input and output for the malaria diagnostic system.

DISCUSSION

Diabetes mellitus poses a significant health burden globally, with Nigeria experiencing a substantial number of cases and associated mortality. Traditional healthcare systems often struggle to provide timely diagnosis and treatment, leading to preventable complications and deaths. The adoption of machine learning, particularly SOM algorithms, presents an opportunity to enhance diagnostic capabilities. By analyzing clinical data, such as age, gender, and various blood sugar levels, the SOM model can effectively classify patients as either diabetic or non-diabetic with high accuracy. This automated approach not only streamlines the diagnostic process but also facilitates early intervention, ultimately reducing the burden of diabetes-related complications and mortality.

CONCLUSION

The development of a Diabetes Mellitus Diagnostic System (DMDS) utilizing a self-organizing map (SOM) algorithm demonstrates promising results in accurately identifying diabetic patients. By leveraging machine learning techniques, healthcare providers can enhance diagnostic capabilities and streamline patient care processes. The implementation of such automated systems has the potential to significantly reduce the burden of diabetes-related complications and mortality, particularly in developing nations like Nigeria. Further research and collaboration are recommended to refine and expand the use of machine learning in improving healthcare outcomes for diabetes mellitus and other chronic diseases.

RECOMMENDATIONS

The developed model will facilitate the diagnosis and treatment of malaria parasites. If adopted for implementation, will reduce the problems with the manual method and the interface user-friendliness will always encourage patients to go for diagnosis when they start feeling any of these signs and symptoms mentioned above.

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Below is the dataset we intend to use for the training, validation, and testing of the model using MATLAB

PROSTATE CANCER SYMPTOMS AND SIGNS					
S/N	Age(yrs)	PSA (ng/mL)	DRE	Prost. W (g)	Prost. Vol.
1	68	54	3	80	90
2	78	20.5	3	80	160
3	83	15.5	0	200	70
4	85	22.6	2	80	50
5	71	24	1	55	70
6	65	1.5	1	90	40
7	61	34	0	120	15
8	76	64	1	70	45
9	70	18	1	55	70
10	81	39	0	60	80
11	64	14	2	80	50
12	82	23	0	78	60
13	64	34.5	2	60	90
14	73	21.3	0	70	160
15	64	34	0	90	70
16	53	33.2	0	80	50
17	72	10.2	0	80	70
18	71	71	1	200	40
19	67	54	0	80	15
20	86	38	3	55	45
21	75	31	3	90	70
22	58	18	1	120	80
23	58	6.5	0	70	50
24	70	24	0	55	60
25	53	78	0	75	90
26	55	21	0	80	160
27	75	14	0	75	70
28	75	12	2	90	50
29	75	34.8	3	80	160
30	53	33.2	0	80	50
31	72	10.2	0	80	70
32	71	71	1	200	40
33	67	54	0	80	15
34	86	38	3	55	45
35	75	31	3	90	70
36	58	18	1	120	80
37	58	6.5	0	70	50
38	70	24	0	55	60
39	53	78	0	75	90

40	55	21	0	80	160
41	75	14	0	75	70
42	75	12	2	90	50
43	75	34.8	3	80	160
44	82	21.7	3	100	70
45	76	64	1	70	45
46	70	18	1	55	70
47	81	39	0	60	80
48	64	14	2	80	50
49	82	23	0	78	60
50	64	34.5	2	60	90
51	73	21.3	0	70	160
52	64	34	0	90	70
53	53	33.2	0	80	50
54	72	10.2	0	80	70
55	71	71	1	200	40
56	67	54	0	80	15
57	86	38	3	55	45
58	75	31	3	90	70
59	58	18	1	120	80
60	58	6.5	0	70	50
61	70	24	0	55	60
62	53	78	0	75	90
63	55	21	0	80	160
64	75	14	0	75	70
65	67	67	3	74	40
66	75	15	0	84	15
67	70	59	0	50	45
68	54	54.3	0	85	70
69	70	23	0	50	80
70	68	54	3	80	90
71	78	20.5	3	80	160
72	83	15.5	0	200	70
73	64	14	2	80	50
74	82	23	0	78	60
75	64	34.5	2	60	90
76	73	21.3	0	70	160
77	64	34	0	90	70
78	53	33.2	0	80	50
79	72	10.2	0	80	70
80	71	71	1	200	40
81	67	54	0	80	15
82	86	38	3	55	45

83	75	31	3	90	70
84	58	18	1	120	80
85	58	6.5	0	70	50
86	70	24	0	55	60
87	53	78	0	75	90
88	55	21	0	80	160
89	75	14	0	75	70
90	67	67	3	74	40
91	75	15	0	84	15
92	70	59	0	50	45
93	54	54.3	0	85	70
94	70	23	0	50	80
95	68	54	3	80	90
96	53	33.2	0	80	50
97	72	10.2	0	80	70
98	71	71	1	200	40
99	67	54	0	80	15
100	86	38	3	55	45
101	75	31	3	90	70
102	58	18	1	120	80
103	58	6.5	0	70	50
104	70	24	0	55	60
105	53	78	0	75	90
106	55	21	0	80	160
107	75	14	0	75	70
108	75	12	2	90	50
109	75	34.8	3	80	160
110	82	21.7	3	100	70
111	64	34	0	90	70
112	53	33.2	0	80	50
113	72	10.2	0	80	70
114	71	71	1	200	40
115	67	54	0	80	15
116	86	38	3	55	45
117	75	31	3	90	70
118	58	18	1	120	80
119	58	6.5	0	70	50
120	70	24	0	55	60

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