Developing Fuzzy Inference System for Disease Prediction

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Abstract

Knowledge-based systems can be developed using fuzzy set theory and fuzzy logic, which are well-suited to and applicable for a wide range of medical tasks, including, but not limited to, the interpretation of sets of medical findings, the differentiation of syndromes in eastern medicine, the diagnosis of diseases in Western medicine, the mixed diagnosis of integrated western and eastern medicine, the optimal selection of medical treatments integrating western and eastern medicine, and real-time monitoring of patient data. In this research, we introduce a Fuzzy Inference System developed to aid in the processing of real-time medical diagnostics. The primary goal is to improve the quality of healthcare delivery by equipping hospital managers with a set of tools based on medical decision making processes. The goal of this method is to identify potential patient risk factors throughout the screening process. The automation of this procedure is advantageous since it allows for immediate answers that do not require the intervention of a physician (and hence may be carried out by nurses), but it also represents a loss of potential revenue for the hospital.

Keywords: Medicine, Fuzzy logic, Patients, Blood pressure, Diagnosis

I.INTRODUCTION

Computational intelligence has been utilized to create intelligent systems that have helped with several difficult challenges in recent years. Moreover, fuzzy logic has shown to be an effective component of decision-making systems like expert systems and pattern categorization systems. Some current medical expert systems already make use of fuzzy set theory.

As the global population rises and individuals adopt more urbanized lifestyles, so too does the demand placed on healthcare facilities. This places considerable strain on the Medicare healthcare system. However, getting to the hospital might be challenging for those who are elderly, crippled, financially strapped, geographically dispersed, etc. This means their health might deteriorate to the point of death.

The Internet is now crucial to our modern way of life. The Internet has various applications in the fields of education, finance, business, industry, entertainment, social networking, retail, e-commerce, and many more. The Internet of Things is the industry's next big thing (IoT).

Thus, remote health care systems were established to deal with the above-mentioned complex challenges associated with the Medicare health care system. In this scenario, the patient's vital signs are monitored by electronic sensors and transmitted through the internet to the hospital server, where a doctor may view the data, make a diagnosis, and prescribe the necessary treatment without the patient ever setting foot inside the facility.

II.MEDICAL DIAGNOSIS USING FUZZY INFERENCE SYSTEM

The creation of Fuzzy Medical Expert Systems to aid in medical diagnosis is a relatively new breakthrough in the realm of Expert Systems. Capturing an expert's knowledge in the medical issue domain, representing it in a modular, extensible structure, and transforming it to users in the same problem area is the goal of medical expert systems. The medical expert system sometimes relies on information that is ambiguous, imprecise, vague, partial, inconsistent, or just plain wrong.

There are a variety of systems in development with the goal of introducing a healthcare infrastructure that guarantees the protection of human health in light of rising technology. Researchers agree that FIS works well as either a primary or secondary component of expert systems. Diagnostic monitors must take into account the fact that the human body is a dynamic system showing extremely complicated behavior, far more so than systems adopting the consultation system paradigm.

For this reason, the instantaneous values of the body's observable parameters, or any time-ignorant derivation thereof, virtually never provide an adequate description of the body's current condition. Therefore, a diagnostic monitor has to know the subject's medical background. The monitor is able to maintain this level of awareness because to its internal state variables, which act as a form of memory. This is because these state variables are imprecise on a fuzzy diagnostics screen.

III.PROPOSED METHOD

In this study, we apply the results of the intelligent system to the field of preventative medicine. Traditional preventive medicine considers three broad categories of preventative action:

Primary prevention is taking the right steps to ensure general health and specialized protective factors, such immunization, clean living conditions, and safety precautions in the workplace. They are highly efficient in lowering the rates of death and disability caused by a wide variety of accidents and diseases. Lifestyle, environmental, and biological interventions that are part of broader efforts to promote health can lead to a more substantial drop in death rates. Health and disease preventive dissemination techniques should be a priority at this stage of intervention.

The early detection and treatment of illnesses constitute the secondary prevention. The purpose of medical science is to detect treatable diseases in their earliest stages, such as cancer, hypertension, diabetes, STDs, and so on. Disability, comorbidities, and other negative outcomes can be reduced by secondary prevention for various age-related, chronic degenerative illnesses.

When a disease has already taken hold of a patient and is actively promoting squeals, tertiary prevention is in charge of keeping the patient from completely failing at varied points when the anatomical and physiological modifications begin to become noticeable. It aims to restore the person to the fullest extent feasible, allowing them to support themselves.

IV.CASE STUDY

Membership functions can be used to model any variable that takes on a linguistic value. Boolean logic only accepts the two possible truth values. A logical proposition is either "fully true" or "totally false" in the traditional sense.

In contrast, premises in fuzzy logic have degrees of truth from 0-1 that can make them either mostly true or mostly false. Fuzzy Sets theory pushes the envelope with its "degree of truth" idea. Labeling the groupings qualitatively (using linguistic terms such as: high, warm, active, small, close, etc.). Additionally, the group's constituents are distinguished by a spectrum of relative importance (value indicating the degree to which an element belongs to a whole).

Algebra, differential, and difference equations ("crisp" mathematical models) provide the foundation of most existing intelligent systems. Since the rules of physics underlying the process are well-understood and well-defined, mathematical models may be created for some types of systems, such as electromechanical models. However, we encounter innumerable practical challenges on a daily basis, making it impossible to gather an adequate degree of information necessary for the physical modeling to be built. Aside from the monetary and time costs, this is a tedious operation. These kinds of networks are prevalent in fields as diverse as the chemical and food processing industries, banking, and biotechnology. Experts who are immersed in the process in question are the only ones who can provide the kind of insight necessary to build such systems. There is a high possibility that mathematical models would oversimplify or misrepresent this information.

This sophisticated system, built on the basis of these ideas, was created with the help of the MATLAB programme and the fuzzy toolkit plug-in. In a related work, researchers used a method used in medical diagnostics and added the idea of intuitionistic fuzzy sets to it.

The case study's input and output variables were chosen after consulting an analysis of a prominent medical staff operating in the health industry's market. The conversation was free-flowing, with all questions directed toward the field of preventive medicine. As a result, the following factors were considered and included in the input selection:

- Body mass index;
- Blood pressure;
- Physical activities;

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- Eating habits (saturated fat, sugar, salt, among others that correlate with health problems);
- Smoking;
- Alcohol;
- Dependence on drugs;
- Severity level in the first medical care;
- Family history (major diseases correlated with this variable).

Preventive medicine was the outcome.

The information from the transcripts of interviews with medical professionals from various regions was used to standardize all of the model's variables. These readings help locate the content that performs the analysis.

In order to model the data, Gaussian Membership Functions were used for every single variable.

The first input variable, Body Mass Index, was modeled using low, medium, and high values of the Gaussian Membership function, taking into account doctors' assessments of their patients' physical health. The evidence is in figure 1.

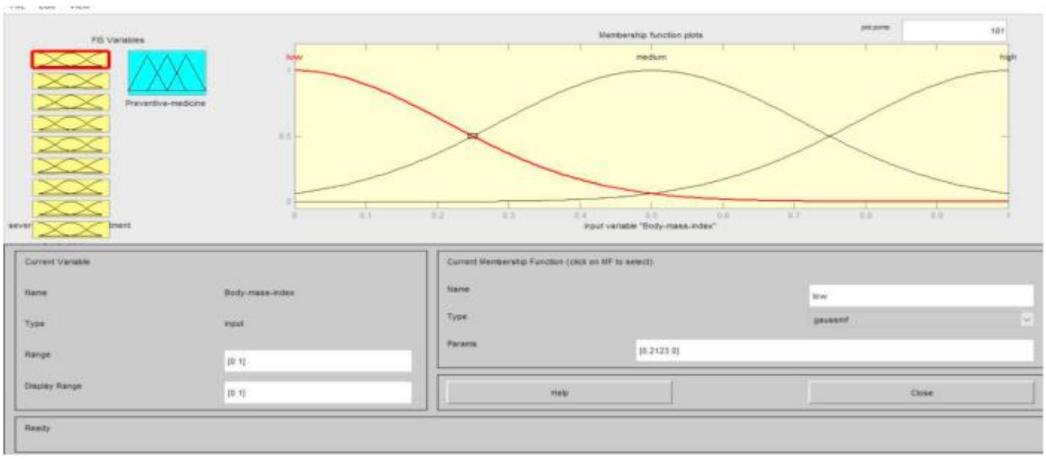

Figure 1: Gaussian Memberships Functions of input variables

The second factor is blood pressure, which was selected since it is both a reliable and a quick predictor of an individual's health. Three Gaussian membership functions, one each for normal, borderline, and elevated blood pressure, were used to model the data.

Sedentary behavior was the third factor analyzed. This is due to the fact that many people, such as those who walk a great distance to and from work, do not engage in organized sports but nonetheless value leading a physically active lifestyle. Three Gaussian membership functions, one each for a low, moderate, and high level of sedentary behavior, were used to simulate this distribution.

In order to standardize the fourth variable, eating behaviors, a cross-analysis was performed using items that are commonly over-consumed and have direct links to diseases such as high cholesterol, high blood pressure, and diabetes. A model was developed using three Gaussian membership functions, one each for poor, average, and good dietary practices.

The final variable is whether or not the customer smokes, which was normalized from the customer's tobacco consumption and modeled using two Gaussian membership functions.

Similar to how smoking was normalized, the sixth variable, alcoholism, was modeled using two Gaussian membership functions to represent heavy and light drinkers.

The seventh variable, drug dependency, was represented using two Gaussian membership functions, one for people who take drugs and one for those who do not.

The eighth factor was the intensity of the first therapy administered. These five levels of risk (low, small, medium, high, and extremely high) are represented by the five Gaussian membership functions.

Family history was the last variable to be normalized, and it was done so on the basis of previous interactions with the client's family, in which medical events were studied with parents and grandparents, albeit in a roundabout way (via questionnaire or access to hospital information regarding their last visit).

Twenty emergency room physicians were polled to create rules for the system based on these data points. Three hundred forty "if then otherwise" rules were gathered. Picture 2 illustrates this point.

Figure 3 shows the modeled system output variable.

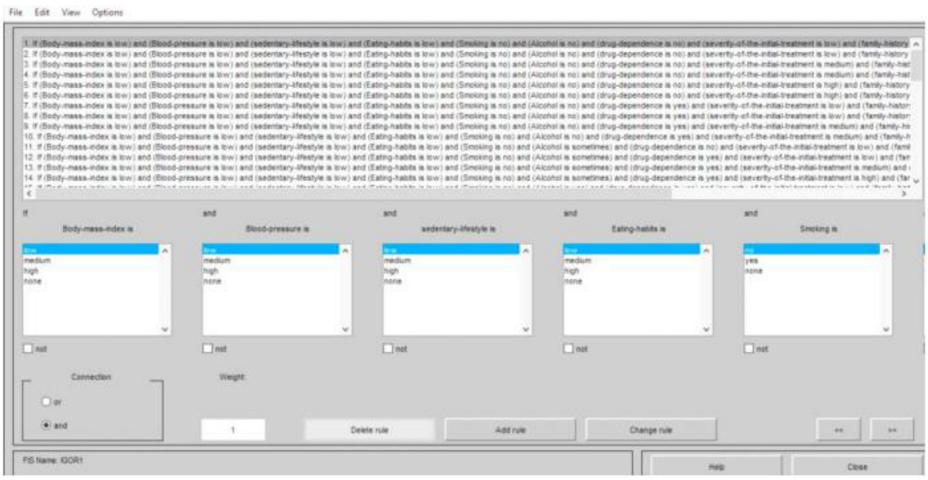

Figure 2: MATLAB rules editor used in this case study

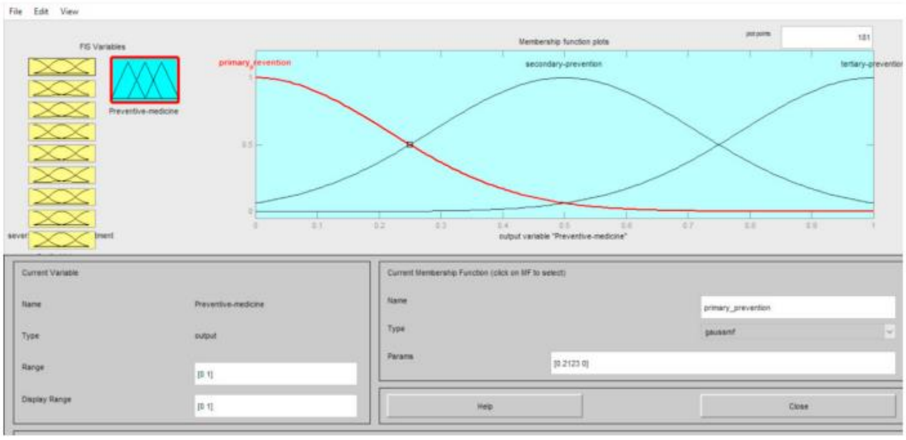

Figure 3: Membership functions used to model Preventive Medicine

Primary, secondary, and tertiary preventative care levels are assigned based on the value of the output variable. Input values and the system's rules combine to produce the output variable.

Fig. 4 shows the results from the intelligent fuzzy system.

Figure 4: Output of Fuzzy Inference System

The numbers shown in the Input area in this picture are what should be entered following a patient interview. In other words, the outcomes depend on the numbers that reflect the responses (output).

The patient in this case is overweight, has hypertension, is a couch potato, has poor eating habits, smokes, drinks excessively, and may even be using narcotics. The patient's initial appointment included a review of his family history, leading doctors to conclude that he faces a significant risk. The system has placed this individual in the tertiary care category.

Over the course of a month, many nurses put the Fuzzy Intelligent System through its paces at a hospital with over 200 patients. The medical diagnosis improved in accuracy by 13%, according to the results. The quality of care provided to patients this month was rated as excellent, and the hospital was able to reduce both wait times and overall expenses. After another month of tweaking and testing, the Fuzzy Intelligent System's medical diagnosis accuracy had dropped to 9 percent. In contrast, wait times increased by forty minutes, and costs rose by 20%, for patients who were treated by nurses who did not use the automated system, which categorized patients by risk level using a questionnaire with the same characteristics.

V.CONCLUSIONS

There is evidence that new medical expense distribution channels can be created with the help of the Fuzzy Intelligent System. It has been shown effective to assess health risks of new patients, and automation allows for better speed of action time, therefore supporting this project. Increased revenue and enhanced hospital branding are two other benefits of this development. as this mode of employment is considered socially responsible, cutting down on wait times and expenses while increasing customer satisfaction.

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