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Fuzzy Supervised Neural Training Algorithm for varied Diabetes recognition

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ABSTRACT

Diabetes is a metabolic disorder associated with Blood Glucose Level. Most of the approaches applied in diagnosis are subjective in nature at best and tied toward Type I and Type II diabetes recognition, with none geared toward form of diabetes recognition. Fuzzy Supervised Neural Network Training Algorithm has been designed and implemented with Matrix Laboratory (MATLAB) and Hypertext Preprocessor as the simulation language. This paper demonstrates the practical application of algorithm techniques in medical diagnosis in determining patient's status.

Keywords: Supervised-Neural-Network, Fuzzy set, Fuzzy Logic, Algorithm

1 Introduction

In Nigeria about 2million persons are living with diabetes, many people are living with the condition unaware of the seriousness of the disease and its consequences as those diagnosed are often poorly managed due to lack of resources or because the health care professionals who care for them have poor knowledge about diabetes and how to provide good care. Diabetes might overtake those suffering from Tuberculosis, Malaria, HIV/AIDS, and other terminal diseases by the year 2030 if adequate attention was not paid toward the provision of health education; monitoring, treatment and management are not provided to the masses quickly (Kemi, 2012).

Diabetes is a chronic, debilitating disease requiring life-long management which invariably reduces the risk of serious, long-term complications such as kidney infection, liver disease and glaucoma etc. Offering the long-term monitoring and treatment needed is not easy for the healthcare systems of sub-Saharan Africa in general and Nigeria in particular, which are more focused on treatment and management of acute infection. Awareness of the early symptoms of diabetes is low, even among healthcare professionals. 85% of diabetes cases are undiagnosed, remaining without treatment and increasing the chances of untimely death (DLF, 2011). The professional knowledge in these regions if available is tied mainly to type I and type II diabetes and rest in the hand of senior consultants and physicians. Other forms of diabetes such as gestational, Maturity onset Diabetes of the Young (MODY) and Latent Autoimmune Diabetes in Adulthood (LADA) are really difficult to comprehend from the physician standpoint due to their obsolete knowledge, lack of experience and exposure.

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Diabetes is a very difficult disease to monitor and manage in Africa and Nigeria. However, early identification (diagnosis) and treatment of the disease reduces the life-threatening effect and prevents deaths ultimately. The diagnosis of diabetes, therefore, is an important key in the fight against diabetes in terms of treatment and long-term management, where possible. It therefore calls for the attention of health workers in this regard.

This research paper is geared toward proposing an implementing a supervised forward neural network algorithm for the identification of five class of diabetes.

2 Review of Related Literature

The theory of fuzzy logic provides a mathematical strength to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning. In standard set theory, an object does or does not belong to a set. There is no middle ground. In such bivalent systems, an object cannot belong to both its set and its compliment set or to neither of them. This principle preserves the structure of the logic and avoids the contradiction of object that both is and is not a thing at the same time (Zadeh, 1965). However, fuzzy logic is highly abstract and employs heuristic (experiment) requiring human experts to discover rules about data relationship (Angel and Rocio, 2011).

Fuzzy classification assumes the boundary between two neighboring classes as a continuous, overlapping area within which an object has partial membership in each class (Kuang et al., 2011). Fuzzy logic highlights the significant of most applications in which categories have fuzzy boundaries, but also provides a simple representation of the potentially complex partition of the feature space. (Sun and Jang**,** 1993 and Ahmad, 2011) Conventional approaches of pattern classification involve clustering training samples and associating clusters to given categories. The complexity and limitations of previous mechanisms are largely due to the lack of an effective way of defining the boundaries among clusters. This problem becomes more intractable when the number of features used for classification increases (Christos and Dimitros, 2008).

Artificial Neural Networks (ANNs) constitute a class of flexible nonlinear models designed to mimic biological neural systems. An ANN is a mathematical model or computational model based on biological neural networks (Gutiérrez, 2011), as an interconnected group of artificial neurons, which carries out computation using a connectionist approach. Typically, a biological neural system consists of several layers, each with a large number of neural units (neurons) that can process the information in a parallel manner. The models with these features are known as ANN models (Robert, 2000). ANNs have been widely applied to solve many difficult problems in different areas, including pattern recognition (matching), signal processing, language learning, electronic medical record processing, tele-diagnosis and computer networking (Robert, 2000). Neural network utilize dataset. The data set is divided into three distinct sets: training, testing and validation sets. The training set is the largest set and is used by neural network to learn patterns present in the data. The testing set is used to evaluate the generalization ability of a supposedly trained network. A final check on the performance of the trained network is made using validation set. Learning methods in neural networks can be broadly classified into three basic types Supervised, unsupervised and reinforced learning (Diogo et al. 2008).

Supervised learning is the machine learning task of inferring a function from supervised training data. The training data consist of a set of training examples. In supervised learning, each example is a pair consisting of an input object (typically a vector) and a desired output value (also called the supervisory signal). A supervised learning algorithm analyzes the training data and produces an inferred function, which is called a classifier (if the output is discrete) or a regression function (if the output is continuous).

Unsupervised learning studies how systems can learn to represent particular input patterns in a way that reflects the statistical structure of the overall collection of input patterns. By contrast with Supervised Learning or Reinforcement Learning, there are no explicit target outputs or environmental evaluations associated with each input; rather the unsupervised learner brings to bear prior biases as to what aspects of the structure of the input should be captured in the output. Unsupervised learning is important since it is likely to be much more common in the brain than supervised learning (Benedetti et al., 2005).

Reinforcement learning, one of the most active research areas in artificial intelligence, is a computational approach to learning whereby an agent tries to maximize the total amount of reward it receives when interacting with a complex, uncertain environment. In Reinforcement Learning, provide a clear and simple account of the key ideas and algorithms of reinforcement learning. Their discussion ranges from the history of the field's intellectual foundations to the most recent developments and applications. The only necessary mathematical background is familiarity with elementary concepts of probability (Richard and Andrew, 2011).

The two most widely used neural networks are the feed-forward networks and recurrent or interactive (feedback) networks, kohonen's self-organizing network, Adaptive resonance Theory (ART) and Counter propagation network are others (Chakraborty, 2010).

Feed-forward ANNs allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. They are extensively used in pattern recognition (Chakraborty, 2010).

This multi-layered structure of a feed-forward network is designed to function as a biological neural system. The input units are the neurons that receive the information (stimuli) from the outside environment and pass them to the neurons in a middle layer (i.e., hidden units). These neurons then transform the input signals to generate neural signals and forward them to the neurons in the output layer. The output neurons in turn generate signals that determine the action to be taken. It is important to note that all information from the units in one layer is processed simultaneously, rather than sequentially, by the units in an "upper" layer (kuan and white*,* 1994).

Feedback Network or Recurrent Neural Networks: Feedback networks can have signals travelling in both directions by introducing loops in the network. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found (Chakraborty, 2010).

Kohonen's Self-Organizing Network is a two-layer, feed-forward network (Beale and Jackson, 1990 and Dayhoff, 1990).The first is an input layer and the second is a grid or map arranged in a one or two-dimensional array. The second layer is known as a competitive layer. Incoming patterns are classified by the nodes that they activate in the competitive layer. Similarities among patterns are mapped into closeness relationships on the competitive layer. After training, the pattern relationships and groupings are observed from this layer.

Adaptive Resonance Theory (ART) is an unsupervised, competitive learning algorithm (Beale and Jackson, 1990). It is a two-layer network arranged in feedback and feed-forward connection. The layers have different functions, unlike the Multilayer or Kohonen networks. The first layer can be either an input or a comparison layer and the second layer can be either an output or a recognition layer. Both are interchangeable during training.

3 Methodology and Design

Existing diabetes models are tied to two classes; type I and type II, with none of these existing models capable to diagnose the three current classes of diabetes namely; Gestational diabetes, Maturity Onset Diabetes of the Young (MODY) and Latent Autoimmune Diabetes in Adulthood (LADA).

Numerous algorithm has be proposed for solving real work problems such tele-diagnosis through tele-surgery, but still date few Fuzzy-neural network algorithm has be proposed for training, validating and recognition or diagnosis for diabetes which span five class.

3.1 The Proposed Fuzzy Supervised Neural Network Training Algorithm

The proposed Algorithm imbibe artificial intelligence techniques in tying the symptoms of diabetes to the differential diagnosis of five class in addition with the occurrence factors thereby establishing a conclusive boundary. Unlike the current approaches, in which success or failure are based on the wills and experiences of relevant personnel designing and administrating the approach in other to elicit relevant recognition points. This algorithm is artificial intelligence based; therefore success and failure are not dependent on human intuitions, but success, is closely linked within tuned-up approaches within the carefully and systematic implemented. The Algorithm is depicted on Figure 1

INPUT:

Types of Diabetes (TYPE1,TYPE2,GESTATIONAL,MODY,LADA)

No. of Symptoms (P1, P2,…, Pn) = 15

P; Fuzzy parameters (Symptoms Codes)

Degree of membership function

≥ 0.50 = High degree membership function (serious)

≤ 0.50 = Low degree Membership Function (minor)

Fuzzy predefined Rules

More than five symptoms = Not diagnose with a class diabetes

Exactly four symptoms = Might be diagnose with a class of diabetes

Three symptoms and below = Diagnose with a class of diabetes

Glucose Level (125md/dl) = High

Age Range (R)

1 – 21yrs of age = teenager

30 – 40yrs of age = pre-Adult

> 41yrs of age = post-Adult

12 – 50 = pre-menopause

Origin (descent)

Caucasians; Americans, Europe's, Asians, North- Africa, Half-caste

Blacks; African, Black-Americans, Blacks Indians, Half-caste

Plus; either Caucasians or blacks

// INITIALIZATION

1. Randomly pick a patient *K;*
2. Save identification (diagnosis) Result in *Knot;*

// Loop till terminal point

3. For P = 1 to n do;

// Type 1 diabetes

4. Diagnose for Type 1 Diabetes;
5. If TYPE I symptoms is *serious*, patient age range is *teenager*, glucose level is *high,* patient origin is *Plus* and pancreas destruction is *swift* THEN Type 1;
6. Else if
7. Might be Type 1; (*exhibiting fours symptoms of Type I Diabetes*)
8. Else
9. Not Type 1;

// Type 2 diabetes

10. Diagnose for Type 2 Diabetes;
11. If TYPE 2 symptoms is *serious*, patient age is *post-Adult,* glucose level is *high* and patient origin is *black* THEN Type 2;
12. Else if
13. Might be Type 2; (*exhibiting fours symptoms of Type II Diabetes*)
14. Else
15. Not Type 2;

//Gestational diabetes

16. Diagnose for Gestational Diabetes;
17. If Gestational symptoms is *serious,* patient age is *pre-menopause,* glucose level is *high,* patient origin is *plus* and patient is *pregnant* THEN Gestational diabetes;
18. Else if (*exhibiting fours symptoms of Gestational Diabetes*)
19. Might be Gestational Diabetes;
20. Else
21. Not Gestational Diabetes;

// MODY diabetes

22. Diagnose for MODY Diabetes;

23. If MODY symptoms is *serious,* patient age is *teenager,* glucose level is *high,* patient origin is *caucasians* and mutated autosomal dominant gene is *present* THEN MODY diabetes;
24. Else if (*exhibiting fours symptoms of MODY Diabetes*)
25. Might be MODY diabetes;
26. Else
27. Not MODY diabetes;

// LADA diabetes

28. Diagnose for LADA Diabetes;
29. If LADA symptoms is *serious;* patient age is *pre-Adult,* glucose level is *high,* patient origin is *Caucasians* and pancreas destruction is *progressive* THEN LADA diabetes;
30. Else if (*exhibiting fours symptoms of LADA Diabetes*)
31. Might be LADA diabetes;
32. Else
33. Not LADA diabetes;

//Save results in *Knot;*

34. Return diabetes result for patient K

Figure 1: The Proposed Fuzzy Supervised Neural Network Training Algorithm

4 Implementation and Discussion

The implementation of our result was dual fold; the neural training dataset was handled conveniently utilizing Matrix Laboratory (MATLAB) which serves as our simulation tool in achieving the our results because of its interactive environment for algorithm development, data visualization, data analysis, and numerical approach which was relevant to our numerical dataset which was more appropriate than with spreadsheets or traditional programming languages, such as C/C++ or Java. After pruning the dataset utilizing MATLAB, the algorithm was fully implemented utilizing Hypertext Preprocessor (PHP), which served as the language of implementation.

4.1 Discussion

The implemented algorithm provides an interactive base in determining varied diabetes diagnosis objectively as opposed to the subjective approach which is achievable utilizing the algorithm. The result was satisfactory having been able to distinct diagnosis several diabetic patient and subsequently classified into varied classes.

5 Conclusions

This paper has demonstrates the practical application of fuzzy supervised diabetes training algorithm in the medical sector in determining and diagnosing varied diabetes identification.

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