IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 6, Issue 2, February 2017

Cutomized Prediction of Heart Disease with Adaptive Neuro Fuzzy Inference System

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Abstract: Cardiovascular Diseases are the leading cause of death globally.Cardiovascular disease is a class of diseases that involve the heart or blood vessels. It includes coronary artery diseases (CAD) such as angina and myocardial infarction (commonly known as a heart attack). There is a need for medical practitioners to predict the heart disease before they occur in the patients. Nowadays use of computer technology has in the field of medicine has highly increased. Application of Artificial Intelligence would help for the complex and uncertain medical tasks such as diagnosis of diseases [2]. The main focus of this paper is to develop a neuro fuzzy system that would analyse the various life style parameters of a person and give a feedback on the health factor related to Cardiovascular Diseases.

Keywords: ANFIS, Heart Attack, Prediction, Risk factor.

I. INTRODUCTION

The heart is like any other muscle in body. It needs an adequate blood supply to provide oxygen so that the muscle can contract and pump blood to the rest of the body. It pumps blood to itself via the coronary arteries. These arteries originate from the base of the aorta (the major blood vessel that carries oxygenated blood from the heart) and then branch out along the surface of the heart.
Due to various reasons, the arteries narrow make it difficult for adequate blood to reach the heart. This can cause the heart muscle to ache like any other muscle in the body. If the arteries continue to narrow, it may take less activity to stress the heart and provoke symptoms. The classic symptoms of chest pain or pressure and shortness of breath due to Athero Sclerotic Heart Disease (ASHD) or Coronary Artery Disease (CAD) are called angina.

If one of the coronary arteries become completely blocked usually due to a plaque that ruptures and causes a blood clot to form. Then blood supply to part of the heart may be lost. This causes a piece of heart muscle to die. This is called a heart attack or myocardial infarction (Death of heart muscles). There are risk factors that increase the potential to develop plaque within coronary arteries and cause them to narrow. Atherosclerosis (Hardening of heart muscles) is the term that describes this condition. Factors that put people at increased risk for heart disease are: Smoking, High blood pressure (Hypertension), High cholesterol, Diabetes, Family history of heart problems, Lack of exercise, Obesity, poor diet, and excessive alcohol consumption, among others. High blood pressure results in 13% of Cardiovascular Diseases (CVD) deaths, while tobacco results in 9%, diabetes 6%, lack of exercise 6% and obesity 5%. It is estimated that 90% of CVD is preventable [1][3]. With the advent of computer technology, intelligent systems such as Artificial Neural Networks (ANN), Fuzzy Systems and Genetic Algorithms play a crucial role in predicting or diagnosis of diseases [2].

II. RISK FACTORS

While the individual contribution of each risk factor in CVD varies between different communities or ethnic groups the overall contribution of these risk factors is very consistent. Some of these risk factors, such as age, Obesity, (Body Mass Index - BMI), gender, Poor diet, family history, long term ailments are immutable.

However, many important cardiovascular risk factors are modifiable by lifestyle change, social change, drug treatment (for example prevention of hypertension, hyperlipidemia, and diabetes). For better incite, the contribution of each risk factor has briefed out in this section.

A. Age

Age is by far the most important risk factor in developing cardiovascular or heart diseases, with approximately a boosting of risk with each decade of life.[3] Coronary fatty streaks can begin to form in adolescence.[4] It is estimated that 82 percentage of people who die of coronary heart disease are 65 and older.[5] The serum total cholesterol level increases as age increases which increases the risk of heart disease. In men, this increase levels off around age 45 to 50 years. In women, the increase continues sharply until age 60 to 65 years [6].

Aging is also associated with changes in the mechanical and structural properties of the vascular wall, which leads to the loss of arterial elasticity and reduced arterial compliance and may subsequently lead to coronary artery disease [7].

B. Gender

Coronary heart diseases are 2 to 5 times more common among middle-aged men than women [6]. In a study done by the World Health Organization, sex contributes to approximately 40% of the variation in sex ratios of coronary heart disease mortality.[8] One of the proposed explanations for gender differences in cardiovascular diseases is hormonal difference. Among men and women, there are notable differences in body weight, height, body fat distribution, heart rate, stroke volume, and arterial compliance [7]. In the very elderly, age-related large artery pulsatility and stiffness is more pronounced among women than men.

C. Tobacco

Cigarettes are the major form of smoked tobacco. Risks to health from tobacco use result not only from direct consumption of tobacco, but also from exposure to second-hand smoke [1]. Approximately 10% of cardiovascular disease is attributed to smoking; however, people who quit smoking by age 30 have almost as low a risk of death as never smokers [9].

D. Genetics

Cardiovascular disease in a person's parent increases their risk by 3 fold.[10]

E. Exercise

Insufficient physical activity (defined as less than 5 x 30 minutes of moderate activity per week, or less than 3 x 20 minutes of vigorous activity per week) is currently the fourth leading risk factor for mortality worldwide [1]. The risk of ischemic heart disease and diabetes mellitus is reduced by almost a third in adults who participate in 150 minutes of moderate physical activity each week (or equivalent) [11]. In addition, physical activity assists weight loss and improves blood glucose control, blood pressure, lipid profile and insulin sensitivity.

F. Diet

High dietary intakes of saturated fat, trans-fats and salt, and low intake of fruits, vegetables and fish are linked to cardiovascular risk, although whether all these associations are a cause is disputed. The World Health Organization attributes approximately 1.7 million deaths worldwide to low fruit and vegetable consumption. The amount of dietary salt consumed is also an important determinant of blood pressure levels and overall cardiovascular risk.Frequent consumption of high-energy foods, such as processed foods that are high in fats and sugars, promotes obesity and may increase cardiovascular risk [1].

G. Alcohol consumption

The relationship between alcohol consumption and cardiovascular disease is complex, and may depend on the amount of alcohol consumed. There is a direct relationship between high levels of alcohol consumption and risk of cardiovascular disease. Drinking at low levels without episodes of heavy drinking may be associated with a reduced risk of cardiovascular disease [12]. Overall alcohol consumption at the population level is associated with multiple health risks that exceed any potential benefits [1][13].

According to statistics heart disease is one of the most important causes of deaths all over the world. Many factors such as clinical symptoms and the relation between functional and the pathologic manifestations complicate the diagnosis of heart disease. This diagnosis is very much essential in healthcare industry and hence research is carried out to develop Medical Decision Support Systems (MDSS) to help physicians to make the correct decision. Early detection, therapy and life style alterations could help people avoid the cardiovascular complications and the risk of heart attacks.

Over the last few decades, neural networks and fuzzy systems have established their reputation as alternative approaches to intelligent information processing systems. Both have certain advantages over classical methods, especially when vague data or prior knowledge is involved.

III. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

The ANFIS has the structure and computational principles, which are inspired by the neurophysiologic properties of the human brain. Neuro fuzzy techniques have emerged from the fusion of ANNs and Fuzzy Inference System (FIS) and form a popular framework for solving the real world problems [14][15]. A neuro fuzzy system is based on a fuzzy system, which is trained by a learning algorithm derived from neural network theory. From the point of view of FIS, the learning capability of ANN could be advantageous, while for ANN, the formation of linguistic rule base by FIS is advantageous. There have been several approaches for the integration of ANN and FIS [16-18].

The FIS is designed based on the past known behavior of the target system. Then the FIS is expected to be able to reproduce the behavior of target system. While constructing a FIS for a specific application, the rule structure makes it easy to incorporate human expertise about the target system directly into the modeling process. Fuzzy modeling takes the advantage of domain knowledge that might not be easily or directly employed in other modeling approaches.

Training of ANFIS needs to specify the initial FIS, Data partitioning method and Data clustering method. Fuzzy reasoning also known as approximate reasoning, is an inference procedure that derives conclusions from a set of fuzzy if-then rules and known facts. The basic structure of a FIS consists of three conceptual components; A rule base which contains a selection of fuzzy rules, a data base which defines the membership functions used in the fuzzy rules and a reasoning mechanism which performs the inference procedure, upon the rules and given facts to derive a reasonable output or conclusion.

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The antecedent of a rule defines a fuzzy region in the input space, while the consequent of a rule specifies the output in the fuzzy region. There are three types of FIS viz, Mamdani model, Sugeno fuzzy model and Tsukamoto fuzzy model. The details of which are given in the literature [19]

The architecture of a two input, two rule ANFIS is shown in Figure 1. The ANFIS had a five layered network structure, whose learning procedure could be explained with literature [19].

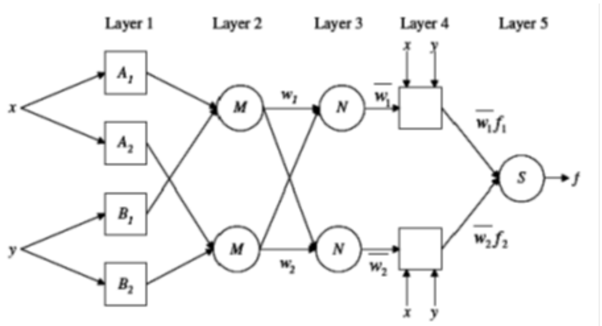

Fig. 1 Architecture of a 2 input ANFIS

A. Literature Review

When the literature is investigated there are diverse types of works in Fuzzy and ANFIS. Few have been listed here. An ANFIS based artificial intelligence system has been designed and developed for lung cancer diagnosis [20]. On the other hand, a fuzzy rule based expert system was implemented for asthma diagnosing[21]. Likewise, Ucar et al. [22] carried out a study about tuberculosis disease diagnosis by using adaptive neuro fuzzy inference system and rough sets.

Recently a research designed a fuzzy expert system for heart disease diagnosis, according to the result obtained from designed system, it was correct in 94% [23][24]. Most of the studies have applied ANFIS method to Cleveland Clinic Foundation heart disease dataset which has been obtained from the well-known UCI machine learning data repository. The dataset consists of 303 subjects. In this dataset, fields are divided in some sections and each section has a value [25].

IV. PROPOSED WORK

Clinical decisions are often made based on doctors' intuitions and heuristics experience rather than on the knowledge rich data hidden in the database. They lead to unwanted biases, errors and excessive medical costs which affects the quality of treatment provided to patients. Motivated by the necessity of such a system, this paper presents a decision support system for heart disease classification using ANFIS.

A. Description

Though various factors play an important role in creating the risks for heart disease, this work has concentrated on three criteria. They are Age, Body Mass Index (BMI) and K-Factor (KF) which is a function of Diet, Exercise, Ailments and Therapeutic information.

Good nutrition is a significant part in leading a healthy lifestyle. Combined with physical activity, nutrition can help to reach and maintain a healthy weight, reduce the risk of chronic diseases (like heart disease and cancer), and promote the overall health.

BMI has been taken into account for obesity. The BMI is an attempt to quantify the amount of tissue mass (muscle, fat, and bone) in an individual, and then categorize that person as under weight, normal weight, overweight, or obese based on that value. BMIis a value derived from the mass (weight) and height of an individual. The BMI is defined as the body mass divided by the square of the body height, and is universally expressed in units of kg/m^2, resulting from mass in kilograms and height in metres.

Commonly accepted BMI ranges are underweight: under 18.5 kg/m^2, normal weight: 18.5 to 25, overweight: 25 to 30, obese: over 30. People of Asian descent have different associations between BMI, percentage of body fat, and health risks than those of European descent, with a higher risk of type 2 diabetes and cardiovascular disease at BMIs lower than the WHO cut-off point for overweight, 25 kg/m^2 [26].

Ailments are chronic condition or disease that is persistent or long-lasting or a disease that comes with time. The term chronic is often applied when the course of the disease lasts for more than three months.

The therapeutic measure for every disease will vary. The medication and dosage details are used to analyse the severity of the illness and KF value is calculated accordingly. This KF value is derived from the linear combination of the above parameters, the coefficients (contributing weightage) of which are obtained through the standard Least Square (LS) technique. The proposed decision support system is shown in Figure 2. And the input values considered for the proposed system are shown in Table 1.

$$KF = \{D, E, A, T\} \text{– } (1)$$

Where

D – Diet Details

E – Exercise Duration

A – Ailment Details

T – Therapeutic Information

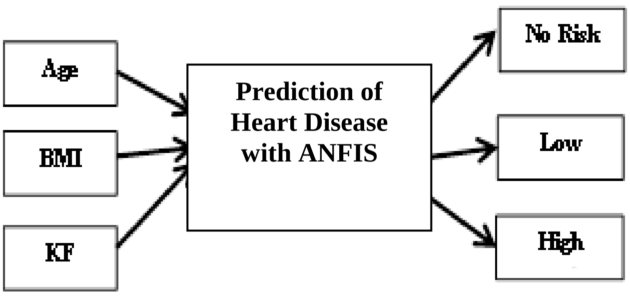

Fig. 2Decision Support System with ANFIS

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B. Neuro-Fuzzy Modelling

Three variables were used as input to the fuzzy system. They are Age, BMI and KF. The bell shaped Gaussian functions are used for the C of the input and linear membership function for output variable. The output variable will indicate whether the person has no risk, low or high risk of heart attack. The crisp and fuzzy values are mentioned in Table 2.

The membership function curve of the input variables, Age (Input 1), BMI (Input 2), and KF (Input 3), are shown in Figure 3**.** The curve defines how each point in the input space is mapped to the membership value between 0 and 1.With crisp inputs and outputs, a FIS implements a non linear mapping from its input space to output space. Thismapping is done by a number of fuzzy if-then rules, each describing the local behavior of the mapping. The input and output data have been generated with the knowledge obtained through literature and practicing physicians. The FIS follow the grid partitioning and Subtractive clustering in the analysis of input and output space.

Table 1. Input Variables for the Proposed System

Patient ID	Age	BMI	Diet	Exercise Duration	Ailments	Therapy
#001	45	28 (Over weight)	Irregular, Junk Foods	60 minutes / week	Hyper Tension	Oral Medicine once in a day
#002	67	31(Obese)	Fatty foods	100 minutes / week	Diabetes, Asthma	Insulin (Both Fast acting and Long acting – Twice a day), Oral medicine for breathing difficulty
#003	73	29 (Over weight)	Regular, Carbohydrate Foods	180 minutes / week	Diabetes, Hyper Tension	Oral Medicines for both
#004	55	20 (Normal)	Regular, Protein and fibres	210 minutes / week	Nil	Nil
#005	49	18 (Under Weight)	Poor Diet	Nil	Anaemic	Iron Supplements

Table 2. Inputs of Neuro Fuzzy System

Input Parameter	Crisp Value	Fuzzy Value
Age	30 - 50	Adult
	40 – 60	Middle Aged
	50 - 70	Older
BMI	15 – 25	Under Weight
	20 – 30	Normal
	25 – 35	Obese
KF	0 – 0.5	Low
	0.25 – 0.75	Normal
	0.5 - 1	High

After the first stage of fuzzy modeling, a rule base has been obtained that can more or less describe the system behavior of the target system by means of linguistic terms. Using a given input/output data set, the ANFIS method constructed a FIS, whose membership function parameters were tuned using a hybrid of Least Squares and Back Propagation algorithms.

The fuzzy rules were generated using the set of input and output. The antecedent parts of the rules were combined using the maximum and product operator. Each of the rule's weight was determined using the prod implication method. The result was aggregated with sum which is the sum of each rule's output set. Because decisions are based on the testing of all of the rules in a FIS, the rules were combined to make a decision. This was done during aggregation process by combining the fuzzy sets that represent the output of each rule into a single fuzzy set.

The input for the defuzzification process is the fuzzy set (the aggregate output fuzzy set) and the output is a single number. The aggregate of a fuzzy set encompasses a range of output values, and so must be defuzzified in order to resolve a single output value from the set. For the defuzzification process, weighted Average method was used.

DOI 10.17148/IJARCCE.2017.6204

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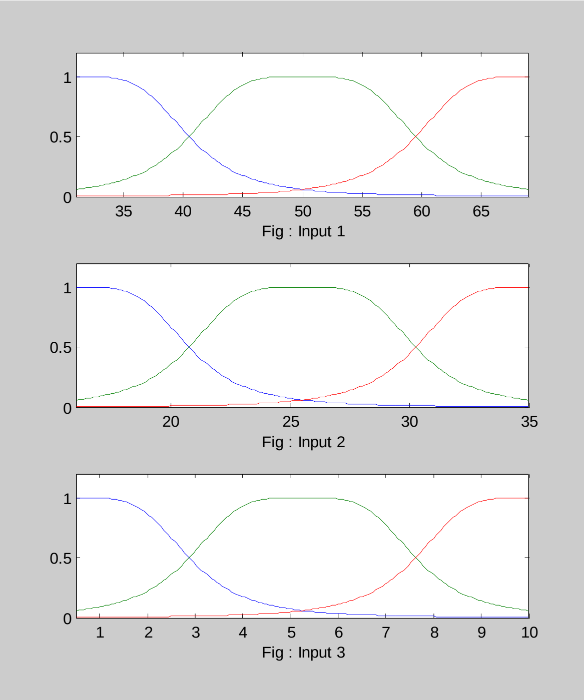

Fig. 3 Membership Function Representation

C. System Validation

System validation is the process by which the input vectors from a new input/output data set are presented to the trained FIS model and checking how well the FIS model predicts the corresponding output values. Mean square error (MSE) was used to evaluate the predictive performance of the model. MSE is a well acceptable indicator that describes the differences between actual data and the predicted values. After training the system, the system was tested with a set of testing dataset to verify the accuracy of the predicted values. The degree to which the system output match the actual data set is used to provide an evaluation of the system's predictive abilities. MSE between the actual data set and the predicted values was used to evaluate the system.

V. CONCLUSION

This paper has given a methodology to analyse the life style parameters of a person with an adaptive neuro fuzzy inference system that acts as a decision support system for the doctors to predict the risk of heart disease. This system will help the patient to know their level of risk in heart disease. The worsening of the disease could be avoided by changing the life style with proper diet, exercise and medications. In the future an attempt could be made to develop this work with more input parameters for different databases.

ACKNOWLEDGMENT

I hereby thank the physicians, diabetic specialists and the cardiologists for their valuable inputs and suggestions in developing this work.

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