

A Fuzzy Analysis to The Risk Factors of Type 2 Diabetes

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Abstract—*The diabetic population in Taiwan has been steadily increasing in the recent years. According to the data from the National Health Insurance Administration (MOHW), the prevalence of diabetes in Taiwanese adults has reached 5%, and is increasing every year. In 2016, diabetes caused 1.5 million deaths globally. The World Health Organization (WHO) revealed that one in 11 adults has diabetes, but one in two adults with diabetes is undiagnosed. By 2040, one in ten adults will have diabetes. This shows that diabetes is an important public health issue.*

Keywords—Risk Factors, Diabetes, Fuzzy Theory.

I. INTRODUCTION

Due to changes in the population structure, diet, and lifestyle in Taiwan, diabetes has become a chronic disease that cannot be ignored in the country. In the "Statistical Results of Death Causes for People in 105 Countries", according to the mortality rate, diabetes was the fifth leading cause of death [1] and the death toll of 9,960 was 4.5% higher than that of 104 [2]. For several consecutive years, it was the fastest-growing disease among the top ten causes of death. It is evident that the severity of diabetes poses a health threat to the Chinese people. However, the various chronic complications that accompany it are not only hidden in other causes of death, but also cause a heavy burden on individuals, families, and society. Therefore, diabetes can be considered as one of the major challenges in the national health policy [3]. According to the World Health Organization, at least 171 million people in the world currently suffer from diabetes, and by 2030 the number may double, reaching 366 million people. Therefore, diabetes is a slowly progressive disease. About 50% of the patients did not know that they had diabetes at the beginning, and because about two-thirds of the patients did not properly control the condition, they are prone to complications such as vascular disease. (coronary heart disease, stroke, hypertension, vascular obstruction, retinopathy, etc.), neuropathy, nephropathy, and amputation [4], but its prolonged medical attention and visits can cause huge waste of medical resources and severely affect the disease. From the perspective of health care, the cost of living with diabetes accounts for more than 10% of total expenditure on diabetes. The average medical cost for diabetics is 4.3 times that of nondiabetic patients. Diabetes prevalence and mortality have increased year by year and have become

public health and The main issues of universal health insurance, so early detection of diabetes and appropriate treatment can not only reduce the occurrence of future complications, in order to maintain the quality of daily life of diabetic patients, but also can reduce the cost of health care. With the increase in the number of people with diabetes and the prolonged duration of caries, the occurrence of diabetes-related complications will inevitably continue to grow. The purpose of this study is to address the five to six-year incubation period for prediabetes and then turn into diabetes, the patient's physiological changes, to find out the physiologically possible risk factors, and to organize rules that can be organized for practical reference. To reduce or delay the occurrence of diabetes-related acute and chronic complications.

II. RESEARCH METHOD

This research uses the theory of class fuzzy. This study uses the data of the National Health Department of the Ministry of Health and Welfare. Through the exploration of experts and literature, the factors that may be related to diabetes are determined as the variables used in the research, and important factors are found out to model and find out. The rules in the data assist the diabetes medical care team to more quickly determine whether people are pre-diabetic. This study uses the Fuzzy System to perform the risk assessment of diabetes, effectively learns and provides the If-Then Rule, and integrates the ambiguity of the fuzzy ensemble with the learning of the phrenic neural network. The sinusoidal neural network provides the algorithm as a lower-level learning, branching, and optimization; the fuzzy sequel puts reasoning on the high-level hierarchy of semantics and language, so the leader is an ideal complementary combination and is expected to be able to The low-level computing and learning ability of the road leads to the high-level hierarchy of the fuzzy series [5].

The structure is shown in Figure 1. This study will use the rules established in the Diagnostic Test for Diabetes to establish the knowledge base, and set the fuzzy interval of the risk factors to derive its own assignment. The execution rule compares and triggers actions and pushes out the final graphical result to calculate its output.

Fuzzy Inference System (FIS) [6] is a well-known artificial intelligence approach, that is based on the theory of fuzzy sets and fuzzy logic to extend the classical crisp sets theory. In the literature, the FIS model has been widely employed in the medical field[7-10].

The basic architecture of the FIS model as shown in Fig. 1, consists of three main phases:

- Fuzzification: transform the crisp input into linguistic variables (fuzzy input).
- Inference Engine (IE): uses the fuzzy input and the rules defined in the knowledge base module, to derive fuzzy sets for each variables.
- Defuzzification: transform the obtained fuzzy output by the IE into crisp output

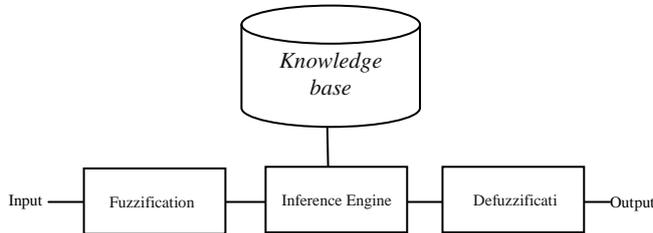


Fig. 1. The main structure of the FIS model

III. DIABETES RISK ASSESSMENT

This is the stage of risk assessment by the fuzzy expert system, based on the steps of

1. Fuzzification (input clear value and assignment letter)
2. Definition of fuzzy rules
3. Ambiguity (output assignment letter)
4. Defuzzification Such integration into a multi-layered network structure.

IV. FUZZY SYSTEM DESIGN

Since this study systematically examines the results of the delivery of diseases, in order to further explore whether the improvement of their living habits can affect the risk of developing diabetes, this study will conduct a risk assessment design. The first stage will be the general physical examination data of the cases. In the second phase, the life habits of the individual cases were hypothetically simulated to compare the results of the risk values obtained in the previous stage. It was assessed whether the quality of life habits could affect the degree of risk. In the study of the weights selected according to the weights and weights, three parameters such as waist circumference, blood pressure and age were used in the first phase. Body mass index and waist circumference were both the criteria for measuring obesity, so the item was not selected; while the second stage was simulated assessments for this study, including the BMI, the input risk level of the exercise, as shown in the figure 1.2.3.

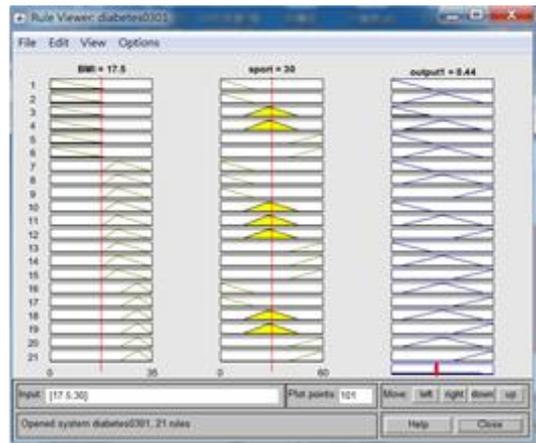
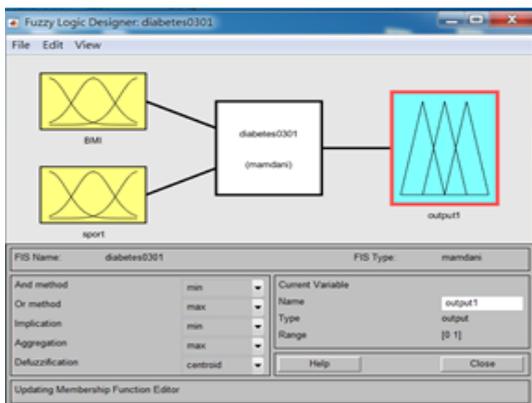


Fig 2 & 3. FUZZY set

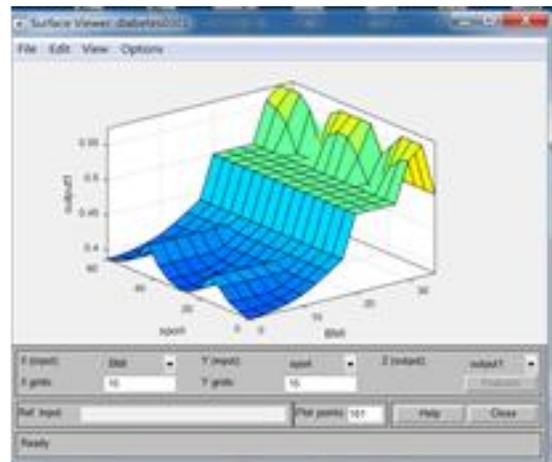


Fig. 4. 3D Perspective View

V. CONCLUSION

This study can easily allow the medical care team to make judgments in the early prediction rules for diabetes. The medical care team provides faster judgment methods. In addition, patients can make judgments without measuring through medical instruments and avoid the waste of medical resources. Therefore, they have clinical application value. Furthermore, from the perspective of preventive medicine, the early detection of early treatment is the main objective of preventive medicine. It can also be controlled before the patient develops diabetes further, thereby avoiding waste of medical resources.

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