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New Hybrid Intelligent Systems for Diagnosis and Risk Evaluation of Arterial Hypertension

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New Hybrid Intelligent Systems for Diagnosis and Risk Evaluation of Arterial Hypertension

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Preface

In this book, a new approach for diagnosis and risk evaluation of arterial hypertension is introduced. The new approach was implemented as a hybrid intelligent system combining modular neural networks and fuzzy systems. The different responses of the hybrid system are combined using fuzzy logic. Finally, two genetic algorithms are used to perform the optimization of the modular neural networks parameters and fuzzy inference system parameters. The experimental results obtained using the proposed method on real patient data show that when the optimization is used, the results can be better than without optimization.

This book is intended to be a reference for scientists and physicians interested in applying soft computing techniques, such as neural networks, fuzzy logic, and genetic algorithms, all of them applied in medical diagnosis, but also in general to classification and pattern recognition and similar problems. We consider that this book can also be used to find novel ideas for new lines of research or to continue the lines of research proposed by authors of the book.

In Chap. 1, a brief introduction to the book is presented, where the intelligent techniques are used in the proposed approach. In addition, the main contribution, motivations, application, and a general description of the proposed methods are mentioned.

We present in Chap. 2 the application of fuzzy logic for arterial hypertension classification. A fuzzy system was developed based on the knowledge of medical experts in hypertension classification. Simulation results show the advantages of using fuzzy logic in this real-world problem. This chapter also allows readers to understand better the problem of hypertension.

In Chap. 3, we explain a neuro-fuzzy hybrid model for the diagnosis of high blood pressure or hypertension to provide a diagnosis as accurate as possible based on intelligent computing techniques, such as neural networks and fuzzy logic.

In Chap. 4, we present a detailed explanation of a neuro-fuzzy hybrid model used as a new Artificial Intelligence method to classify high blood pressure (HBP). The neuro-fuzzy hybrid model uses techniques such as neural networks, fuzzy logic, and evolutionary computation. In this case, the genetic algorithms are used for optimizing the structure of the neuro-fuzzy hybrid model.

In Chap. 5, a method to diagnose the blood pressure (systolic pressure, diastolic pressure, and pulse) of a patient is proposed. This method consists of a modular neural network and its response with average integration. The proposed approach consists on applying these methods to find the best architecture of the modular neural network and the lowest prediction error. Simulation results show that the modular network produces a good diagnosis of the blood pressure of a patient.

In Chap. 6, a hybrid intelligent system is presented as a powerful combination of soft computing techniques for reducing the complexity in solving difficult problems. Nowadays, cardiovascular diseases, such as arterial hypertension (high blood pressure), have a high prevalence in the world population. We design in this research work a hybrid model using modular neural networks, and as response integrator, we use fuzzy systems to provide an accurate risk diagnosis of hypertension, so we can prevent future diseases in people based on the systolic pressure, diastolic pressure, and pulse of patients.

We gratefully acknowledge the Consejo Nacional de Ciencia y Tecnologia (CONACYT) for the support of this research project under grant number 246774. Our thanks go to the Ph.D. students Ivette Miramontes, Juan Carlos Guzman, and Martha Pulido who enthusiastically participated in the creation of the database and programming the algorithms to build the system and obtaining the simulation results. We are also grateful for the professional support we have received from Cardiodiagnostico of the Excel Medical Center in Tijuana, Mexico, which provided us with the guidelines for the research and the data and studies from their patients. Also, we thank to Prof. Dr. Fevrier Valdez and MC Alejandra Mancilla that actively participate in this research project. Of course, we want to thank our institution, Tijuana Institute of Technology, for always supporting our research work.

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March 2017

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Contents

Chapter 1
Introduction

Abstract In the book we present a novel model for classification, diagnosis and risk evaluation of high blood pressure using new hybrid intelligent systems, combining Modular Neural Networks, Fuzzy Logic and Genetic Algorithms. We focused on the development of hybrid intelligent systems; for classification of blood pressure levels using the experience of cardiologists and the guidelines of European Society of Cardiology, and for constructing a fuzzy logic classification method based on patient's Blood pressure.

Keywords Hybrid Intelligent Systems · Modular Neural Networks · Blood pressure classification

The book presents a novel model for classification, diagnosis and risk evaluation of high blood pressure (HBP) or arterial hypertension using new hybrid intelligent systems, combining Modular Neural Networks, Fuzzy Logic and Genetic Algorithms. This book focuses on the development of hybrid intelligent systems; first for classification of blood pressure levels using the experience of cardiologists and the guidelines of European Society of Cardiology (ESC) [1], and for constructing a fuzzy logic classification method based on patient's Blood pressure. The second model developed was for classification based on a fuzzy rule base optimization using a hierarchical genetic algorithm, reducing the number of rules used in the final system to give more accurate results for the classification of levels of hypertension. The third part is the complete architecture of the hybrid system based on Modular Neural Networks and Fuzzy Inference Systems for classification, diagnosis and risk evaluation of HBP. The Modular Neural Network is used for modeling the trend of the blood pressure during the period of 24 h using the information of the ambulatory blood pressure monitoring readings, and this trend is given to the classification module, in parallel a module of fuzzy inference systems is used for providing the risk of hypertension depending on variables of the patients and the trend of the blood pressure. At the end, the Model gives the classification level of blood pressure and the estimation risk of develop hypertension.

P. Melin and G. Prado-Arechiga, *New Hybrid Intelligent Systems for Diagnosis and Risk Evaluation of Arterial Hypertension*, SpringerBriefs in Computational Intelligence, DOI 10.1007/978-3-319-61149-5_1

The motivation of this research work derives from the importance of developing new methods using Computational Intelligence for application in medicine, particularly in the area of cardiology to diagnose cardiovascular diseases. In this particular case to help medical doctors diagnose, classify and determine the possible risk of developing high blood pressure and their complications.

The HBP, together with Diabetes Mellitus (DM) and Obesity, are problems of Public Health in all over the world. HBP and DM are Chronic Degenerative Diseases with great mortality. Therefore, we must make a great effort to carry out an adequate and opportune diagnosis, treatment and control.

However, studies of Public Health show us that in order to increase the percentage of adults with controlled hypertension is very important and necessary the diagnosis and the appropriate pharmacological treatment, so that they have blood pressure levels under control and with this there will be fewer complications [2]. In order to achieve this, the staff in charge of caring for patients with HBP, must have the necessary tools to do it [3].

And why it is important to detect hypertension, because it is one of the most important risk factors for cardiovascular disease, cerebrovascular disease and renal failure that are important causes of mortality [3]. In Mexico between 2000 and 2006, the prevalence of HBP remained so high that it affected 31.6% of Mexican adults [4].

The complications of HBP such as Cardiovascular Disease: Myocardial Infarction, Cerebrovascular Disease, Renal Failure are directly related to the magnitude of the increase in blood pressure and the time of evolution. Also early treatment of hypertension has important benefits in terms of prevention of complications as well as lower risk of mortality [5]. In addition, it is of relevant importance if we consider that, in 2006, 47.8% of these adults with hypertension were found in the survey, that is, they had not been diagnosed. In addition, of the previously diagnosed adults, only 39.0% received pharmacological treatment [4].

In the last national health survey or ENSANUT 2012 [6], it was observed that the prevalence of HBP in Mexico was 31.5%, of which 47.3% were unaware that they had this disease (diagnosis by finding the survey). In addition, there were significant differences between regions (34.3% higher in the north than in the south); between localities (19.4% higher in urban than in rural).

HBP affects 31.5% of Mexican adults and is among the highest in the world. Therefore, a problem of this magnitude requires attention and participation of all sectors of society, so we decided to provide computational models that can help health workers to determine in a more timely manner the diagnosis supported by the official Mexican Standard of arterial hypertension and the degree of control of arterial hypertension in a patient, before and after starting treatment. With a database obtained through a 24 h Ambulatory Blood Pressure Monitor or 24 h ABPM, a more accurate study was carried out to determine the degree of hypertension and its behavior in daily life and in periods of exertion, exercise or Work or in periods of less activity, rest, rest or sleep. Also we agree that a problem of this magnitude requires attention and participation of all sectors of society, to jointly provide the strengths of face area to improve the control of this important disease, as in this case the areas of Medicine and Computing.

Today there are different techniques of intelligent computing, such as: fuzzy systems, neural networks, evolutionary computing which are used in the areas of medicine. Hypertension is one of the most dangerous diseases that seriously threaten the health of people around the world. This type of disease often leads to fatal outcomes, such as: Heart attack, cerebrovascular accident, and kidney failure.

One of the most dangerous aspects of HBP is that the person does not know that he has the disease, in fact, almost a third of people who have high blood pressure do not know it. The only way to know if the blood pressure is high is through regular checkups and studies.

At the present time in medicine we can find very few models that have been developed to diagnose HBP and to be able to treat it in time, is for that reason that the implementation of a suitable method of prognosis, has always been a research of great importance in the medicine since this helps deal with long illnesses and save many lives today. The prognosis provides medicine with the ability to make projected mid- and long-term decisions due to the accuracy and inaccuracy of predicted data and this leads to better control of the health of any patient.

On the other hand for a medical doctor it is important to be able to know the behavior that a patient's blood pressure will have in the future and in this way to make the right decisions that improve the patient's health and avoid unwanted situations that in the worst case can lead to early death of the person because their blood pressure was not treated in time.

With the use of neural networks and fuzzy systems the solution of complex problems is sought, not as a sequence of steps, but as the evolution of computer systems inspired by the human brain, and gifted by "intelligence." With these techniques the new hybrid methods were developed that allow us to model the behavior of the Blood Pressure in the people, to be able to give a diagnosis of the blood pressure and its classification and risk.

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Chapter 2
Fuzzy Logic for Arterial Hypertension Classification

Abstract One of the most dangerous diseases for humans is the high blood pressure (HBP) or hypertension, which is a kind of disease that often leads to fatal outcomes, such as heart attack, stroke and renal failure. The HBP seriously threats the health of people worldwide. One of the dangerous aspects is that people may not know that they have it. In fact, nearly one-third of people who have high blood pressure don't know it. The only way to know if the blood pressure is high is through the regular checkups. Therefore, we have developed a Fuzzy System for the diagnosis of the HBP. Firstly, the input parameters include Systolic Blood Pressure and Diastolic Blood Pressure. Secondly, we have as an output parameter: Blood Pressure Levels (BPL). The input linguistic values include Low, Normal Low, Normal, Normal High, High, Very High, Too High and Isolated Systolic Hypertension. Finally, we have 14 fuzzy rules to determine out diagnosis.

Keywords Fuzzy system · Hypertension · Diagnosis

2.1 Introduction

Nowadays different artificial intelligence techniques, such as fuzzy systems are largely used in the medical areas. As we know, the control of hypertension is considered when the systolic blood pressure >140 mmHg and the diastolic blood pressure >90 mmHg. Thus, the use of an expert system that provides information to the user about the factors and dangers of high blood pressure is very important.

Fuzzy logic is used to model nonlinear systems, which are difficult to model mathematically. It is a logic system that is based on fuzzy set theory and continuous variables. Conclusions that are based on vague, imprecise, missing input information are simply provided by fuzzy logic (FL) [12]. Fuzzy logic uses different concepts, i.e. fuzzification, defuzzification, membership function, linguistic variables, domain, rules etc. In Boolean algebra or Boolean logic, crisp sets are used, which only have two values 0 and 1, but in fuzzy logic, sets have an infinite number of values between 0 and 1. In Boolean logic an element is completely inclusive or

P. Melin and G. Prado-Arechiga, *New Hybrid Intelligent Systems for Diagnosis and Risk Evaluation of Arterial Hypertension*, SpringerBriefs in Computational Intelligence, DOI 10.1007/978-3-319-61149-5_2

exclusive membership is used, but in a fuzzy sets completely inclusive, exclusive or between these two memberships is used. Also the fuzzy system is a system in which fuzzy rules are used with membership functions (MF) to find the conclusion or result. Fuzzy logic has been applied to many areas or fields of application, for example fuzzy logic has played an important role in the field of medicine. They are used in control, automobiles, household appliances and decision making systems [3, 5, 15].

HBP is a chronic medical condition in which the blood pressure in the arteries is elevated. The normal level for blood pressure is below 120/80, where 120 represent the systolic measurement (peak pressure in the arteries) and 80 represents the diastolic measurement (minimum pressure in the arteries). Blood pressure between 120/80 and 139/89 is called pre-hypertension (to denote increased risk of hypertension), and a blood pressure of 140/90 or above is considered hypertension.

Hypertension may be classified as essential or secondary. Essential hypertension is the term for high blood pressure with an unknown cause. It accounts for about 95% of cases [4]. Secondary hypertension is the term for high blood pressure with a known direct cause, such as kidney disease, tumors or others.

The chapter is organized as follows: in Sect. 2.2 a methodology for hypertension is presented, in Sect. 2.3 simulation and results of the prediction of the data that will be the input to the fuzzy system are presented, in Sect. 2.4 the design and development of the fuzzy logic system is described, and in Sect. 2.5 the conclusion obtained after the tests with the fuzzy system of diagnosis of hypertension.

2.2 Methodology

2.2.1 Type of Blood Pressure Diseases

HBP is the most common disease and it markedly increases both morbidity and mortality from cardiovascular and many other diseases. Different types of hypertension are observed when the disease is sub-categorized. These types are shown in Table 2.1.

Table 2.1 Definitions and classification of the blood pressure levels (mmHg) [7]

Category	Systolic		Diastolic
Hypotension	<90	And/or	<60
Optimal	<120	And	<80
Normal	120–129	And/or	80–84
High normal	130–139	And/or	85–89
Grade 1 hypertension	140–159	And/or	90–99
Grade 2 hypertension	160–179	And/or	100–109
Grade 3 hypertension	≥ 180	And/or	≥ 110
Isolated systolic hypertension	≥ 140	And	<90

In Table 2.1 the blood pressure (BP) category is defined by the highest level of BP, whether systolic or diastolic. Isolated systolic hypertension should be graded 1, 2 or 3 according to the systolic BP value in the rages indicated.

2.2.2 Risk Factors

Some of the primary risk factors for essential hypertension include the following [1]:

- Obesity
- Lack of exercise
- Smoking
- Consumption of salt
- Consumption of alcohol
- Stress level
- Age
- Sex
- Genetic factors.

2.2.3 Fuzzy Logic and Hypertension

Nowadays we cannot be comfortable with the traditional medical analysis because the complexity of medical practices makes traditional quantitative approaches of analysis inappropriate [11, 12]. Every trust worthy expert knows that his/her medical knowledge and resulting diagnosis can contain a great deal of uncertainty with imprecise formulations. Medical processes can be so complex and unpredictable that physicians sometimes must make decisions based on intuition. Computers are capable of making calculations at high and constant speed and of recalling large amounts of data and can, therefore, be used to manage decision networks of high complexity [8, 10]. Fuzzy logic developed by Zadeh [14] makes it possible to define these inexact medical entities as fuzzy sets. Fuzzy logic together with the appropriate rules of inference provides a power framework for managing uncertainties pervaded in medical diagnosis [6, 9, 10]. Fuzzy logic technology is adopted in this paper for the management of hypertension. This is because, fuzzy logic can adequately address the issue of uncertainty and lexical imprecision of knowledge [2], but fuzzy systems still require human experts to discover rules about data relationship.

By applying fuzzy logic, a fuzzy rule base system for the management hypertension was developed with the help of the domain expert [13].

2.3 Simulation and Results

The following graphic interface in Fig. 2.1 shows the information to be simulated and used for prediction of blood pressure following the result is selected.

The following graphic interface in Fig. 2.2 simulates the monitoring of blood pressure of a patient, which is based on the provided information. A prediction of its next blood pressure is performed, and the result of the prediction is systolic and diastolic and this information is the input to the fuzzy system.

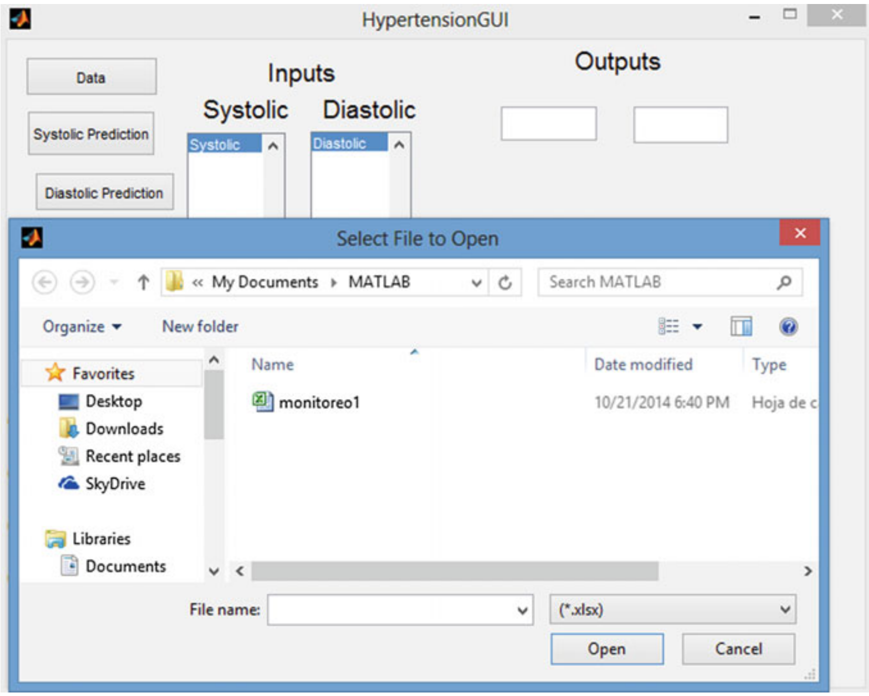

Fig. 2.1 Graphic interface and select file window

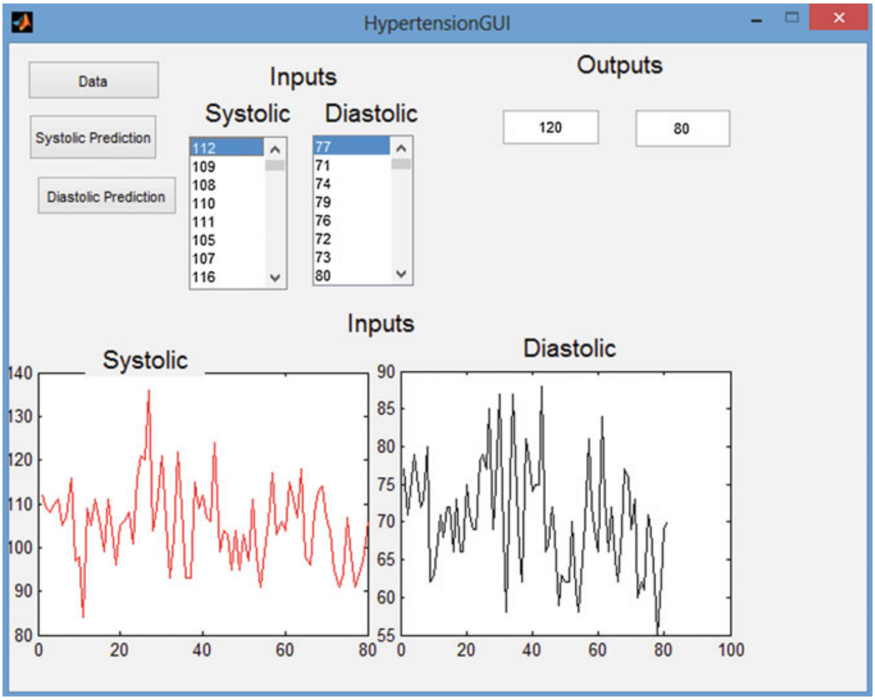

Fig. 2.2 Simulation and results of the graphic interface

2.4 Design and Development of the Fuzzy Logic System

A fuzzy logic system is a collection of membership functions and fuzzy rules that are used to make the diagnosis. This design has been divided into several steps. The steps are fuzzification, rule evaluation and finally defuzzification.

In this study, we propose a fuzzy system for the diagnosis of HBP. The fuzzy system has 2 inputs including the Systolic and Diastolic, and 1 output BP_level, in the inputs we have eight membership functions, such as Low, low normal, normal, high normal, high, very high, too high and isolated systolic Hypertension(ISH) and in the output there are eight member functions such as Hypotension, Optimal, Normal, High normal, Grade 1, Grade 2, Grade 3 and Isolated Systolic Hypertension (ISH) and Mamdani inference engine and centroid defuzzification.

The analysis focused on how to design a fuzzy logic system for the diagnosis of hypertension. This is performed by using a range of systolic and diastolic blood

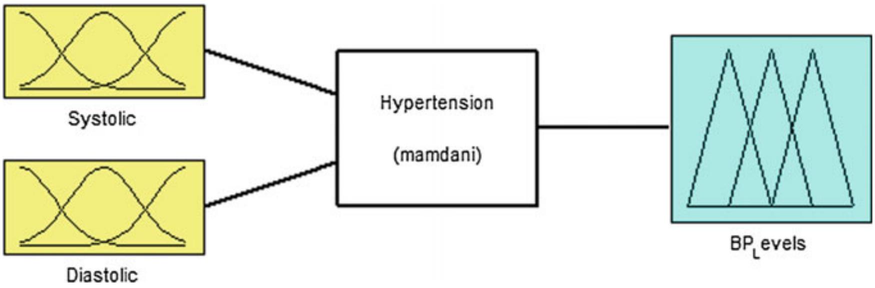

Fig. 2.3 Fuzzy system for diagnosis of hypertension

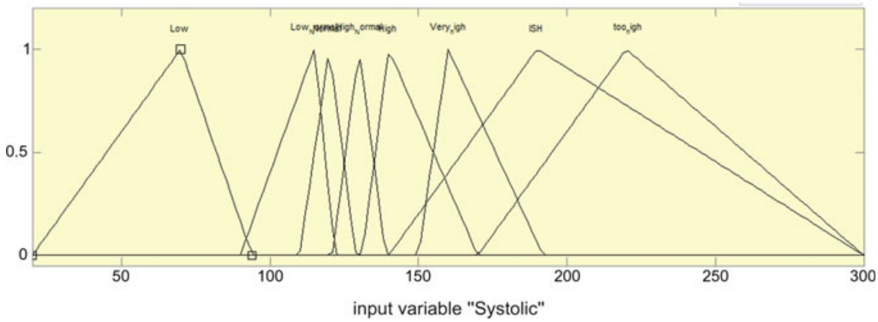

Fig. 2.4 Linguistic variable and membership functions of "Systolic"

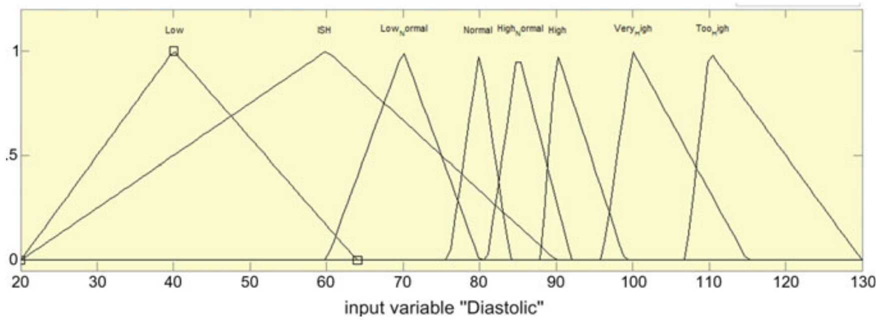

Fig. 2.5 Linguistic variable and membership functions of the input "Diastolic"

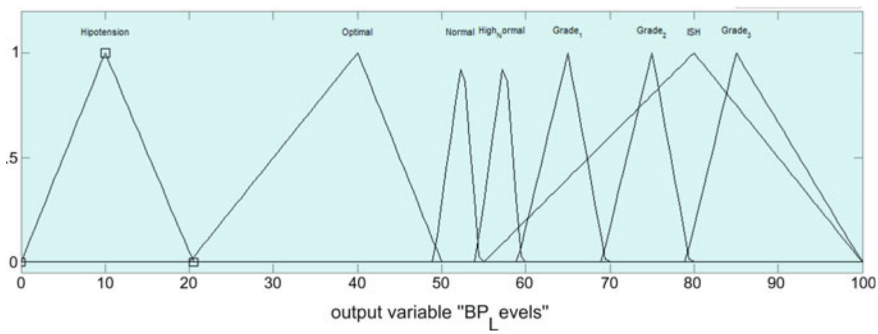

Fig. 2.6 Linguistic variable and membership functions of the output “BP_level”

1. If (Systolic is Low) and (Diastolic is Low) then (BP_Levels is Hipotension) (1)
2. If (Systolic is Low_Normal) and (Diastolic is Low_Normal) then (BP_Levels is Optimal) (1)
3. If (Systolic is Normal) and (Diastolic is Normal) then (BP_Levels is Normal) (1)
4. If (Systolic is High_Normal) and (Diastolic is High_Normal) then (BP_Levels is High_Normal) (1)
5. If (Systolic is High) and (Diastolic is High) then (BP_Levels is Grade_1) (1)
6. If (Systolic is Very_high) and (Diastolic is Very_High) then (BP_Levels is Grade_2) (1)
7. If (Systolic is too_high) and (Diastolic is Too_High) then (BP_Levels is Grade_3) (1)
8. If (Systolic is ISH) and (Diastolic is ISH) then (BP_Levels is ISH) (1)
9. If (Systolic is Very_high) and (Diastolic is High) then (BP_Levels is Grade_2) (1)
10. If (Systolic is too_high) and (Diastolic is Very_High) then (BP_Levels is Grade_3) (1)
11. If (Systolic is too_high) and (Diastolic is High) then (BP_Levels is Grade_3) (1)
12. If (Systolic is High) and (Diastolic is Very_High) then (BP_Levels is Grade_2) (1)
13. If (Systolic is High) and (Diastolic is Too_High) then (BP_Levels is Grade_3) (1)
14. If (Systolic is Very_high) and (Diastolic is Too_High) then (BP_Levels is Grade_3) (1)

Fig. 2.7 Fuzzy rules of the fuzzy system for diagnosis of hypertension

pressure. First, the linguistic values and corresponding membership functions have been determined in the following figures: Fig. 2.3 shows the fuzzy system of diagnosis of hypertension, Fig. 2.4 shows the linguistic variable and membership functions of “Systolic”, Fig. 2.5 shows the linguistic variable and membership functions of the “Diastolic input, Fig. 2.6 shows the linguistic variable and membership functions of the “BP_level output.

Now we show in the following figures more details of the fuzzy system: Fig. 2.7 shows the rules of the fuzzy system for diagnosis of hypertension, Fig. 2.8 shows the results of the rules of the fuzzy system of diagnosis of hypertension and finally Fig. 2.9 shows the surface view of the fuzzy system for diagnosis of hypertension.

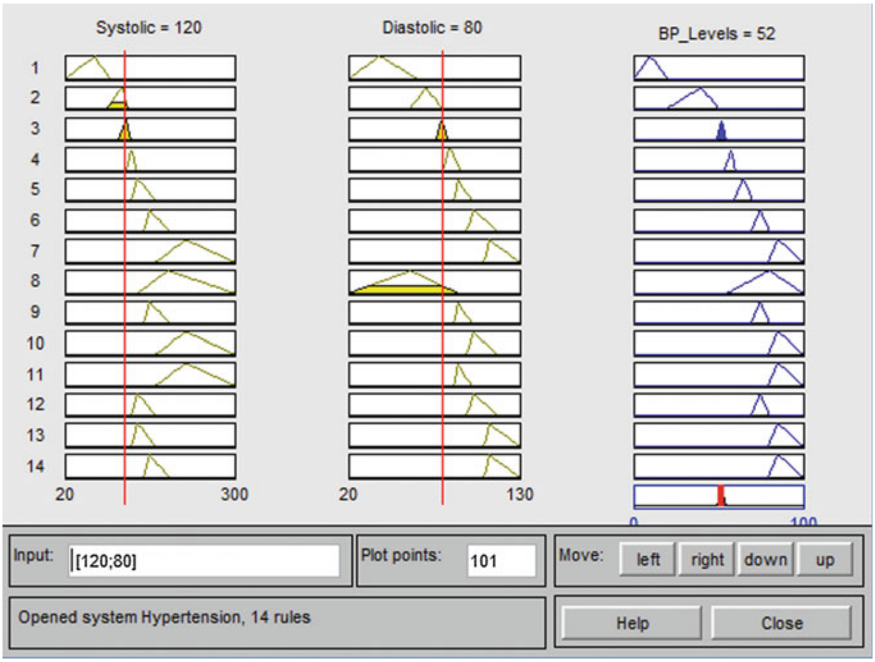

Fig. 2.8 The inference with the rules of the fuzzy system for diagnosis of hypertension

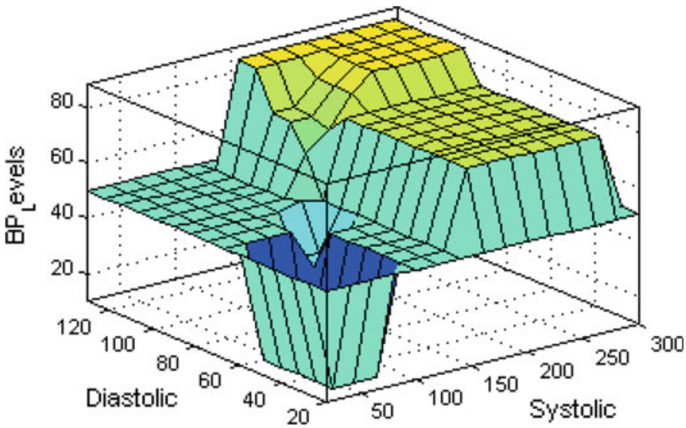

Fig. 2.9 Surface view of the fuzzy system for diagnosis of hypertension

2.5 Conclusions

This type of fuzzy systems actually implements human intelligence and reasoning. In this case, using a set of decision rules provides different suggestions for diagnosing diseases, in this case the classification levels of blood pressure. This is a very efficient, less time consuming and more accurate method to determine the level of hypertension. Finally, we can notice that is a very effective method for diagnosis of hypertension, which can help a physician to get a better accuracy when giving a diagnosis to the patient.

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Chapter 3
Design of a Neuro-Fuzzy System for Diagnosis of Arterial Hypertension

Abstract We propose a neuro-fuzzy hybrid model for the diagnosis of high blood pressure or hypertension to provide a diagnosis as accurate as possible based on intelligent computing techniques, such as neural networks and fuzzy logic. The neuro-fuzzy model uses a modular architecture, which works with different number of layers and different learning parameters so we can have a more accurate modeling. So for the better diagnosis and treatment of hypertension patients, an intelligent and accurate system is needed. In this study, we also design a fuzzy expert system to diagnose blood pressure for different patients. The fuzzy expert system is based on a set of inputs and rules. The input variables for this system are the systolic and diastolic pressures and the output variable is the blood pressures level. It is expected that this proposed neuro-fuzzy hybrid model can provide a faster, cheaper and more accurate result.

Keywords Fuzzy system · Blood pressure · Diagnosis

3.1 Introduction

Nowadays different techniques of artificial intelligence, such as fuzzy systems, neural networks and evolutionary computation, are used in the areas of medicine. One of the most important problems in medicine is hypertension diagnosis. Hypertension is one of the most dangerous diseases that seriously threaten the health of people around the world.

One of the most dangerous aspects of HBP is that people perhaps may not know they have it. In fact, nearly a third of the people with HBP do not know. The only way to know if the blood pressure is high is through regular checkups.

Today in Medicine various modeling approaches have been applied to diagnose some future illness of patients and to treat them in time. This is why the implementation of an appropriate method of modeling has always been a major issue in Medicine, because it helps to deal with diseases in time and saves lives. The modeling of future data for medicine provides the ability to make decisions in the

P. Melin and G. Prado-Arechiga, *New Hybrid Intelligent Systems for Diagnosis and Risk Evaluation of Arterial Hypertension*, SpringerBriefs in Computational Intelligence, DOI 10.1007/978-3-319-61149-5_3

medium and long term due to the accuracy or inaccuracy of modeled data and provide better control in the health of any patient.

For a doctor, it is important to know the future behavior of blood pressure for a patient and to make correct decisions that will improve the patient's health and avoid unwanted situations that in the worst case can lead to early death of a person for not having a proper treatment to control blood pressure.

Therefore in this work, blood pressure monitoring tests were performed to 20 people for 6 days with 4 daily intakes at the same time, with different activities in their daily lives to have data with different settings, so we can reach a more concrete conclusion on the fuzzy system when making an accurate diagnosis based on information previously obtained through daily neuro monitoring system. Experiments with different neural network architectures are performed, and thus it was determined, which provided the optimal behavior for prognosis [11].

The idea of using modular neural networks was to divide the information of the systolic and diastolic pressure, as they are complementary to provide a result, and they need to be analyzed separately to yield a better prognosis and thereby obtain better results. Designing an appropriate modular neural network to model the behavior of the blood pressure, using time series, it is with the aim that we can provide results to help decision-making necessary in the future regarding the diagnosis of blood pressure [1].

In the current literature there are papers where they aim at achieving a good diagnosis of blood pressure [4], like in the paper Hypertension Diagnosis using Fuzzy Expert System [8]. The design of a fuzzy expert system to diagnose hypertension for different patients is studied in the paper Genetic Neuro Fuzzy System for Hypertension Diagnosis [7]. This paper proposes and evaluates Genetic Neuro Fuzzy System for diagnosing Hypertension risk Systolic and Diastolic Blood Pressure, Body Mass Index, Heart Rate, Cholesterol, Glucose, Blood Urea, Creatinine and Uric Acid have been taken as inputs to the system. In the paper, Fuzzy Expert System for Fluid Management in General Anesthesia [12] studies the contradictory natures as common facts. Anesthetists use rules of thumb when managing patients. In Article A Neuro-Fuzzy Approach to FMOLP Problems [6] propose the use of fuzzy neural networks for finding a good compromise solution to fuzzy multiple objective linear programs. In the paper Fuzzy expert system for the management of hypertension [5] focused on the use of information and communication technology (ICT) to design a web-based fuzzy expert system for the management of hypertension using the fuzzy logic approach. In Medicine, often on the borderline between science and art, is an excellent exponent: vagueness, linguistic uncertainty, hesitation, measurement imprecision, natural diversity, subjectivity all these are prominently present in medical diagnosis, in the paper Fuzzy Medical Diagnosis [9]. In Article Can Fuzzy Logic Make Things More Clear [10], studies the Clinical decision support and artificial intelligence using fuzzy logic and closed loop techniques are methods that might help us to handle this complexity in a safe, effective and efficient way. In the work entitled "Neuro-Fuzzy and Soft

Computing" by Jang et al. [11], it collects in one place, in consistent notation, all of the information on computational Intelligence (CI), such as Neural Networks (NN), Fuzzy Logic (FL), and Genetic Algorithms (GA). In article of an Experimental Study of Intelligent Computer Aided Diagnostic and Therapy [2] the limitations of the conventional methods for the diagnosis of diseases have been highlighted. In the article of Design and development of Fuzzy Expert System for diagnosis of hypertension [3] present an interesting study. The aim of this study is to design a Fuzzy Expert System (FES) for diagnosis of hypertension risk for patients aged between 20's, 30's and 40's years and is divided into male and female gender. In the article A Note on Hypertension Classification Scheme and Soft Computing Decision Making System [13], a soft computing diagnostic support system for the risk assessment of hypertension is proposed. The work entitled Pre-diagnosis of hypertension using artificial neural network [14], deals with Artificial Neural Networks solving the problems of diagnosing hypertension using Backpropagation learning algorithm. The network is constructed using various factors which are classified into some categories, to be trained tested and validated using the respective data sets.

This chapter is organized as follows: in Sect. 3.2 a methodology of hypertension is presented, in Sect. 3.3 the Development and final design of the neural-fuzzy hybrid model is presented, in Sect. 3.4 the conclusion obtained after the tests with the neuro-fuzzy hybrid model for blood pressure diagnosis is presented.

3.2 Methodology

3.2.1 Blood Pressure

Blood pressure is needed to deliver oxygen and nutrients to body organs. In the human body the blood circulates through the blood vessels. They are mainly arteries and veins. The blood flowing through the vessels constantly exerts pressure on the vessel walls. The pressure is determined by the heart's pumping strength and elasticity of the vessels.

In general, the heart contracts and expands again, on average, 60–80 times per minute. This pressure pumps blood into the arteries to deliver oxygen and nutrients to body organs. The blood vessels branch more and more to become capillary blood vessels (capillaries). This offers more or less resistance to blood stream, if you have enough pressure.

The pressure is the highest at the time of the heartbeat, when the heart contracts. This pressure is known as systolic blood pressure. The contraction phase of the heart which increases blood pressure is called systolic. Blood pressure is low between two heartbeats, that is, when the heart muscle relaxes. Blood pressure at this point is called diastolic blood pressure. The phase in which the heart relaxes and blood pressure decreases is called diastole.

Blood pressure is measured in mmHg. For example: 120/80 mmHg means that the systolic blood pressure is 120 mmHg and diastolic blood pressure of 80.

3.2.2 Low Blood Pressure (Hypotension)

Unlike hypertension, hypotension is not life threatening and does not cause other potentially serious diseases. It helps protect against many cardiovascular diseases, such as heart attack or stroke.

However, people with low blood pressure (hypotension) may also exhibit symptoms, which can make them suffer sometimes of dizziness; impaired concentration and fatigue are also possible symptoms. In addition, mental performance can be affected. Healthy people who have low blood pressure may have trouble concentrating and can be reacting more slowly.

The so-called primary hypotension (essential) is the most common form of low blood pressure and is not classified as a disease. It occurs mainly in young women.

Basically, low blood pressure can be considered as a simple measured value and not a disease. The World Health Organization (WHO) has defined as less than 100/60 mmHg in women and less than 110/70 mmHg in men as low blood pressure (hypotension) . However, the appearance of these symptoms with these values depends on the individuals. Particularly sensitive individuals may also experience dizziness and lightheadedness with higher values.

3.2.3 High Blood Pressure (Hypertension)

Blood pressure increases with the increasing pumping power of the heart or when blood vessels contract. High blood pressure (hypertension) is a disease of the cardiovascular system. Increased blood pressure is widespread, particularly in industrialized countries.

The risk of hypertension increases with age. However, hypertension can also be suffered by young people. Hypertension can also be caused by hormones, such as adrenaline and noradrenaline, but also because of kidney disease or drugs.

However, in 95% of the cases, the hypertension has no obvious organic cause. Physical inactivity, obesity, excessive alcohol or salt and stress are the most common causes of hypertension, initially, hypertension has no symptoms. Often, people affected do not perceive it. More than half of those affected do not know they are part of the group of hypertensive patients. This is dangerous, since a permanently high blood pressure increases the risk of damage to vital organs such as heart, brain, kidneys and eyes. Some possible consequences are myocardial infarction, heart failure, stroke, kidney failure, and vision loss [9].

3.3 Development and Final Design of the Neuro Fuzzy Hybrid Model

In Fig. 3.1 the neuro-fuzzy hybrid model is illustrated in which we have as input the values of the blood pressure of a person, which are divided into systolic and diastolic pressure, and are for 24 samples. These values enter the neural network as two inputs, the first one is the systolic and the diastolic is the second, once they enter the network and the process of learning and prediction is performed two outputs are obtained, which are introduced as inputs to the fuzzy system are obtained. Once the systolic and diastolic blood pressures are used in the fuzzy system, this in turn classifies the information and produces a final diagnosis, and this is finally sent to the Graphical Unit Interface (GUI).

Finally, once we have the fuzzy system and a well-defined architecture of the modular neural network, we can continue with the GUI in which we work combining the above mentioned techniques of intelligent computing.

First we show in Fig. 3.2 the GUI of the final neuro fuzzy hybrid model, where we are able to add the Excel file with the data of the patients, and this shows the information in a graphic as it is shown in Figs. 3.3 and 3.4. Figure 3.4 shows the modeling of the systolic and diastolic pressures and finally Fig. 3.5 shows the final results, such as the fuzzy system output values and diagnosis.

Figure 3.3 shows the graphic interface and the select file window, which has the information to be simulated and used for modeling of blood pressure.

Figure 3.4 shows the graphic interface with the models of the systolic and diastolic pressures.

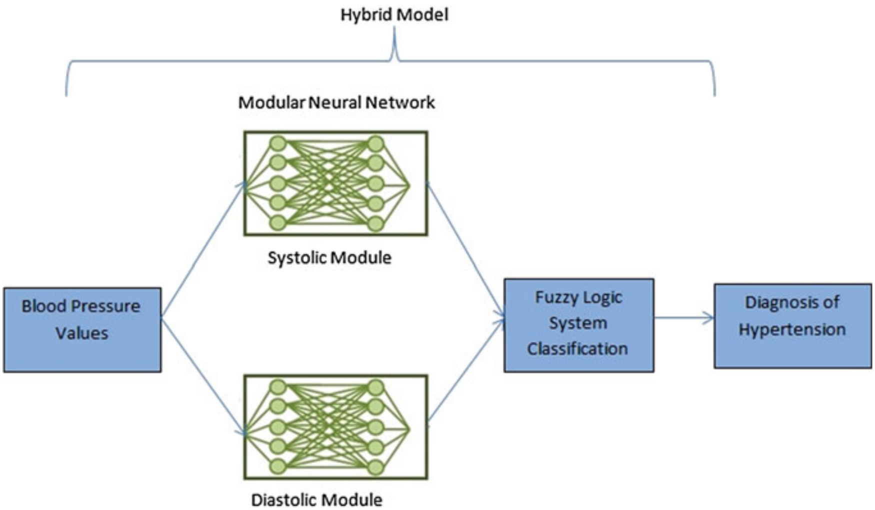

Fig. 3.1 Neuro fuzzy hybrid model

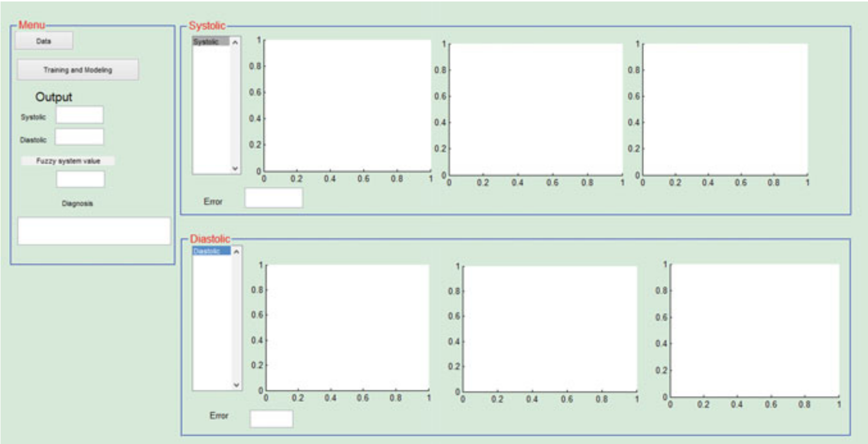

Fig. 3.2 Final GUI of the neuro fuzzy hybrid model

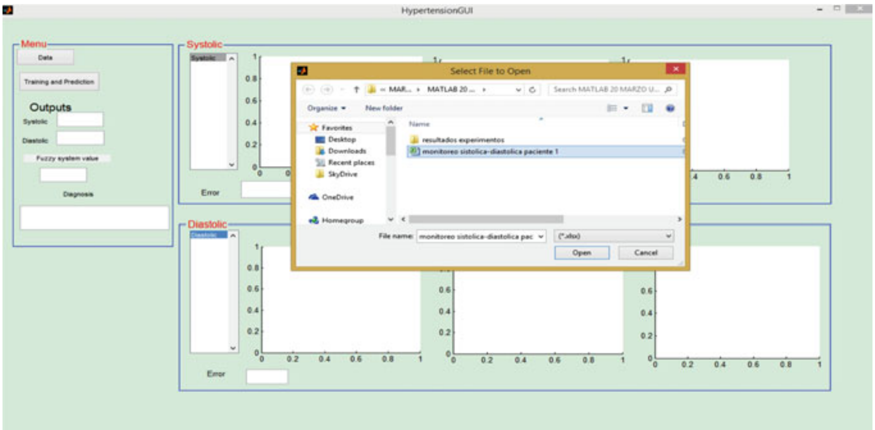

Fig. 3.3 Graphic interface and select file window

Figure 3.5 shows the graphic user interface with the modeling of the monitoring of blood pressure of a patient, which is based on the provided information. The modeling of new data is obtained, and the results of the modeling are the systolic and diastolic pressure and this information is the input to the fuzzy system.

Once the training process and modeling are done, the graphical interface displays the following information, as shown in Fig. 3.5, in which we have the "systolic" and "diastolic" pressures, while the outputs are modeled in 3 parts. The first graph is modeling the inputs, the second graph shows the training and the third graph shows the modeling of new data, and finally the interface shows the fuzzy output result and diagnosis.

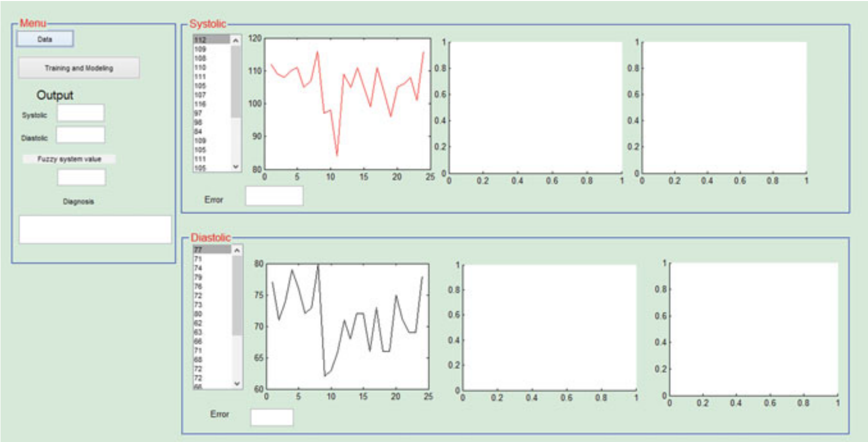

Fig. 3.4 Modeling the systolic and diastolic inputs to the modular neural network

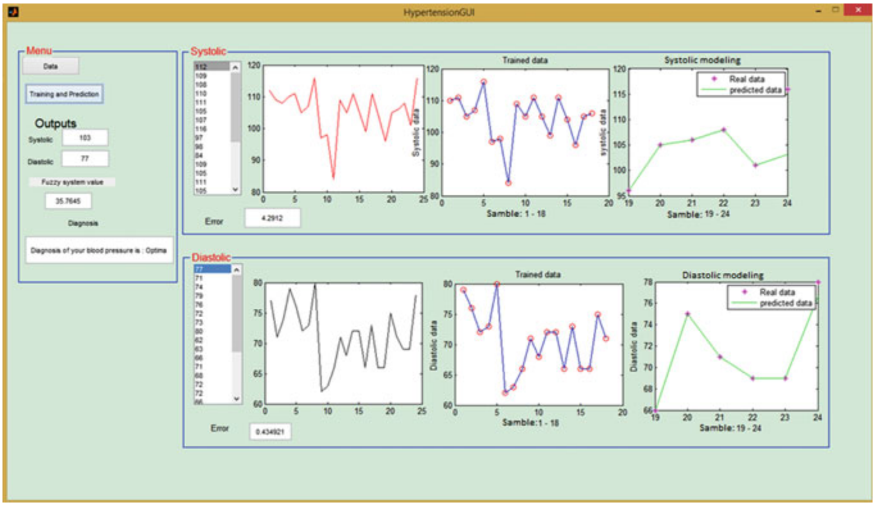

Fig. 3.5 Training, modeling and results of the diagnosis of blood pressure

3.4 Conclusions

This type of fuzzy systems actually implements the human intelligence and reasoning. Using a set of decision rules, we can provide different suggestions for diagnosing diseases, in this case hypertension. This is a very efficient, less time consuming and more accurate method to calculate the risk of hypertension. Finally, we can note that is a very effective method for a diagnosis of hypertension, which can help a physician to achieve a better accuracy when giving a diagnosis to the patient.

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Chapter 4
Neuro-Fuzzy Modular Approaches for Classification of Arterial Hypertension with a Method for the Expert Rules Optimization

Abstract A Neuro fuzzy hybrid model (NFHM) is used as a new Artificial Intelligence method to classify high blood pressure (HBP). The NFHM uses techniques such as: neural networks, fuzzy logic and evolutionary computation, in the last technique genetic algorithms (GAs) are used. The objective is to model the behavior of blood pressure based on monitoring data of 24 h per patient and to obtain the trend, which is classified using a fuzzy system based on rules given by an expert, these rules were optimized by a genetic algorithm to obtain the best possible number of rules for the classifier with the lowest classification error. Results are presented to show the advantage of the proposal model.

Keywords Neural networks · Genetic algorithms · Fuzzy logic · Blood pressure

4.1 Introduction

Recently different techniques of artificial intelligence, such as fuzzy systems and neural networks have increasingly been used in the medical areas [1–8]. We propose a neuro fuzzy hybrid model for the classification of blood pressure to provide a diagnosis as accurate as possible based on intelligent computing techniques, such as neural networks, fuzzy logic and genetic algorithm [9–11]. The neuro-fuzzy model uses a modular architecture, which works with different number of layers and different learning parameters so we can have a more accurate modeling. For better diagnosis and treatment of hypertension patients, an intelligent and accurate system is needed [12–14]. In this study, we also design a fuzzy expert system to diagnose high blood pressure for different patients. The fuzzy expert system is based on a set of inputs and rules. The input variables for this system are the systolic and diastolic pressures and the output variable is the blood pressures level. It is expected that this proposed neuro fuzzy hybrid model can provide a faster, cheaper and more accurate result [15]. We have some references of work done to diagnose blood pressure. First we have HBP diagnosis using fuzzy expert system [16], the second one is genetic

P. Melin and G. Prado-Arechiga, *New Hybrid Intelligent Systems for Diagnosis and Risk Evaluation of Arterial Hypertension*, SpringerBriefs in Computational Intelligence, DOI 10.1007/978-3-319-61149-5_4

neuro fuzzy system for Hypertension Diagnosis [17] and the third is Design of a Fuzzy Expert System [18] and a Multi-Layer Neural Network System for Diagnosis of Hypertension [19].

The implementation of an appropriate method for modeling has always been a major concern for the physician that seeks the best diagnosis possible for the patients. Hypertension diagnosis is a very important problem in medicine. Hypertension is a dangerous disease that seriously threatens the health of persons. This disease often leads to fatal results, such as [6, 20]:

- Heart attack
- Cerebrovascular accident
- Renal insufficiency.

The main dangerous aspect of HBP is that the persons may not know they have this disease, about one-third of the people with high blood pressure do not know it. The regular checkups, is the only way to know if the blood pressure is high.

Nowadays in medicine is very common to use modeling approaches applied to diagnose some future illness and to treat them in the best way possible. The reason of the implementation of an appropriate method of modeling has always been an important topic in medicine, because it helps to treat diseases in time and save lives. The future data are modeled in medicine to help make decisions in the medium and long term due to the accuracy or inaccuracy of the modeled data and helps to have a better control in the health of the patient.

For a physician, it is important to know the future behavior of blood pressure for a patient, since this allows him to have a better notion to make correct decisions that improve the patient's health and avoid future problems which can lead to a premature death, due to not have an adequate treatment to control the blood pressure.

The chapter is organized as follows: In Sect. 4.2 the problem statement and the proposed method are presented, Sect. 4.3 shows the simulation results of the proposed method, Sect. 4.4 presents the comparison of results and Sect. 4.5 offers the conclusions.

4.2 Problem Statement and Proposed Method

Therefore, in this study, 30 patients were monitored for 24 h and 45 samples were obtained throughout the day per patient, each patient has different types of activities in their daily life and this helps us to have different cases in each person, and this gives us a better reliability when we use the classifier for the diagnosis depending on the level of blood pressure that each patient have. In the fuzzy system when doing a diagnosis based on the information obtained that is the trend of the information, the experiments of the 30 patients were provided to the neural network to find the degree of accuracy in the classification at each of the blood pressure levels [21].

Modular neural networks were used to provide the input information, which are the systolic and diastolic pressures and are obtained for each patient, each one enters to a module of the modular neural network, then learns and models the information to finally give a tendency which will be sent to the fuzzy system to classify it in the best way and give a correct diagnosis and help the doctor to the decision making of each patient [20, 22].

4.2.1 Blood Pressure

Blood pressure is the force that the blood exerts against the walls of the arteries. When the heart beats, it pumps blood to the arteries, this is when its pressure is higher and it is called systolic pressure. When the heart is at rest between one beat and another, the blood pressure decreases and this is called diastolic pressure.

Both systolic and diastolic blood pressure is used in blood pressure. In general, the systolic pressure is mentioned first and then the diastolic. A reading with values of:

- 119/79 or less is considered normal blood pressure
- 140/90 or higher is considered high blood pressure.

Between 120 and 139 for the highest number, or between 80 and 89 for the lowest number is pre-hypertension. In this case, pre-hypertension means that someone can develop high blood pressure unless action is taken.

High blood pressure does not usually have symptoms, but can cause serious problems, such as strokes, heart failure, infarction, and kidney failure.

A person can control the blood pressure with a healthy lifestyle like exercise and DASH diet and, if necessary, medications.

4.2.2 Type of Blood Pressure Diseases

Hypertension is the most common disease and increases both morbidity and mortality from cardiovascular diseases. Different types of hypertension are seen when the disease is sub-categorized. These types are shown in Table 2.1 in Chap. 2.

4.2.3 Hypotension

Low blood pressure, also known as hypotension, would be thought of as unimportant. However, for many people, hypotension can cause symptoms of dizziness and fainting. In more severe cases, low blood pressure can be life threatening.

Blood pressure varies from person to person, a blood pressure reading of 90 mmmillimeters of mercury (mm Hg) or less of systolic blood pressure (the highest number on a blood pressure reading) or 60 mm Hg or lower diastolic blood pressure (The lower number) is usually considered as low blood pressure.

Causes of hypotension can range from dehydration to serious medical or surgical disorders. Low blood pressure can be treated, but it is important to know what is causing the disease so that it can be treated properly.

4.2.4 Hypertension

High blood pressure is a chronic condition that involves increasing blood pressure. One of the characteristics of this disease is that no clear presentations of the symptoms are seen and that these do not manifest for a long time.

At present, cardiovascular diseases are the leading cause of mortality in Spain. However, hypertension is a treatable condition. Failure to follow the doctor's recommendations can lead to serious complications, such as a myocardial infarction, bleeding or cerebral thrombosis, which can be avoided if properly controlled.

The first consequences of hypertension are suffered by the arteries, which harden a measure that supports high blood pressure continuously, become thicker and can spoil the passage of blood through them. This is known as arteriosclerosis.

4.2.5 Risk Factors

The Risk factors for hypertension are the following [16]:

- Sex
- Genetic factors
- Stress level
- Consumption of alcohol
- Smoking
- Consumption of salt
- Obesity
- Lack of exercise
- Age.

4.2.6 Modular Neural Network Model for Classification of BP

The modular neural network consist in the following parameters: 3 modules, number of layers of 1–3, neurons number of 1–20, to train the modular neural

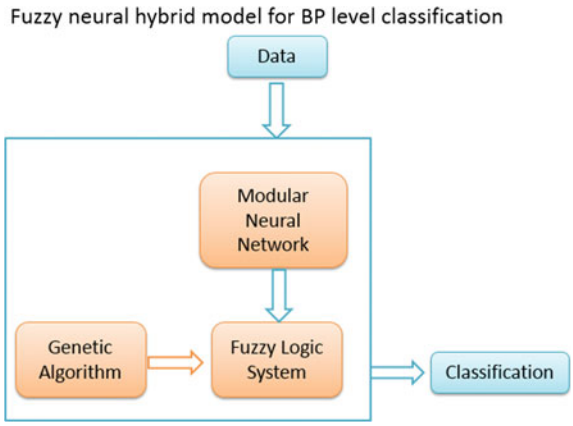


Fig. 4.1 General neuro fuzzy hybrid model

network: 1000 epochs, learning rate of =0.01, the error goal 0.0000001, 3 delays with the 70% of the data and training method of Levenberg-Marquardt (trainlm) [17, 23–26].

Figure 4.1 shows the general neuro-fuzzy hybrid model in which we have as input the data of the blood pressure of a person, these values enter the neural network and two outputs are obtained, which are introduced as inputs to the fuzzy system that is optimized with a genetic algorithm to get better results as a final diagnosis. In Fig. 4.2 shows the specific neuro-fuzzy hybrid in which it shows how the model works in a specific way.

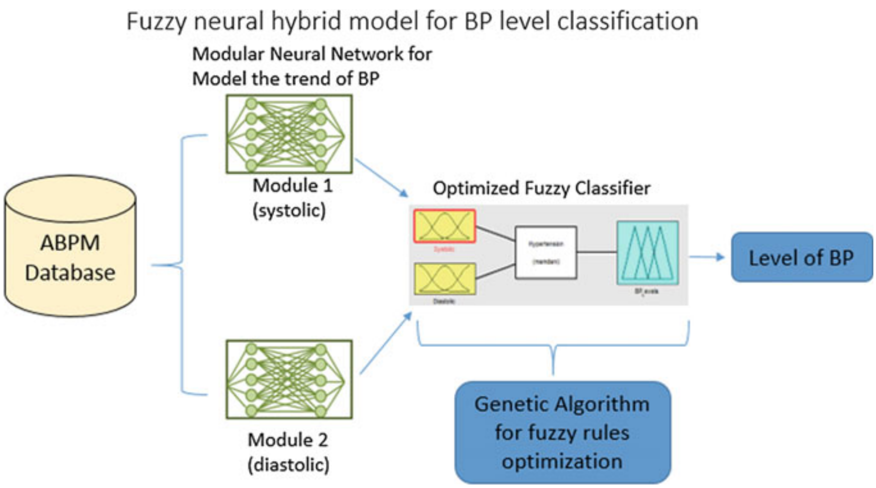


Fig. 4.2 Specific neuro fuzzy hybrid model

4.2.7 Design of the Fuzzy Systems for the Classification

4.2.7.1 Design of the Fuzzy Classifier 1

Throughout the performed tests with the neuro-fuzzy hybrid model, we have been improving the fuzzy classifier, which we first had as a fuzzy system with two inputs, which are the systolic and diastolic with eight membership functions each and an output with eight membership functions, 14 fuzzy rules, and of Mamdani type.

In the first input called systolic, the range is from 20 to 300, in the second input called diastolic, the range is from 20 to 130 and at the output we have blood pressure levels such as Hypotension, Optimal, Normal, High Normal, Grade 1 hypertension, Grade 2 hypertension, Grade 3 hypertension and isolated systolic hypertension; we specify each of the ranges in the fuzzy rules. Figure 4.3 shows the first fuzzy classifier:

The Fuzzy rules for the first classifier of blood pressure levels are:

1. If (Systolic is Low) and (Diastolic is Low) then (BP_Levels is Hypotension) (1)
2. If (Systolic is Low_Normal) and (Diastolic is Low_Normal) then (BP_Levels is Optimal) (1)

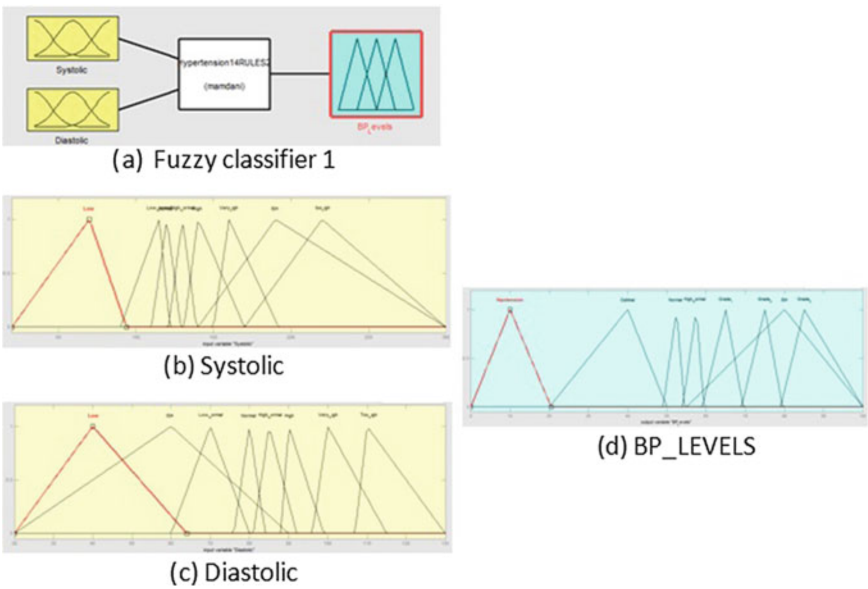


Fig. 4.3 First fuzzy logic system for the classification of blood pressure levels. **a** Structure of the fuzzy logic classifier 1. **b** Systolic input for the fuzzy logic classifier. **c** Diastolic input for the fuzzy logic classifier. **d** BP_LEVELS is the output of the fuzzy logic classifier

3. If (Systolic is Normal) and (Diastolic is Normal) then (BP_Levels is Normal) (1)
4. If (Systolic is High_Normal) and (Diastolic is High_Normal) then (BP_Levels is High_Normal) (1)
5. If (Systolic is High) and (Diastolic is High) then (BP_Levels is Grade_1) (1)
6. If (Systolic is Very_high) and (Diastolic is Very_High) then (BP_Levels is Grade_2) (1)
7. If (Systolic is too_high) and (Diastolic is Too_High) then (BP_Levels is Grade_3) (1)
8. If (Systolic is ISH) and (Diastolic is ISH) then (BP_Levels is ISH) (1)
9. If (Systolic is Very_high) and (Diastolic is High) then (BP_Levels is Grade_2) (1)
10. If (Systolic is too_high) and (Diastolic is Very_High) then (BP_Levels is Grade_3) (1)
11. If (Systolic is too_high) and (Diastolic is High) then (BP_Levels is Grade_3) (1)
12. If (Systolic is High) and (Diastolic is Very_High) then (BP_Levels is Grade_2) (1)
13. If (Systolic is High) and (Diastolic is Too_High) then (BP_Levels is Grade_3) (1)
14. If (Systolic is Very_high) and (Diastolic is Too_High) then (BP_Levels is Grade_3).

4.2.7.2 Design of the Fuzzy Classifier 2

The second fuzzy system with two inputs, which are systolic and diastolic with seven membership functions each and an output with ten membership functions, 24 fuzzy rules based on an expert, and of Mamdani type.

In the first input called systolic, the range is from 20 to 300, in the second input called diastolic, the range is from 20 to 130 and at the output we have blood pressure levels such as Hypotension, Optimal, Normal, High Normal, Grade 1 hypertension, Grade 2 hypertension, Grade 3 hypertension and isolated systolic hypertension grade 1, isolated systolic hypertension grade 2 and isolated systolic hypertension grade 3, we specify each of the ranges in the fuzzy rules. Figure 4.4 illustrates the second fuzzy classifier:

The Fuzzy rules for the second classifier of blood pressure levels are:

1. If (Systolic is Low) and (Diastolic is Low) then (BP_Levels is Hypotension)
2. If (Systolic is Low_Normal) and (Diastolic is Low_Normal) then (BP_Levels is Optimal)
3. If (Systolic is Normal) and (Diastolic is Normal) then (BP_Levels is Normal)
4. If (Systolic is Normal) or (Diastolic is Normal) then (BP_Levels is Normal)
5. If (Systolic is High_Normal) and (Diastolic is High_Normal) then (BP_Levels is High_Normal)

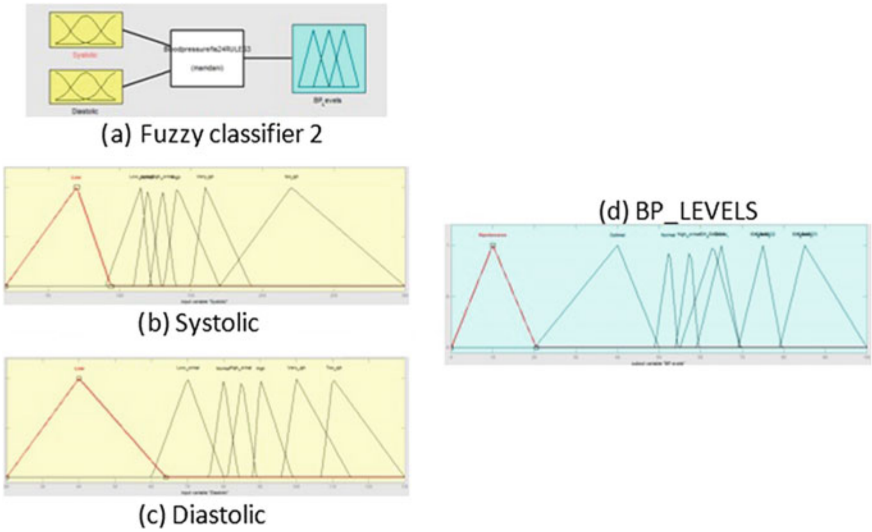


Fig. 4.4 Second fuzzy logic system for the classification of blood pressure levels. **a** Structure of the fuzzy logic classifier number 2. **b** Systolic input for the fuzzy logic classifier 2. **c** Diastolic input for the fuzzy logic classifier 2. **d** BP_LEVELS is the output of the fuzzy logic classifier 2

6. If (Systolic is High_Normal) or (Diastolic is High_Normal) then (BP_Levels is High_Normal)
7. If (Systolic is High) and (Diastolic is High) then (BP_Levels is Grade_1)
8. If (Systolic is High) or (Diastolic is High) then (BP_Levels is Grade_1)
9. If (Systolic is Very_high) and (Diastolic is Very_High) then (BP_Levels is Grade_2)
10. If (Systolic is Very_high) or (Diastolic is Very_High) then (BP_Levels is Grade_2)
11. If (Systolic is too_high) and (Diastolic is Too_High) then (BP_Levels is Grade_3)
12. If (Systolic is too_high) or (Diastolic is Too_High) then (BP_Levels is Grade_3)
13. If (Systolic is Very_high) and (Diastolic is High) then (BP_Levels is Grade_2)
14. If (Systolic is too_high) and (Diastolic is Very_High) then (BP_Levels is Grade_3)
15. If (Systolic is too_high) and (Diastolic is High) then (BP_Levels is Grade_3)
16. If (Systolic is High) and (Diastolic is Very_High) then (BP_Levels is Grade_2)
17. If (Systolic is High) and (Diastolic is Too_High) then (BP_Levels is Grade_3)
18. If (Systolic is Very_high) and (Diastolic is Too_High) then (BP_Levels is Grade_3)

19. If (Systolic is High) and (Diastolic is Normal) then (BP_Levels is ISH_GRADE1)
20. If (Systolic is High) and (Diastolic is High_Normal) then (BP_Levels is ISH_GRADE1)
21. If (Systolic is Very_high) and (Diastolic is Normal) then (BP_Levels is ISH_GRADE2)
22. If (Systolic is Very_high) and (Diastolic is High_Normal) then (BP_Levels is ISH_GRADE2)
23. If (Systolic is too_high) and (Diastolic is Normal) then (BP_Levels is ISH_GRADE3)
24. If (Systolic is too_high) and (Diastolic is High_Normal) then (BP_Levels is ISH_GRADE3).

Design of the Fuzzy Classifier 3

In the third fuzzy system, it was decided to do it with the total number of possible rules based on the number of membership functions of the inputs and using the product of this, it was obtained that would be 49 fuzzy rules. The purpose of this fuzzy system is to test with the total of possible rules and then to optimize this fuzzy system with genetic algorithms, to find the number of optimal rules through the classification error.

The number of rules in a complete set of rules is equal to:

$$\prod_{i=1}^{n} m_i$$

where m_i, is the number of membership functions for input i and n is the number of inputs.

The third fuzzy classifier has two inputs which are systolic and diastolic with seven membership functions each and an output with ten membership functions, 49 fuzzy rules which are all possible, Mamdani type.

In the first input called systolic, the range is from 20 to 300, in the second input called diastolic, the range is from 20 to 130 and at the output we have blood pressure levels such as Hypotension, Optimal, Normal, High Normal, Grade 1 hypertension, Grade 2 hypertension, Grade 3 hypertension and isolated systolic hypertension grade 1, isolated systolic hypertension grade 2 and isolated systolic hypertension grade 3, we specify each of the ranges in the fuzzy rules. Figure 4.5 shows the third fuzzy classifier:

The Fuzzy rules for the third classifier of blood pressure levels are:

1. If (Systolic is Low) and (Diastolic is Low) then (BP_Levels is Hypotension)
2. If (Systolic is Low_Normal) and (Diastolic is Low_Normal) then (BP_Levels is Optimal)

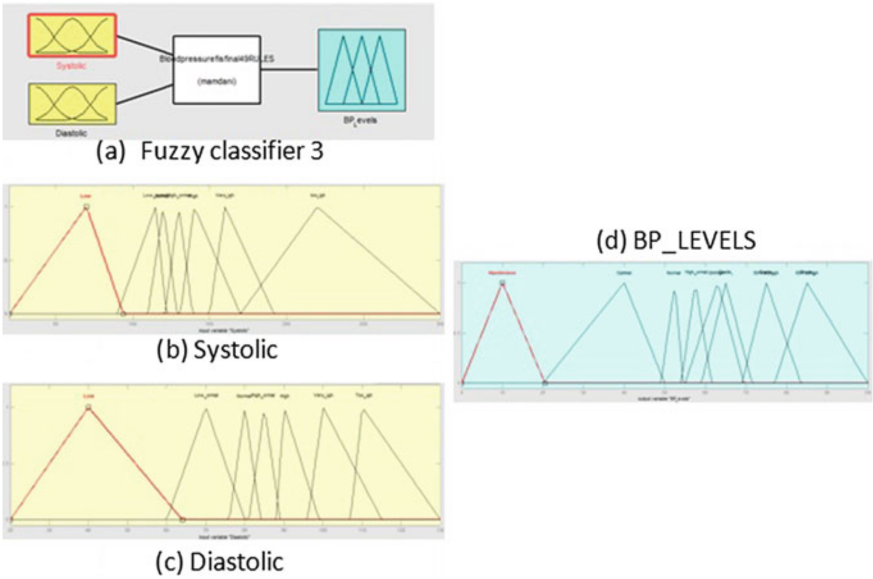


Fig. 4.5 Third fuzzy logic system for the classification of blood pressure levels. **a** Structure of the fuzzy logic classifier 3. **b** Systolic input for the fuzzy logic classifier 3. **c** Diastolic input for the fuzzy logic classifier 3. **d** BP_LEVELS is the output of the fuzzy logic classifier 3

3. If (Systolic is Normal) and (Diastolic is Normal) then (BP_Levels is Normal)
4. If (Systolic is High_Normal) and (Diastolic is High_Normal) then (BP_Levels is High_Normal)
5. If (Systolic is High) and (Diastolic is High) then (BP_Levels is Grade_1)
6. If (Systolic is Very_high) and (Diastolic is Very_High) then (BP_Levels is Grade_2)
7. If (Systolic is too_high) and (Diastolic is Too_High) then (BP_Levels is Grade_3)
8. If (Systolic is Very_high) and (Diastolic is High) then (BP_Levels is Grade_2)
9. If (Systolic is too_high) and (Diastolic is Very_High) then (BP_Levels is Grade_3)
10. If (Systolic is too_high) and (Diastolic is High) then (BP_Levels is Grade_3)
11. If (Systolic is High) and (Diastolic is Very_High) then (BP_Levels is Grade_2)
12. If (Systolic is High) and (Diastolic is Too_High) then (BP_Levels is Grade_3)
13. If (Systolic is Very_high) and (Diastolic is Too_High) then (BP_Levels is Grade_3)

14. If (Systolic is High) and (Diastolic is Normal) then (BP_Levels is ISHGRADE_1)
15. If (Systolic is High) and (Diastolic is High_Normal) then (BP_Levels is ISHGRADE_1)
16. If (Systolic is Very_high) and (Diastolic is Normal) then (BP_Levels is ISHGRADE_2)
17. If (Systolic is Very_high) and (Diastolic is High_Normal) then (BP_Levels is ISHGRADE_2)
18. If (Systolic is too_high) and (Diastolic is Normal) then (BP_Levels is ISHGRADE_3)
19. If (Systolic is too_high) and (Diastolic is High_Normal) then (BP_Levels is ISHGRADE_3)
20. If (Systolic is Low) and (Diastolic is Low_Normal) then (BP_Levels is Optimal)
21. If (Systolic is Low) and (Diastolic is Normal) then (BP_Levels is Normal)
22. If (Systolic is Low) and (Diastolic is High_Normal) then (BP_Levels is High_Normal)
23. If (Systolic is Low) and (Diastolic is High) then (BP_Levels is Grade_1)
24. If (Systolic is Low) and (Diastolic is Very_High) then (BP_Levels is Grade_2)
25. If (Systolic is Low) and (Diastolic is Too_High) then (BP_Levels is Grade_3)
26. If (Systolic is Normal) and (Diastolic is Low) then (BP_Levels is Normal)
27. If (Systolic is Normal) and (Diastolic is Low_Normal) then (BP_Levels is Normal)
28. If (Systolic is Normal) and (Diastolic is High_Normal) then (BP_Levels is High_Normal)
29. If (Systolic is Normal) and (Diastolic is High) then (BP_Levels is Grade_1) (1)
30. If (Systolic is Normal) and (Diastolic is Very_High) then (BP_Levels is Grade_2)
31. If (Systolic is Normal) and (Diastolic is Too_High) then (BP_Levels is Grade_3)
32. If (Systolic is High) and (Diastolic is Low) then (BP_Levels is Grade_1)
33. If (Systolic is High) and (Diastolic is Low_Normal) then (BP_Levels is Grade_1)
34. If (Systolic is Very_high) and (Diastolic is Low) then (BP_Levels is Grade_2)
35. If (Systolic is Very_high) and (Diastolic is Low_Normal) then (BP_Levels is Grade_2)
36. If (Systolic is too_high) and (Diastolic is Low) then (BP_Levels is Grade_3)
37. If (Systolic is too_high) and (Diastolic is Low_Normal) then (BP_Levels is Grade_3)
38. If (Systolic is Low_Normal) and (Diastolic is Low) then (BP_Levels is Optimal)

39. If (Systolic is Low_Normal) and (Diastolic is High_Normal) then (BP_Levels is High_Normal)
40. If (Systolic is Low_Normal) and (Diastolic is Very_High) then (BP_Levels is Grade_2)
41. If (Systolic is Low_Normal) and (Diastolic is Too_High) then (BP_Levels is Grade_3)
42. If (Systolic is Low_Normal) and (Diastolic is Normal) then (BP_Levels is Normal)
43. If (Systolic is Low_Normal) and (Diastolic is High) then (BP_Levels is Grade_1)
44. If (Systolic is High_Normal) and (Diastolic is Low) then (BP_Levels is High_Normal)
45. If (Systolic is High_Normal) and (Diastolic is Low_Normal) then (BP_Levels is High_Normal)
46. If (Systolic is High_Normal) and (Diastolic is Normal) then (BP_Levels is High_Normal)
47. If (Systolic is High_Normal) and (Diastolic is High) then (BP_Levels is Grade_1)
48. If (Systolic is High_Normal) and (Diastolic is Very_High) then (BP_Levels is Grade_2)
49. If (Systolic is High_Normal) and (Diastolic is Too_High) then (BP_Levels is Grade_3).

4.2.8 The Optimization of the Fuzzy System Using a Genetic Algorithm (GA)

After realizing the three fuzzy systems we decided to optimize the classifier number 3 and compare it with the classifier 2, which has fuzzy rules based on an expert, for which we use an optimization algorithm, in this case a genetic algorithm. Where in this case we optimize the fuzzy system, as shown in the Fig. 4.6 and the chromosome has 122 genes, which help us to optimize the structure of the fuzzy system in this case fuzzy rules and membership functions, Genes 1–72 (real numbers) allow to manage the parameters of the membership functions for inputs and output, genes 73–121 are the rules. The gene 122 allows reducing the number of rules, activating or deactivating them. In Fig. 4.6 we show the structure of the chromosome for the rules optimization in the classifier [5, 9–11, 16].

The parameters used in the algorithm are generations: 100, population: 100, selection: roulette, mutation: 0.06 crossing: 0.5.

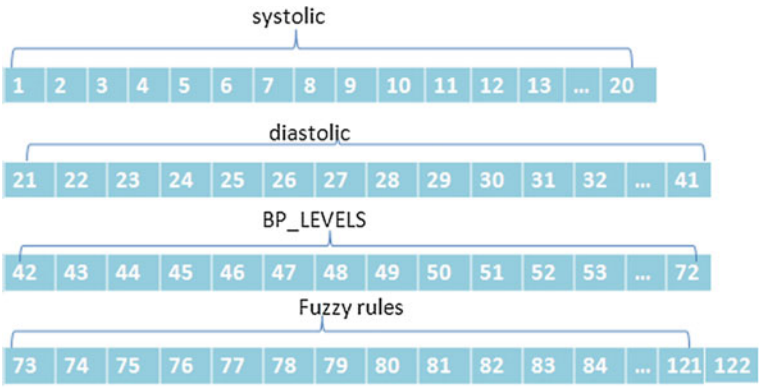


Fig. 4.6 Structure of the chromosome

4.2.8.1 Design of the Fuzzy Classifier 4 Optimized with GA

The fourth fuzzy classifier has two inputs, which are systolic and diastolic with seven membership functions each and an output with ten membership functions, 21 optimized fuzzy rules, Mamdani type.

In the first input called systolic, the range is from 20 to 300, in the second input called diastolic, the range is from 20 to 130 and at the output we have blood pressure levels such as Hypotension, Optimal, Normal, High Normal, Grade 1 hypertension, Grade 2 hypertension, Grade 3 hypertension and isolated systolic hypertension grade 1, isolated systolic hypertension grade 2 and isolated systolic hypertension grade 3, we specify each of the ranges in the fuzzy rules. Figure 4.7 shows the fourth fuzzy classifier.

The Fuzzy rules for the fourth classifier of blood pressure levels are:

1. If (Systolic is Low) and (Diastolic is Low) then (BP_Levels is Hypotension)
2. If (Systolic is Low_Normal) and (Diastolic is Low_Normal) then (BP_Levels is Optimal)
3. If (Systolic is Normal) and (Diastolic is Normal) then (BP_Levels is Normal)
4. If (Systolic is High_Normal) and (Diastolic is High_Normal) then (BP_Levels is High_Normal)
5. If (Systolic is High) and (Diastolic is High) then (BP_Levels is Grade_1)
6. If (Systolic is Very_high) and (Diastolic is Very_High) then (BP_Levels is Grade_2)
7. If (Systolic is too_high) and (Diastolic is Too_High) then (BP_Levels is Grade_3)

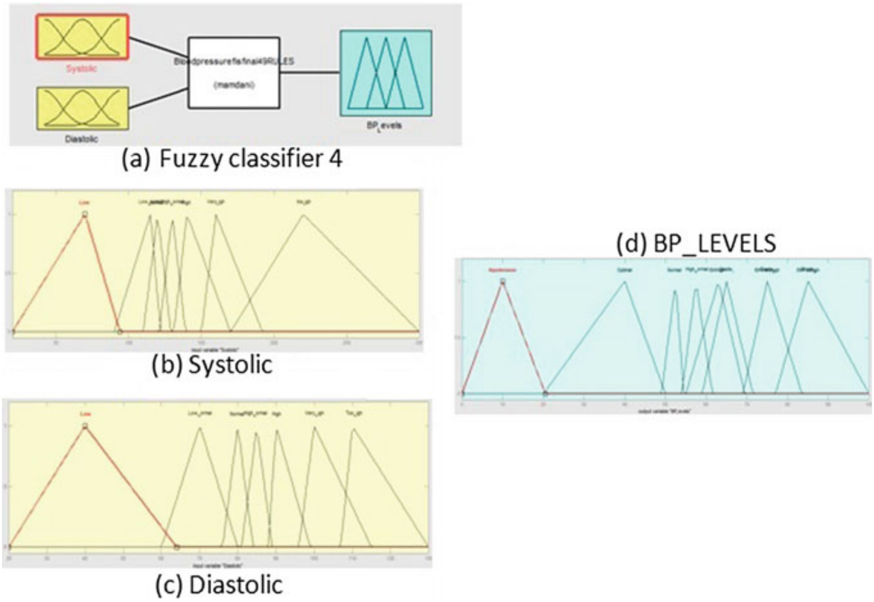


Fig. 4.7 Fourth fuzzy logic system for the classification of blood pressure levels. **a** Structure of the fuzzy logic classifier 4, **b** Systolic input for the fuzzy logic classifier 4. **c** Diastolic input for the fuzzy logic classifier 4. **d** BP_LEVELS is the output of the fuzzy logic classifier 4

8. If (Systolic is Very_high) and (Diastolic is High) then (BP_Levels is Grade_2)
9. If (Systolic is too_high) and (Diastolic is Very_High) then (BP_Levels is Grade_3)
10. If (Systolic is too_high) and (Diastolic is High) then (BP_Levels is Grade_3)
11. If (Systolic is High) and (Diastolic is Very_High) then (BP_Levels is Grade_2)
12. If (Systolic is High) and (Diastolic is Too_High) then (BP_Levels is Grade_3)
13. If (Systolic is Very_high) and (Diastolic is Too_High) then (BP_Levels is Grade_3)
14. If (Systolic is High) and (Diastolic is Normal) then (BP_Levels is ISHGRADE_1)
15. If (Systolic is High) and (Diastolic is High_Normal) then (BP_Levels is ISHGRADE_1)
16. If (Systolic is Very_high) and (Diastolic is Normal) then (BP_Levels is ISHGRADE_2)
17. If (Systolic is Very_high) and (Diastolic is High_Normal) then (BP_Levels is ISHGRADE_2)

18. If (Systolic is too_high) and (Diastolic is Normal) then (BP_Levels is ISHGRADE_3)
19. If (Systolic is too_high) and (Diastolic is High_Normal) then (BP_Levels is ISHGRADE_3)
20. If (Systolic is Normal) or (Diastolic is Normal) then (BP_Levels is Normal)
21. If (Systolic is High_Normal) or (Diastolic is High_Normal) then (BP_Levels is High_Normal).

4.3 Simulation Results of the Proposed Method

The following tables show the results obtained for 30 patients, and based on these results we obtain the accuracy rate and error rate, for which we use the following formula:

$$\text{Classification Accuracy Rate} = \frac{\text{Number of Training Instances Correctly Classified}}{\text{Number of Training instances}}$$

The columns with italic, are the wrong classifications of each classifier, in the following table we show the result of the first fuzzy logic system classifier.

We performed experiments using 24-hour monitoring of 30 patients, from which the trend was obtained which was the one that entered to the fuzzy classifier, which gave us the following result based on the accuracy rate in the classification of 30 patients, an accuracy rate of 80% was obtained, which classified 24 of 30 patients correctly based on the result given by the ESH table and a classification error rate of 20%, which is equivalent to 6 of 30 incorrectly classified. Table 4.1 shows the results.

In Table 4.2 we show the result of the second fuzzy logic system classifier.

We performed experiments using 24-hour monitoring of 30 patients, from which the trend was obtained, which was the one that entered to the fuzzy classifier, which gave us the following result based on the accuracy rate in the classification of 30 patients: an accuracy rate of 90% was obtained, which classified 27 of 30 patients correctly based on the result given by the ESH table and a classification error rate of 10%, which is equivalent to 3 of 30 incorrectly classified as Table 4.2 shows.

Table 4.3 shows the result of the third fuzzy logic system used to classify the level of blood pressure. We performed experiments using 24-hour monitoring of 30 patients, from which the trend was obtained which was the one that entered to the fuzzy classifier, which gave us the following result based on the accuracy rate in the classification of 30 patients, an accuracy rate of 66.7% was obtained, which

Table 4.1 Results of the 30 patients who were monitored and classified in the classifier 1

Patient	Systolic	Diastolic	Classifier 1	Fuzzy percentage	ESH BP levels table
1.	*139*	*84*	*Normal*	*50*	*High normal*
2.	135	90	Grade 1	62.3	Grade 1
3.	160	98	Grade 2	72.3	Grade 2
4.	177	110	Grade 3	84.6	Grade 3
5.	142	85	Ish	77.5	Ish_grade 1
6.	160	89	Ish	71.6	Ish_grade 2
7.	182	89	Ish	82.1	Ish_grade 3
8.	85	50	Hypotension	10.2	Hypotension
9.	110	70	Optima	36.6	Optima
10.	125	82	Normal	54	Normal
11.	135	85	High normal	57	High normal
12.	*159*	*94*	*Grade 2*	*70.2*	*Grade 1*
13.	175	105	Grade 2	79.3	Grade 2
14.	180	110	Grade 3	84.2	Grade 3
15.	*110*	*80*	*Optima*	*50*	*Normal*
16.	128	89	High normal	57	High normal
17.	158	70	ISH	77.9	Ish grade 1
18.	*150*	*108*	*Grade 3*	*83.2*	*Grade 2*
19.	199	95	Grade 3	88.6	Grade 3
20.	*179*	*99*	*Grade 3*	*81.8*	*Grade 2*
21.	181	100	Grade 3	82.8	Grade 3
22.	210	90	Grade 3	88.1	Grade 3
23.	140	100	Grade 2	74.5	Grade 2
24.	159	120	Grade 3	88.5	Grade 3
25.	178	115	Grade 3	88.6	Grade 3
26.	*140*	*80*	*Normal*	*50*	*Ish grade 1*
27.	150	89	Ish	68.2	Ish grade 1
28.	179	80	Ish	77.9	Ish grade 2
29.	179	89	Ish	80.6	Ish grade 2
30.	199	82	Ish	77.8	Ish grade 3

classified 20 of 30 patients correctly based on the result given by the ESH table and a classification error rate of 33.3%, which is equivalent to 10 of 30 incorrectly classified. In this case Table 4.3 shows the accuracy rate was very bad result because the classifier was confused with many unnecessary rules, this is why we need to optimize the fuzzy rules to obtain the appropriate number of rules and obtain better results.

Table 4.2 Results of the 30 patients that were monitored and classified in the classifier 2

Patient	Systolic	Diastolic	Classifier 2	Fuzzy percentage	ESH BP Levels table
1.	*139*	*84*	*Grade 1*	*62.4*	*High normal*
2.	135	90	Grade 1	62.5	Grade 1
3.	160	98	Grade 2	70.9	Grade 2
4.	177	110	Grade 3	84.4	Grade 3
5.	142	85	ISH_GRADO1	61.8	Ish grade 1
6.	160	89	Grade 2	70.2	Ish_Grade 2
7.	*182*	*89*	*Grade 2*	*76.7*	*Ish_Grade 3*
8.	85	50	Hypotension	10.2	Hypotension
9.	110	70	Optima	36.6	Optima
10.	125	82	Normal	54.4	Normal
11.	*135*	*85*	*Grade 1*	*61.1*	*High normal*
12.	159	94	Grade 2	70	Grade 1
13.	175	105	Grade 2	78.9	Grade 2
14.	180	110	Grade 3	84.8	Grade 3
15.	110	80	Normal	52	Normal
16.	128	89	High normal	60.7	High normal
17.	158	70	Ish grade 1	70.5	Ish grade 1
18.	150	108	Grade 2	77.1	Grade 2
19.	199	95	Grade 3	81.3	Grade 3
20.	179	99	Grade 2	80.5	Grade 2
21.	181	100	Grade 3	80.9	Grade 3
22.	210	90	Grade 3	80	Grade 3
23.	140	100	Grade 2	69.5	Grade 2
24.	159	120	Grade 3	79.3	Grade 3
25.	178	115	Grade 3	84.5	Grade 3
26.	140	80	Ish grade 1	60.2	Ish grade 1
27.	150	89	Ish grade 1	64.5	Ish grade 1
28.	179	80	Ish grade 2	73.3	Ish grade 2
29.	179	89	Ish grade 2	75.4	Ish grade 2
30.	199	82	Ish grade 3	78.9	Ish grade 3

We show in Table 4.4 the result of the fourth fuzzy logic system classifier:

We performed experiments using 24-hour monitoring of 30 patients, from which the trend was obtained, which was the one that entered to the fuzzy classifier, which gave us the following result based on the accuracy rate in the classification of 30 patients: an accuracy rate of 100% was obtained, which classified 30 of 30 patients

Table 4.3 Results of the 30 patients who were monitored and classified in the classifier 3

Patient	Systolic	Diastolic	Classifier 3	Fuzzy percentage	ESH BP levels table
1.	*139*	*84*	*Ishgrade1*	*62.5*	*High normal*
2.	135	90	Grade 1	64.4	Grade 1
3.	160	98	Grade 2	72.3	Grade 2
4.	177	110	Grade 3	84.6	Grade 3
5.	142	85	Ishgrado1	62.5	Ish grade 1
6.	*160*	*89*	*Grade 2*	*70.2*	*Ish_Grade 2*
7.	*182*	*89*	*Grade 2*	*83.4*	*Ish_Grade 3*
8.	85	50	Hypotension	10.2	Hypotension
9.	110	70	Optima	36.6	Optima
10.	125	82	Normal	54.5	Normal
11.	*135*	*85*	*Grade 1*	*61.5*	*High normal*
12.	*159*	*94*	*Grade 2*	*70.2*	*Grade 1*
13.	175	105	Grade 2	79.3	Grade 2
14.	*180*	*110*	*Grade 2*	*84.2*	*Grade 3*
15.	110	80	Normal	52	Normal
16.	*128*	*89*	*Grade 1*	*64.4*	*High normal*
17.	*158*	*70*	*Grade 2*	*70.5*	*Ish grade 1*
18.	150	108	Grade 2	83.2	Grade 2
19.	199	95	Grade 3	88.6	Grade 3
20.	179	99	Grade 2	81.8	Grade 2
21.	181	100	Grade 3	82.8	Grade 3
22.	210	90	Grade 3	88.1	Grade 3
23.	140	100	Grade 2	74.5	Grade 2
24.	159	120	Grade 3	88.5	Grade 3
25.	178	115	Grade 3	88.6	Grade 3
26.	140	80	Ishgrado1	62.5	Ish grade 1
27.	*150*	*89*	*Grade 1*	*64.4*	*Ish grade 1*
28.	179	80	Ish_grade 2	81.8	Ish grade 2
29.	*179*	*89*	*Grade 2*	*81.7*	*Ish grade 2*
30.	199	82	Ishgrado3	88.5	Ish grade 3

correctly based on the result given by the ESH table and a classification error rate of 0%, which is equivalent to 0 of 30 incorrectly classified. In these experiments, Table 4.4 shows the results were very good since the classifier was successful in the total of the tests.

The following figures show the behavior of the data of a patient, in each figure, the vertical indicates the systolic or diastolic measure of the patient and the

Table 4.4 Results of the 30 patients that were monitored and classified in the classifier 4

Patient	Systolic	Diastolic	Optimized classifier 4	Fuzzy percentage	ESH BP levels table
1.	139	84	High normal	61.3	High normal
2.	135	90	Grade 1	62.5	Grade 1
3.	160	98	Grade 2	74	Grade 2
4.	177	110	Grade 3	84.3	Grade 3
5.	142	85	Ish_grade 1	61.3	Ish grade 1
6.	160	89	Ish_grade 2	71.8	Ish_grade 2
7.	182	89	Ish_grade 3	83.2	Ish_grade 3
8.	85	50	Hypotension	10.2	Hypotension
9.	110	70	Optima	36.6	Optima
10.	125	82	Normal	55.2	Normal
11.	135	85	High normal	60.8	High normal
12.	159	94	Grade 1	71.8	Grade 1
13.	175	105	Grade 2	79.3	Grade 2
14.	180	110	Grade 3	84	Grade 3
15.	110	80	Normal	52	Normal
16.	128	89	High normal	56.9	High normal
17.	158	77	Ish_grade 1	66.4	Ish grade 1
18.	150	108	Grade 2	82.9	Grade 2
19.	199	95	Grade 3	87.8	Grade 3
20.	179	99	Grade 2	81.6	Grade 2
21.	181	100	Grade 3	82.6	Grade 3
22.	210	90	Grade 3	87.4	Grade 3
23.	140	100	Grade 2	75.8	Grade 2
24.	159	120	Grade 3	87.7	Grade 3
25.	178	115	Grade 3	87.8	Grade 3
26.	140	80	Ish grade 1	59.7	Ish grade 1
27.	150	89	Ish grade 1	65.2	Ish grade 1
28.	179	80	Ish grade 2	73.8	Ish grade 2
29.	179	89	Ish grade 2	81.6	Ish grade 2
30.	199	82	Ish grade 3	77.8	Ish grade 3

horizontal part indicates the hours that the patient was monitored, Fig. 4.8 shows the input data for systolic and in Fig. 4.9 for the diastolic, Figs. 4.10 and 4.11 show the learning of the neural network with the data provided and It shows clearly how you learn the behavior in a correct way, finally we have Figs. 4.12 and 4.13 where we show the trend of this data which will give us as a result to send it to the fuzzy system and perform the classification.

Fig. 4.8 The input data for systolic

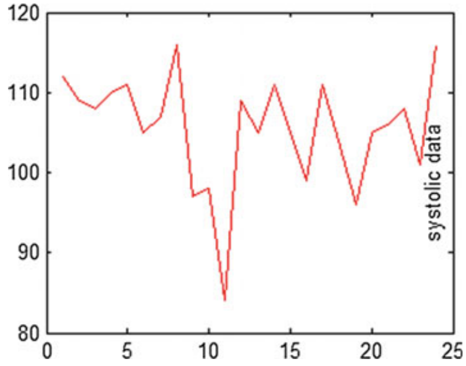


Fig. 4.9 The input data for diastolic

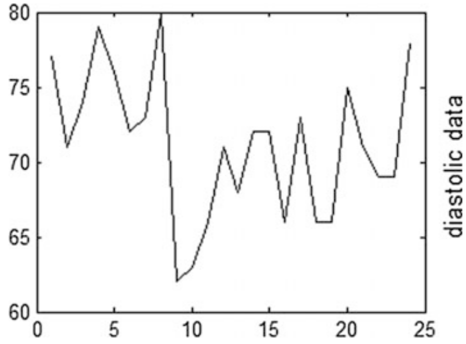
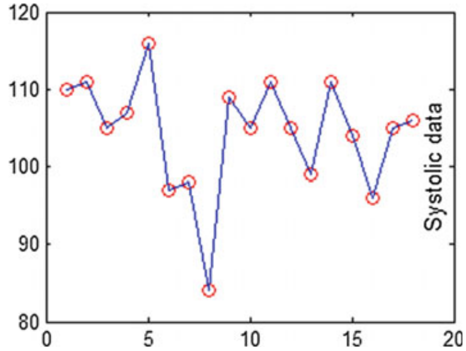


Fig. 4.10 The learning of the neural network with the systolic data provided



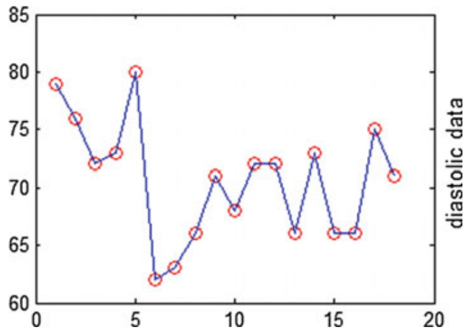


Fig. 4.11 The learning of the neural network with the diastolic data provided

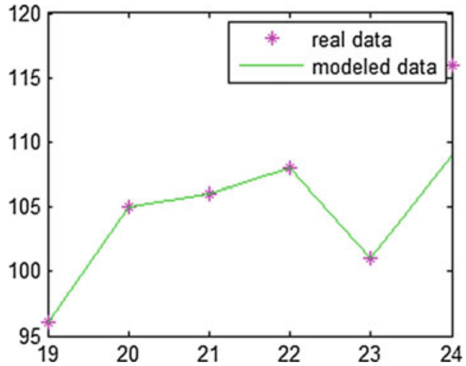


Fig. 4.12 The trend of the systolic data

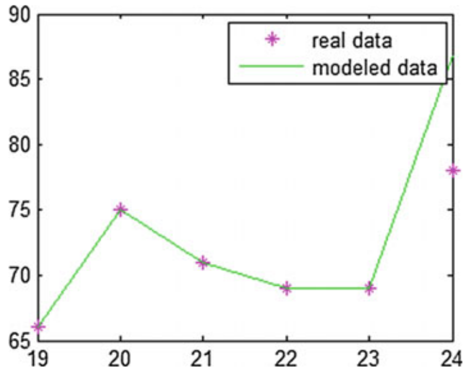


Fig. 4.13 The trend of the diastolic data

4.4 Comparison of Results

We compare the classifier 2 that is based on an expert with the classifier 4 that is optimized with a genetic algorithm, and it based on the total of possible rules based on the European hypertension guide, shown in Fig. 2.1 in Chap. 2.

Of the 30 patients who were monitored, the classification in the first fuzzy system with 24 rules given by an expert, the result was: accuracy rate of 90% with a 10% error, and this is shown in Table 4.5 and in the second optimized fuzzy system with the new computational method reduced to 21 rules gives as a result: 100% accuracy rate and 0% error, this is shown in Table 4.6.

Table 4.5 Results of the 30 patients who were monitored and classified in the classifier based in an expert rules with no optimization

Patient	Systolic	Diastolic	Classifier 2	Fuzzy percentage	ESH BP levels table
1.	*139*	*84*	*Grade 1*	*62.4*	*High normal*
2.	135	90	Grade 1	62.5	Grade 1
3.	160	98	Grade 2	70.9	Grade 2
4.	177	110	Grade 3	84.4	Grade 3
5.	142	85	Ish_grado 1	61.8	Ish grade 1
6.	160	89	Grade 2	70.2	Ish_Grade 2
7.	*182*	*89*	*Grade 2*	*76.7*	*Ish_Grade 3*
8.	85	50	Hypotension	10.2	Hypotension
9.	110	70	Optimal	36.6	Optimal
10.	125	82	Normal	54.4	Normal
11.	*135*	*85*	*Grade 1*	*61.1*	*High normal*
12.	159	94	Grade 2	70	Grade 1
13.	175	105	Grade 2	78.9	Grade 2
14.	180	110	Grade 3	84.8	Grade 3
15.	110	80	Normal	52	Normal
16.	128	89	High normal	60.7	High normal
17.	158	70	Ish grade 1	70.5	Ish grade 1
18.	150	108	Grade 2	77.1	Grade 2
19.	199	95	Grade 3	81.3	Grade 3
20.	179	99	Grade 2	80.5	Grade 2
21.	181	100	Grade 3	80.9	Grade 3
22.	210	90	Grade 3	80	Grade 3
23.	140	100	Grade 2	69.5	Grade 2
24.	159	120	Grade 3	79.3	Grade 3
25.	178	115	Grade 3	84.5	Grade 3
26.	140	80	Ish grade 1	60.2	Ish grade 1
27.	150	89	Ish grade 1	64.5	Ish grade 1
28.	179	80	Ish grade 2	73.3	Ish grade 2
29.	179	89	Ish grade 2	75.4	Ish grade 2
30.	199	82	Ish grade 3	78.9	Ish grade 3

Table 4.6 Results of the 30 patients who were monitored and classified in the classifier with rule expert optimized with GA

Patient	Systolic	Diastolic	Optimized Classifier 4	Fuzzy percentage	ESH BP levels table
1.	139	84	High normal	61.3	High normal
2.	135	90	Grade 1	62.5	Grade 1
3.	160	98	Grade 2	74	Grade 2
4.	177	110	Grade 3	84.3	Grade 3
5.	142	85	Ish_grade 1	61.3	Ish grade 1
6.	160	89	Ish_grade 2	71.8	Ish_grade 2
7.	182	89	Ish_grade 3	83.2	Ish_grade 3
8.	85	50	Hypotension	10.2	Hypotension
9.	110	70	Optima	36.6	Optima
10.	125	82	Normal	55.2	Normal
11.	135	85	High normal	60.8	High normal
12.	159	94	Grade 1	71.8	Grade 1
13.	175	105	Grade 2	79.3	Grade 2
14.	180	110	Grade 3	84	Grade 3
15.	110	80	Normal	52	Normal
16.	128	89	High normal	56.9	High normal
17.	158	77	Ish_grade 1	66.4	Ish grade 1
18.	150	108	Grade 2	82.9	Grade 2
19.	199	95	Grade 3	87.8	Grade 3
20.	179	99	Grade 2	81.6	Grade 2
21.	181	100	Grade 3	82.6	Grade 3
22.	210	90	Grade 3	87.4	Grade 3
23.	140	100	Grade 2	75.8	Grade 2
24.	159	120	Grade 3	87.7	Grade 3
25.	178	115	Grade 3	87.8	Grade 3
26.	140	80	Ish grade 1	59.7	Ish grade 1
27.	150	89	Ish grade 1	65.2	Ish grade 1
28.	179	80	Ish grade 2	73.8	Ish grade 2
29.	179	89	Ish grade 2	81.6	Ish grade 2
30.	199	82	Ish grade 3	77.8	Ish grade 3

4.5 Conclusion

In this study we developed a new model using Neuro Fuzzy Hybrid techniques that actually implements the human reasoning using a set of decision rules for the study of different diseases, such as Hypertension Blood pressure (HBP). This new model Neuro Fuzzy Hybrid Model (NFHM) provides us a faster, safer and accurate tool for an objective diagnostic without inter-observer variability, based in this case on the classification of Hypertension, according to the definitions of the European Guidelines. This method is very efficient therefore takes less time and is more accurate for classify the level of HBP. This can help health systems and health workers, especially in developing countries, who do not have enough specialists for Hypertension, like Cardiologists, internists etc. to improve the degree of accuracy in the diagnosis of this disease with the consequent better opportunity at the start of pharmacological management and dietary hygiene measures. We are aware that this is only the beginning of the implementation of NFHM for the diagnosis of various cardiovascular diseases. In this research work we use Ambulatory Blood Pressure Monitoring (ABPM) for the study of the BP and are aware that there are more parameters that need considered to be a more accurate diagnosis of Hypertension such as different types of patterns like Dipper, Variability, load pressure, etc., And finally, we hope that this work, those who have preceded us, and future work will serve as motivation for other researchers to work on artificial intelligent techniques for applying it in medicine.

Acknowledgements We would like to express our gratitude to the CONACYT and Tijuana Institute of Technology for the facilities and resources granted for the development of this research. We also would like to thank the Cardiodiagnostico of the Excel Medical Center in Tijuana, Mexico for the guidelines and resources given for this research project.

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Chapter 5
Design of Modular Neural Network for Arterial Hypertension Diagnosis

Abstract In this chapter, a method is proposed to diagnose the blood pressure of a patient (Systolic pressure, diastolic pressure and pulse). This method consists of a modular neural network and its response with average integration. The proposed approach consists on applying these methods to find the best architecture of the modular neural network and the lowest prediction error. Simulations results show that the modular network produces a good diagnostic of the blood pressure of a patient.

Keywords Modular neural networks · Systolic · Diastolic · Pulse · Time series · Diagnostic

5.1 Introduction

At the beginning of the twentieth century a cardiovascular disease was a rare cause of death and disability worldwide, but by the end of this century such conditions were set up as a major deaths and permanent damage. In 2001 in the adult population was the number one cause of death in five of the six world regions suggested by the World Health Organization. According to data of this organization, 30% of deaths in the world, that is, 17 million people a year are by disease. The fast increasing mortality from cardiovascular disease in this relatively short process is attributed to various factors such as changes in diet, lack of physical activity and increased life expectancy, which characterize the development of industrialized societies. High prevalence of hypertension in different populations has contributed significantly to the current pandemic diseases such way and estimated five million of the previous deaths are caused by cerebral vascular events, which is closely related to the presence of hypertension [1–3].

Artificial neural networks are inspired by the architecture of the biological nervous system, which consists of a large number of relatively simple neurons that work in parallel to facilitate rapid decision-making [4].

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A neural network is a system of parallel processors connected as a directed graph. Schematically each processing element (neuron) of the network is represented as a node. These connections establish a hierarchical structure that is trying to emulate the physiology of the brain as it looks for new ways of processing to solve the real world problems. What is important in developing the techniques of an NN is if it's useful to learn the behavior, recognize and apply relationships between objects and plots of real-world objects themselves. In this sense, artificial neural networks have been applied to many problems of considerable complexity. Its most important advantage is in solving problems that are too complex for conventional technologies, problems that have no solution or an algorithm of for solution is very difficult to find [5].

This chapter is organized as follows: Sect. 5.2 presents an overview of related works, Sect. 5.3 describes the concepts of neural networks, in Sect. 5.4, we describe the concepts of Hypertension, Sect. 5.5 describes the concept of pulse pressure, in Sect. 5.6 the problem statement and proposed method are presented, Sect. 5.7 shows the simulation results of the proposed method, and Sect. 5.8 offers conclusions and future work.

5.2 Overview of Related Works

Sumathi et al. [4] presented artificial neural networks for solving the problems of diagnosing hypertension using the Backpropagation learning algorithm. They constructed the model using eight risk factors; such as if the person consumes alcohol, smoking, is obese, etc.

Huang et al. [5] presented a work on evaluating the risk of hypertension using an artificial neural network method in rural residents over the age of 35 years in a Chinese area, Hypertension Research.

Vilkov et al. [6], presented a comparative with models of daily blood pressure monitoring was performed in 34 apparently healthy subjects and 72 patients with arterial hypertension (AH). They compared the efficiency of diagnosis of latent AH using models based on artificial neural networks of different architecture.

Kaur et al. [7] outlined the design fuzzy expert system to diagnose hypertension for different patients. Fuzzy expert system is based on set of symptoms and rules. The input parameters for this system are age, body mass index, blood pressure, heart rate, diabetes, physical activity, genetics and the output parameter is risk of hypertension. It is expected that this proposed Fuzzy Expert System can provide a faster, cheaper and more accurate result, as well as application also discusses the fuzzy system for this type of problems of diagnose hypertension [8–12].

Hosseini et al. [13] presented a study to examine risk factors for hypertension and to develop a prediction model to estimate hypertension risk for rural residents over the age of 35 years. Also take some risk factors were significantly associated with the illness, such as a high educational level, a predominantly sedentary job, a positive family history of hypertension, among others, they established predictive models using logistic regression model, and artificial neural network, The accuracy of the models was compared by receiver operating characteristic when the models applied to the validation set, and the artificial neural network model proved better than the logistic regression model.

Nohria et al. [14] presented an Adaptive Neuro-fuzzy inference system (ANFIS) technique for diagnosis of hypertension. For training the ANFIS system patient's data set are collected under the supervision of physician in clinical trials on hypertension patients in hospital. The methodology of ANFIS was used to diagnose and presents the comparison of proposed system with existing fuzzy expert system on the basis of performance matrices i.e. Accuracy and Sensitivity [15].

Zeinab et al. [16] describe a Design of a Fuzzy Expert System and a Multilayer Neural Network System for Diagnosis of Hypertension. This paper presents a study, where they used two methods for the diagnosis of the hypertension. Firstly, a Fuzzy Expert system (FEs) is introduced for the diagnosis of the hypertension in adults. The input parameters include Systolic Blood Pressure (SBP) and Body Mass Index (BMI). Secondly, the multilayer neural network (NN) with 5 inputs, 5 hidden layers and 1 output is employed for the diagnosis of the hypertension. The inputs include SBP, smoking, age, weight and BMI. Finally the results of two systems (FEs and NN) are compared individually.

5.3 Neural Networks

Neural networks are composed of many elements (Artificial Neurons), grouped into layers and are highly interconnected (with the synapses). This structure has several inputs and outputs, which are trained to react (or give values) in a way we want to input stimuli (R values). These systems emulate in some way, the human brain. Neural networks are required to learn to behave (Learning) and someone should be responsible for the teaching or training (Training), based on prior knowledge of the problem environment [17].

5.4 Arterial Hypertension

Hypertension is a disease present in almost all human groups currently inhabiting the planet. It is a very common disease and because cardiovascular complications that accompany it, is a global health problem, recently a study in order to develop policy for the prevention and control of this disease was published. In this study, national surveys on the prevalence of hypertension reported for the different countries were used. In most of them the mercury sphygmomanometer was used to measure blood pressure on a single occasion the numbers reported overestimates Measurements were made on two separate visits in 3 studies.

The social consequences of a disease, such as hypertension are many and may have different approaches. First it can be concluded mortality generated, which is a very strong epidemiological criterion, although the discussion can be extended to cover different topics, among which the inability accompanies business days and years of productive life lost, and finish by doing some considerations on the cost of treatment.

Some of the major risk factors for hypertension include: obesity, Lack of exercise, Smoking, Salt consumption, Alcohol, the stress level, Age, Sex, Ethnicity and Genetic factors.

It is very important to note that the pressure varies from beat to beat, day and night, facing everyday situations such as walking, talking on the phone or exercise. Therefore, variation in blood pressure is a normal phenomenon. The tension is not related to the day and night, but with the activity and rest (sleep) [5, 6].

5.5 Pulse Pressure

The pulse is the number of heart beats per minute, the procedure for how the test is performed and the pulse can be measured in the following regions of the human body: The back of the knees, the groin, the neck, Temple, top or inner side of the foot.

In these areas, an artery passes close to the skin. To measure the pulse at the wrist, place the index and middle fingers on the front of the opposite wrist, below the thumb. Press with the fingers until a pulse is sensed to measure the pulse on the neck, place the index and middle fingers to the side of the Adam's apple in the soft, hollow, and press gently until we locate the pulse. Note: sit or lie down before taking the pulse of the neck. Neck arteries in some people are sensitive to pressure and fainting may occur or decreased heartbeat. Also, do not take the pulse on both sides of the neck at the same time. Doing this can reduce the flow of blood to the head and lead to fainting. Once we find the pulse, we count the beats for a full minute or for 30 s and multiply by two, which will give the beats per minute. In exam preparation to determine the resting heart rate, the person must have been resting for at least 10 min.

Exam preparation

If we are going to determine the resting heart rate, the person must have been resting for at least 10 min, take heart rate during exercise while training and a person a slight finger pressure is made why the test is performed. Pulse measurement provides important information about the health of a person. Any change from normal heart rate can indicate a medical condition (Bernstein). The rapid pulse can be a sign of an infection or dehydration. In emergency situations, the pulse rate can help determine if the patient's heart is pumping. During or immediately after the pulse provides information about your fitness level and health [7–10].

Normal Values

For the resting heart rate the normal values are: Newborns (0–1 month old): 70–190 beats per minute. Babies (1–11 months old): 80–160 beats per minute, Children (1–2 years old): 80–130 beats per minute, Children (3–4 years old): 80–120 beats per minute, Children (5–6 years old): 75–115 beats per minute, Children (7–9 years old): 70–110 beats per minute, Children 10 years and older and adults (including elderly): 60–100 beats per minute, trained athletes: 40–60 beats per minute.

The resting heart rates that are continually high (tachycardia) may indicate a problem and that the person needs to consult a doctor. Also about resting heart rates that are below the normal values (bradycardia). Also, the doctor should check a pulse to observe that is very firm (bounding pulse) and that lasts longer than a few minutes. An irregular pulse can also indicate a problem. A pulse that is hard to find may mean there is blockage in the artery. These blockages are common in people with diabetes or atherosclerosis from high cholesterol. In this case the doctor may order a test known as a Doppler study to assess obstructions.

Bradycardia

Bradycardia is characterized by slow heart rate usually below 60 beats per minute, while the normal resting rate is 60–100 beats per minute [11, 12].

Sinus Tachycardia

In Cardiology, sinus tachycardia is a heart rhythm disorder characterized by an increased frequency of cardiac impulses originating from the sinus node is the natural pacemaker of the heart, and defined with a heart rate greater than 100 beats per minute in an average adult When the normal frequency is 60–100, in adult-although rarely exceeds 200 bpm. Typically, sinus tachycardia begins and ends gradually in contrast with supra-ventricular tachycardia, which appears gradually and may end abruptly [13, 14].

5.6 Problem Statement and Proposed Method

This Section describes the problem statement and the proposed method for blood pressure diagnostic based on modular neural networks with average response integration. One of the main goals is to implement a Modular Neural Network, where the number of modules is 3, the first module is for the Systolic Pressure, in the second module we have the Diastolic Pressure and third module is for the Pulse in order to diagnose the blood pressure of a person.

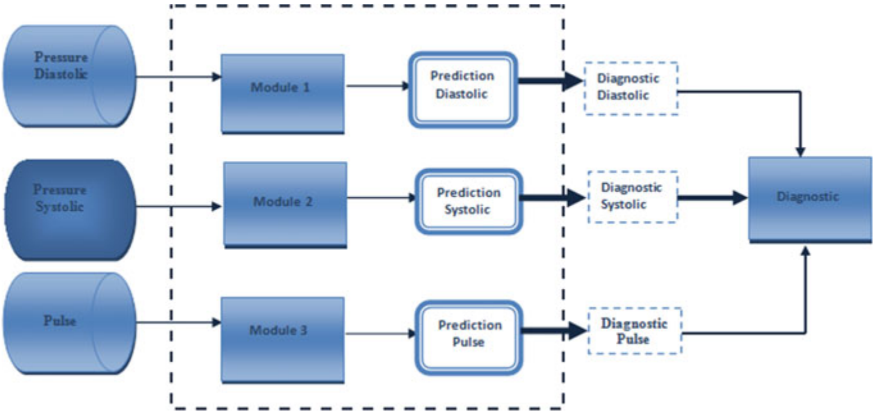

Fig. 5.1 The proposed modular neural network

Figure 5.1 illustrates the Modular Neural Network Model, where we have first the historical data, for the Modular Neural Network, which in this case has 3 modules, as well as the number of layers that this module that could be from 1 to 3 and the number of neurons by layer that could be from 1 to 3. Then after the responses of the modular neural network ensemble are obtained, the integration is performed with the Average Integration method.

In Fig. 5.1 each of the modules is a modular neural network and the corresponding calculations are performed as follows [18, 19]:

The net input $\bar{x}$ of a node is defined by the weighted sum of the incoming signals plus a bias term. For instance, the net input of the output of the node *j*.

$$\bar{x}_j = \sum_i \omega_{ij} + \omega_j$$

$$x = f\left(\bar{x}_j\right) = \frac{1}{1 + \exp\left(-\bar{x}_j\right)} \tag{5.1}$$

where x_i is the output of node i located in any of the previous layers, ω_{ij} is the weight associated with the link connecting nodes i and j, and ω_j is the bias of node j. Since the weights ω_{ij} are actually internal parameters associated with each node j and changing the weights of the node will alter behavior of the node and in turn alter behavior of the whole backpropagation MLP.

A squared error measure for the pth input-output pair is defined as:

$$E_P = \sum (d_k - x_k)^2, \tag{5.2}$$

where d_k is the desired output for the node x_k is the actual output for the node when the input part of the pth data pair is presented.

Historical data of the diastolic pressure historical data were obtained from 16 people with 45 samples, for systolic pressure and pulse were also the data of the same people.

In Table 5.1 the blood pressure (BP) category is defined by the highest level of BP, whether systolic or diastolic. This should be graded as 1, 2 or 3 according to the systolic or diastolic BP values. Isolated systolic hypertension it is according to the systolic BP value in the ranges indicated.

5.7 Simulation Results

This section shows results of the optimization of the modular neural network. The main goal is the diagnosis of high blood pressure, where experiments with 16 persons are presented.

Table 5.2 shows the results of the modular neural network applied to the diagnosis of high blood pressure.

Table 5.3 shows the average of 30 experiments of the modular network for each of the 16 people, the average time, Diastolic, Systolic and pulse are represented.

Figure 5.2 shows results of the best architecture of the Modular Network, where for the first module of Diastolic Pressure, Systolic Pressure and Pulse, 25 neurons were used in the first layer and 30 neurons for the second layer for each the modules, and the Target Error was of 0.002 and 500 epoch were used.

Figure 5.3 shows the plot of the modular neural network modeling for the Systolic Pressure.

Figure 5.4 shows the plot of the modular neural network modeling for the Diastolic Pressure.

Table 5.1 Definitions and classification of the blood pressure levels (mmHg)

Category	Systolic		Diastolic
Optimal	<120	And	<80
Normal	120–129	And/or	80–84
High Normal	130–139	And/or	85–89
Grade 1 Hypertension	140–159	And/or	90–99
Grade 2 Hypertension	160–179	And/or	100–109
Grade 3 Hypertension	≥ 180	And/or	≥ 110
Isolated Systolic hypertension	≥ 140	And/or	<90

Table 5.2 Results of the modular neural network

No. persons	Epoch	Target error	Number of layers	Number of layers	Time	Systolic	Diastolic	Pulse	Diagnostic
Person 1	500	0.02	2	15.13	00:05:06	116	74	67	Optimal
Person 2	500	0.02	2	15.13	00:05:06	106	72	77	Optimal
Person 3	500	0.02	2	15.13	00:05:06	114	70	80	Optimal
Person 4	500	0.02	2	15.13	00:05:06	119	71	72	Optimal
Person 5	500	0.02	2	15.13	00:05:06	145	84	75	Grade 1 Hypertension
Person 6	500	0.02	2	15.13	00:05:06	104	61	90	Optimal
Person 7	500	0.02	2	15.13	00:05:06	125	87	97	High Normal
Person 8	500	0.02	2	15.13	00:05:06	109	64	73	Optimal
Person 9	500	0.02	2	15.13	00:05:06	129	74	57	Normal
Person 10	500	0.02	2	15.13	00:05:06	122	78	65	Normal
Person 11	500	0.02	2	15.13	00:05:06	136	63	65	High Normal
Person 12	500	0.02	2	15.13	00:05:06	136	81	70	High Normal
Person 13	500	0.02	2	15.13	00:05:06	120	75	78	Normal
Person 14	500	0.02	2	15.13	00:05:06	110	62	77	Optimal
Person 15	500	0.02	2	15.13	00:05:06	121	69	70	Normal
Person 16	500	0.02	2	15.13	00:05:06	132	82	60	High Normal

Table 5.3 Average results of the modular neural network

Person	Time	Systolic	Diastolic	Pulse
Person 1	00:13:09	115	73	67
Person 2	00:13:09	105	72	77
Person 3	00:13:09	114	70	80
Person 4	00:13:09	119	71	72
Person 5	00:13:09	145	84	75
Person 6	00:13:09	104	61	90
Person 7	00:13:09	125	87	96
Person 8	00:13:09	109	64	73
Person 9	00:13:09	129	73	56
Person 10	00:13:09	122	77	65
Person 11	00:13:09	136	63	70
Person 12	00:13:09	136	81	71
Person 13	00:13:09	120	74	78
Person 14	00:13:09	110	62	77
Person 15	00:13:09	119	68	70
Person 16	00:13:09	131	82	80

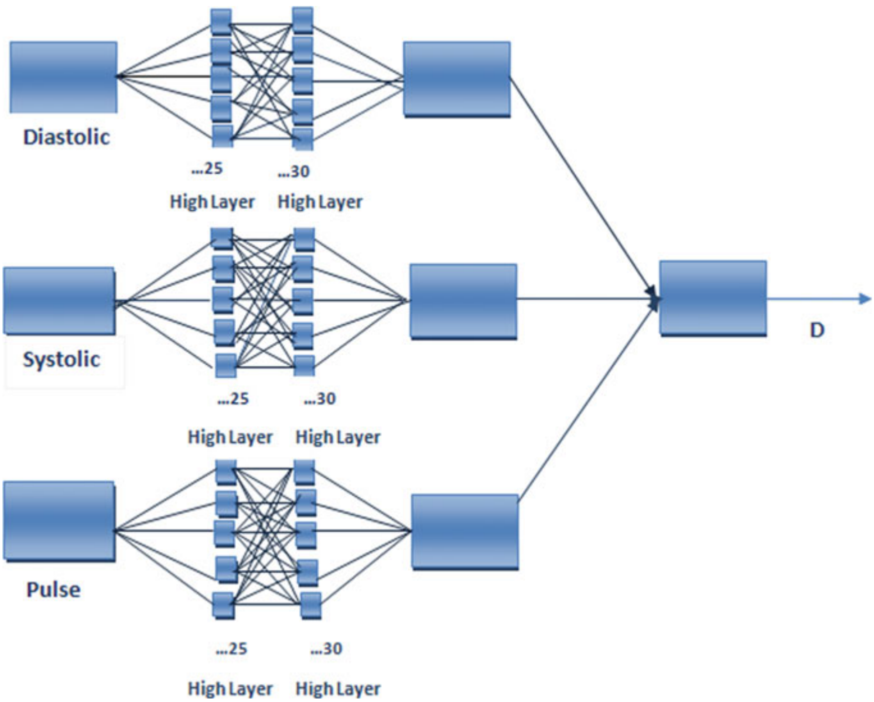

Fig. 5.2 The best architecture for the modular neural network

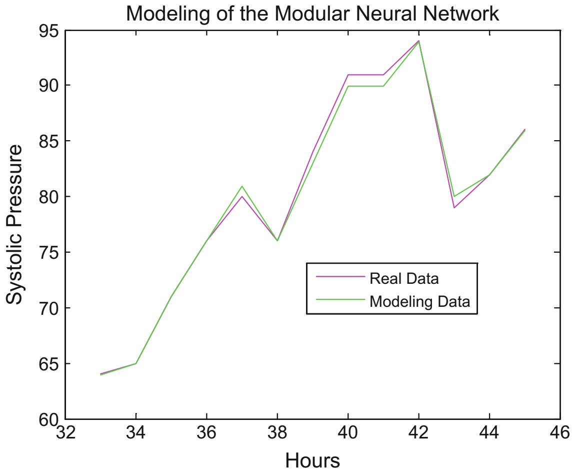

Fig. 5.3 Modeling of systolic pressure of the modular neural network

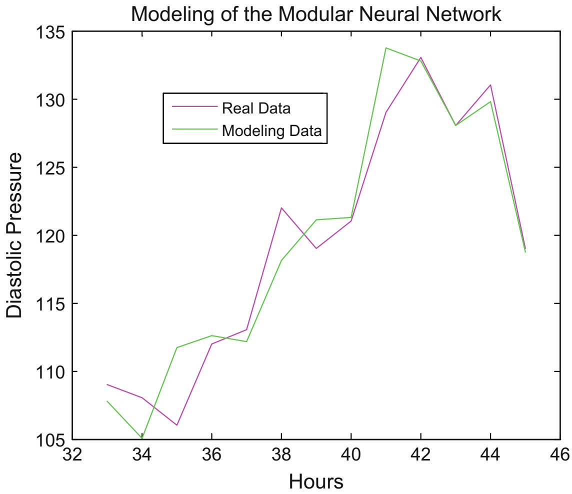

Fig. 5.4 Modeling of diastolic pressure of the modular neural network

Figure 5.5 shows the plot of the modeling of the modular neural network for the Pulse Pressure.

Figure 5.6 shows the plot of the diagnostic error of the modular neural network for the Systolic Pressure.

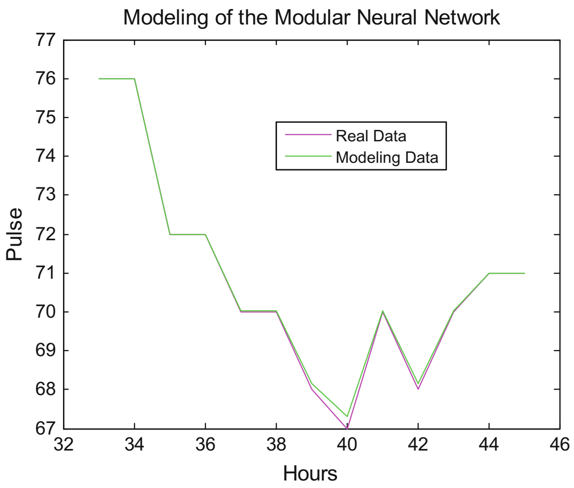

Fig. 5.5 Modeling of pulse of the modular neural network

Fig. 5.6 Diagnostic error of the systolic pressure with modular neural network

Figure 5.7 shows the plot of the diagnostic error of the modular neural network for the Diastolic Pressure.

Figure 5.8 shows the plot of the diagnostic error of the modular neural network for the Pulse.

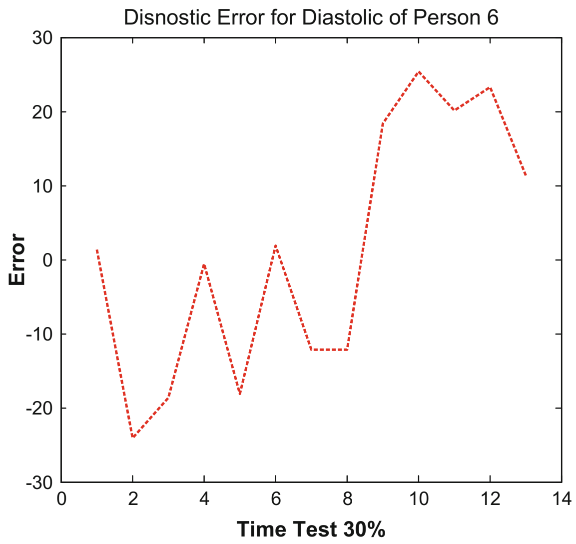

Fig. 5.7 Diagnostic error of the diastolic pressure with the modular neural network

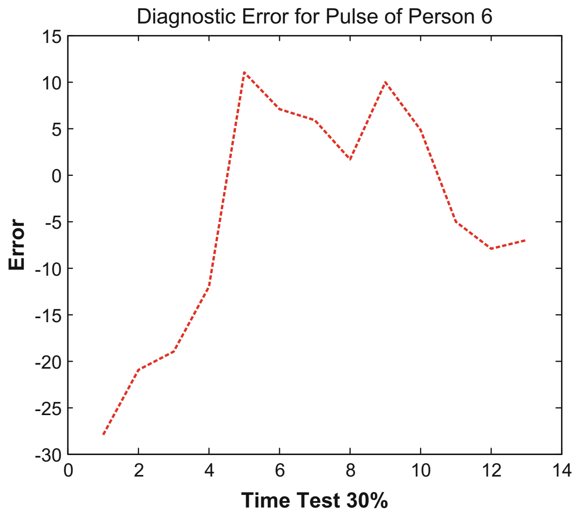

Fig. 5.8 Diagnostic error of the pulse with the modular neural network

5.8 Conclusions

We can conclude that with the proposed method based on Modular Neural Networks good results are obtained in diagnosing the risk of hypertension of person. As we can note in this work, modular neural networks have proven to be a reliable and accurate technique compared to conventional statistical methods for this problem. As is the case in this work, the results obtained in each of the models can be considered good because the margin of error that is obtained is very small and another important part of this research is the training method that is used which is the Levenberg Marquardt algorithm (trainlm). This is a good method as is able to solve diagnosis problems faster and easier and as it guarantees a high learning speed.

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Chapter 6
Intelligent System for Risk Estimation of Arterial Hypertension

Abstract A hybrid intelligent system is constructed of a powerful combination of soft computing techniques for reducing the complexity in solving difficult problems. Nowadays Cardiovascular Diseases, like arterial hypertension (high blood pressure) has a high prevalence in the world population. They are the number one cause of mortality in Mexico, and that is why the HBP is called a silent killer because it often has no symptoms. We design in this research work a hybrid model using modular neural networks, and as response integrator we use fuzzy systems to provide an accurate risk diagnosis of hypertension, so we can prevent a futures disease in people based on the systolic pressure, diastolic pressure and pulse of patients with ages between 15 and 95 years.

Keywords BP (blood pressure) · Hypertension · ABPM (ambulatory blood pressure monitoring) · Fuzzy system · Modular neural network · Systolic pressure · Diastolic pressure · Pulse

6.1 Introduction

A Hybrid intelligent system can be built from a prudent combination of two or more soft computing techniques for solving complex problems. The hybrid system is formed by the integration of different soft computing subsystems, each of which maintains its representation language and an inferring mechanism for obtaining its corresponding solutions. The main goal of hybrid systems is to improve the efficiency and the power of reasoning and expression of isolated intelligent systems [1, 2].

In this research work, we used some recent soft computing techniques, such as modular neural networks and fuzzy inference systems.

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6.1.1 Blood Pressure and Hypertension

Blood pressure is the force exerted by the blood against the walls of blood vessels, especially the arteries [3]. Then we understand as high blood pressure, as the sustained elevation of blood pressure (BP) above the normal limits [4, 5]. The regular blood pressure levels are those below 139 in systolic pressure (when the heart contracts and pushes the blood around the body) and below 89 in diastolic pressure (when the heart relaxes and refill with blood), and is measured in millimeters of mercury (mmHg) [3]. The heart rate is the number of times the heart beats per minute, and this is well known to vary by ages, for example, the heart rate in a child is normal around 160 beats per minute, but in an adult at rest, the normal is between 50 to 90 beats per minute, also can change for some illness, in this case the change is abnormal.

For collecting the blood pressure measurements of patients we used a device called Ambulatory blood pressure monitoring, described below:

A 24 h blood pressure measurement is just the same as a standard blood pressure check: a digital machine measures the blood pressure by inflating a cuff around your upper arm and then slowly releasing the pressure. The device is small enough to be worn on a belt around the waist while the cuff stays on your upper arm for the full 24 h.

The monitors are typically programmed to collect measurements every 15–20 min during the daytime and 30 min at night. At the end of the recording period, the readings are downloaded into a computer, in our case we construct a database consist of ABPM monitoring studies of a patients and students, we show in Appendix A, Figs. A.1 and A.2 the files from the data base obtained from this studies with two different devices as mention in Appendix A. These devices can provide the following types of information, an estimate of the true or mean blood pressure level, the diurnal rhythm of blood pressure, and blood pressure variability [6, 7].

Studies with the Ambulatory blood pressure monitoring (ABPM) device have shown that when more than 50% the readings of blood pressure are higher than 135/85 mmHg during the awake hours, and 120/80 mmHg for the sleep hours, there are signs of target organ damage (kidney, blood vessels, eyes, heart and brain), so that this blood pressure level is already pathogenic and, therefore, has been concluded that the above-mentioned numbers should be considered abnormal [3]. In Appendix A we show some examples of ABPM studies from patients having some blood pressure problems, from the two devices used.

Medical doctors recommend using the ABPM in different cases, for example if we suspect of having white-coat hypertension, in these patients, office blood pressures are substantially higher than ambulatory awake blood pressure averages [7]. We show in the appendix, Fig. A.3 a sample report of a patient with HBP, some samples of the results of ABPM monitoring of patients in whom some of them have the effect of with-coat hypertension by example in Figs. A.5 and A.6, or in Fig. A.4 isolated diastolic hypertension or Fig. A.7 daytime hypertension. If in normal reads of BP in a medical visit with signs of target organ damage the medical doctor can suggest an ABPM monitoring study.

Other causes of sporadic high blood pressure (in crisis), can be symptoms that are suggestive of sudden changes in blood pressure and if we are suspected of having masked hypertension, this means a normal clinic blood pressure and a high ambulatory blood pressure [3, 7].

Figure 6.1 shows an example of how a file obtained from the ABPM is organized and each section of the document is explained below:

(a) **Patient data**: In this section shows patient data, such as the ID with which it is recognized, name and date of the study
(b) **Daytime and nighttime period**: This section shows in which schedules the device was programmed to consider the day and night periods and at what time interval the readings will be taken, in this case it is every 20 min in the day and every 30 min at night.
(c) **Blood pressure load**: This section shows a percentage of readings greater than 135/85 mmHg in the day and readings greater than 120/75 mmHg at night.
(d) **Total Correct Readings**: Shows the percentage of correct readings taken by the ABPM in 24 h.
(e) **Dip**: Percentage of patient's Dipper readings.
(f) **Average time**: It corresponds to the average of the readings of the blood pressure, you can observe the means of the systolic, diastolic and pulse pressure, as was the average of the readings over the 24 h of the study and the average of the blood pressure and the pulse of the day and night.
(g) **Readings**: This section is divided into 6 columns. In the first column is the date of each measurement, in the second column shows the hour in which each measure was realized, in the third column the measurement corresponding to the systolic pressure can be observed.

In the fourth column the measurement corresponding to the diastolic pressure are located, in the fifth column are the measurements of the pulse and in the sixth column are observations that are made of that specific reading.

6.1.2 Neural Network for a Hypertension Diagnosis

Sumathi et al. [8] have used artificial neural networks for solving the problems of diagnosing hypertension using the Backpropagation learning algorithm. They constructed the model using eight risk factors, such as if the person consumes alcohol, smoking, is obese, if have stress [7] just to mention a few.

Hosseini et al. [9] presented a study to examine risk factors for hypertension and to develop a prediction model to estimate hypertension risk for rural residents over the age of 35 years. Also take some risk factors were significantly associated with the illness, such as a high educational level, a predominantly sedentary job, a positive family history of hypertension, among others, they established predictive

(a)

ABPM mode

Patient ID	1034	Date of study	2015/05/21
Patient´s First Name		Patient´s Last Name	

(b)

Day and Night periods	Hour	Time intervals
Daytime period	07 ~ 02	20 min
Nighttime period	02 ~ 07	30 min

(c)

Day BP load (% of Daytime readings ≥ 135/85 mmHg)
Night BP load (% of Nighttime readings ≥ 120/70 mmHg)

Awake	0.0%
Asleep	10.0%

(d)

Total Correct Readings

Correct readings	89.4%

(e)

Dip

24-Hours Sys	3.4%
24-Hours Dia	0.1%

(f)

Hourly Average (standard deviation)

	Awake / Real Asleep	Sys	Dia	Pulse	Valid Readings
24 hours	07 ~ 07	95 (5)	61 (5)	86 (8)	59
Awake	07 ~ 02	96 (5)	61 (5)	86 (9)	49
Asleep	02 ~ 07	93 (6)	61 (6)	85 (4)	10

(g)

Date	Hour	Sys	Dia	Pulse	Comment
2015/05/20	13:43	94	56	83	
2015/05/20	14:00	97	61	87	
2015/05/20	14:28	97	63	83	
2015/05/20	14:43	94	62	91	
2015/05/20	15:00	93	59	89	
2015/05/20	15:20	98	61	94	
2015/05/20	15:40	93	62	97	
2015/05/20	16:00	107	60	92	
2015/05/20	16:20	91	59	90	
2015/05/20	16:40	93	63	90	
2015/05/20	17:09	91	71	81	
2015/05/20	17:20	103	62	84	
2015/05/20	17:40	104	63	84	
2015/05/20	18:00	98	62	79	
2015/05/20	18:21	100	68	83	
2015/05/20	18:40	94	69	88	
2015/05/20	19:00	98	64	85	
2015/05/20	19:24	115	75	114	
2015/05/20	20:08	104	73	91	
2015/05/20	20:20	101	75	103	
2015/05/20	20:43	98	64	92	
2015/05/20	21:00	82	56	90	
2015/05/20	21:20	94	55	86	
2015/05/20	21:40	96	63	90	
2015/05/20	22:00	92	59	80	
2015/05/20	22:23	88	56	81	
2015/05/20	22:40	105	55	92	
2015/05/20	23:09	88	60	77	
2015/05/20	23:20	103	60	80	
2015/05/20	23:43	85	56	78	
2015/05/21	0:00	91	60	77	
2015/05/21	0:20	90	57	74	
2015/05/21	0:40	97	62	80	
2015/05/21	1:04	97	54	73	
2015/05/21	1:20	95	57	66	
2015/05/21	1:40	88	53	73	
2015/05/21	2:00	91	55	80	
2015/05/21	2:30	101	57	78	

Fig. 6.1 Example of data obtained through ABPM

models using logistic regression model, and artificial neural network, The accuracy of the models was compared by receiver operating characteristic when the models applied to the validation set, and the artificial neural network model proved better than the logistic regression model.

For estimating Ambulatory Systolic Blood Pressure variations based on corporal acceleration and heart rate measurements Hosseini et al. [10] use neural network models. The temporal correlation of the estimation residual, modeled by a first - order autoregressive process, is used for training the neural network in a maximum likelihood framework, which yields a better estimation performance. As data are collected at irregular time intervals, the first order autoregressive model is modified for taking into account this irregularity. The results are compared by those of a neural network trained using an ordinary least square method.

6.1.3 Fuzzy Logic and Arterial Hypertension

There are some recent works on using fuzzy logic in this area, for example for diagnosis of hypertension, Guzman et al. [11] have proposed a Mamdani fuzzy system model, based on the European Hypertension classification [4], which is shown in Table 6.1.

The model has two inputs, the first is the systolic blood pressure and the second is the diastolic blood pressure and this is done by taking into consideration all ranges of blood pressure, and the model has one output that is for the blood pressure level.

A fuzzy rule-based system for the diagnosis of heart diseases has been presented by Barman et al. [12]. The inputs are the Chest pain type, the resting blood pressure, Serum cholesterol in mg, Numbers of Years of being a smoker, fasting blood sugar, maximum heart rate achieved, and resting blood rate. The angiographic disease status of the heart of patients has been recorded as the output. This is to state that the diagnosis of heart disease by angiographic disease status is assigned by a number between 0 and 1, and this number indicates whether the heart attack is mild or massive.

Table 6.1 Definitions and classification of office blood pressure levels (mmHg)

Category	Systolic		Diastolic
Optimal	<120	And	<80
Normal	120–129	And/or	80–84
High normal	130–139	And/or	85–89
Grade 1 hypertension	140–159	And/or	90–99
Grade 2 hypertension	160–179	And/or	100–109
Grade 3 hypertension	≥ 180	And/or	≥ 110
Isolated systolic hypertension	≥ 140	And	<90

6.1.4 Fuzzy Logic and Pulse

For measuring health parameters of patients, Patil et al. [13] have proposed a wireless sensor network system for continuous monitors pulse and temperature of patients remotely or in the hospital, and it transmits the bio-signals to the Doctor and Patient mobile phone. Data stored in a database is passed to the fuzzy logic controller to improve accuracy and amount of data to be sent to the remote user. The FLC system receives context information from the sensor as input (the patient age and pulse), and output is the status of the patient pulse.

We want to provide a risk diagnosis in patients with high blood pressure, for this, we used a modular neural network, where each module works independently, is built and trained for a specific task [2]. We used a response integrator of the modules and for giving the risk diagnosis, fuzzy inference systems.

6.2 Proposed Method

Measurements of the blood pressure are obtained by the ABPM device for 100 people, and these data have been obtained from students of the master and doctorate in computer science from Tijuana Institute of Technology. In addition, the Cardio-Diagnostic Center of Tijuana has provided blood pressure measures of his patients for this research, a databases with corresponding data to the systolic pressure, diastolic pressure and pulse is created.

The modular neural network is trained with 47 measures of 27 patients (70% for training phase and 30% for testing phase) in the database, in others words, the first module was trained with the measures of systolic pressure, the second with the diastolic pressure and the third module with the pulse, the network is modeling the data for learning the blood pressure behavior.

The architecture for the modular neural network was changed in each experiment, showing the better results with the next parameters:

Training method: Levenberg-Marquardt
Hidden Layers: 3
Neurons: 32, 18, 13
Error goal: 1.00 E^{-5}
Epochs: 300.
In Table 6.3 all experiment is shown.

We used fuzzy inference systems as integrators, the fuzzy model develop by Guzman et al. [11] is taken to obtain a blood pressure classification and the second fuzzy inference system to obtain the pulse level, this because there is no numerical relationship between blood pressure and pulse, but there can be a connection with some diseases. On the other hand, the age enters independently of the fuzzy system because it's an important variable to determinate the variation of the pulse, the output of the two integrators will be evaluated by traditional system rules, for

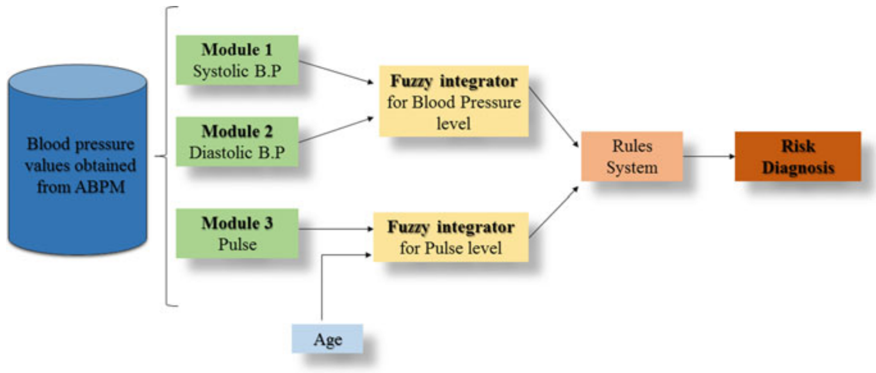

Fig. 6.2 Proposed method

provide a risk diagnosis of a cardiovascular disease which the patient could have. In Fig. 6.2 the complete proposal is illustrated.

6.3 Methodology

In this research work, we propose a Mamdani fuzzy inference system for finding the pulse level, as illustrated in Fig. 6.3, and this was modeled empirically [14]; it has two inputs including the age and the pulse and has one output which corresponds to

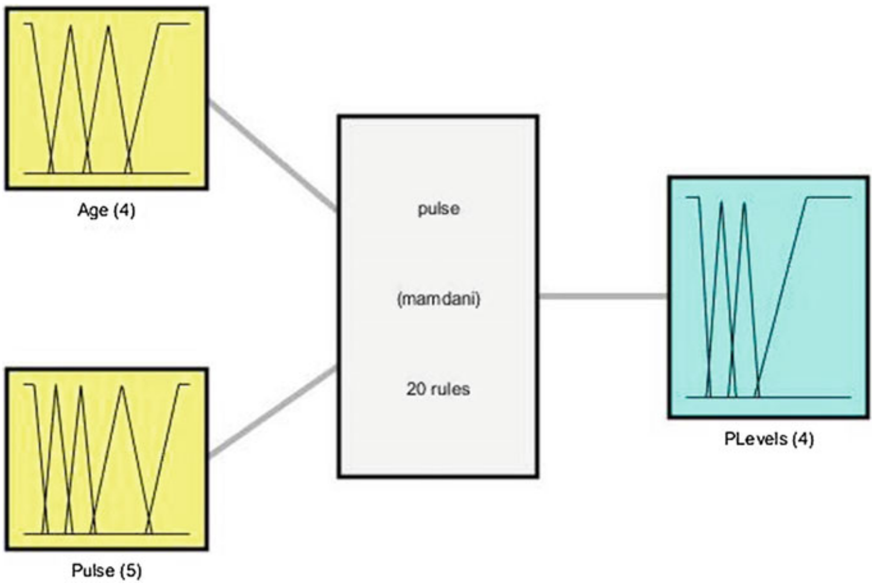

Fig. 6.3 Pulse fuzzy system

the Pulse level. The membership functions used on the age input are trapezoidal for “children” and “elder”, and triangular for “young” and “middle”, the membership functions used for the pulse input are trapezoidal for “low’ and “very high”, and triangular for “low”, “normal” and “high” linguistic terms.

For the output trapezoidal membership functions are used for low and very low, and triangular for below normal, excellent and above normal.

Figure 6.4 shows the input and output variables; we can analyze the input for age and has a range of 0–100, and the pulse has a range of 0–220 because is the maximum level of the pulse in a person.

For the output of the fuzzy system this is considered in a range from 0 to 100% because this is the range how well or how badly the patient is from low pulse to very high.

The rule set of the FLC contains 20 rules, which depends on the age and pulse for determining which pulse level the patient has. In Table 6.2 we present the rule set for this case and in Fig. 6.5 the surface is presented.

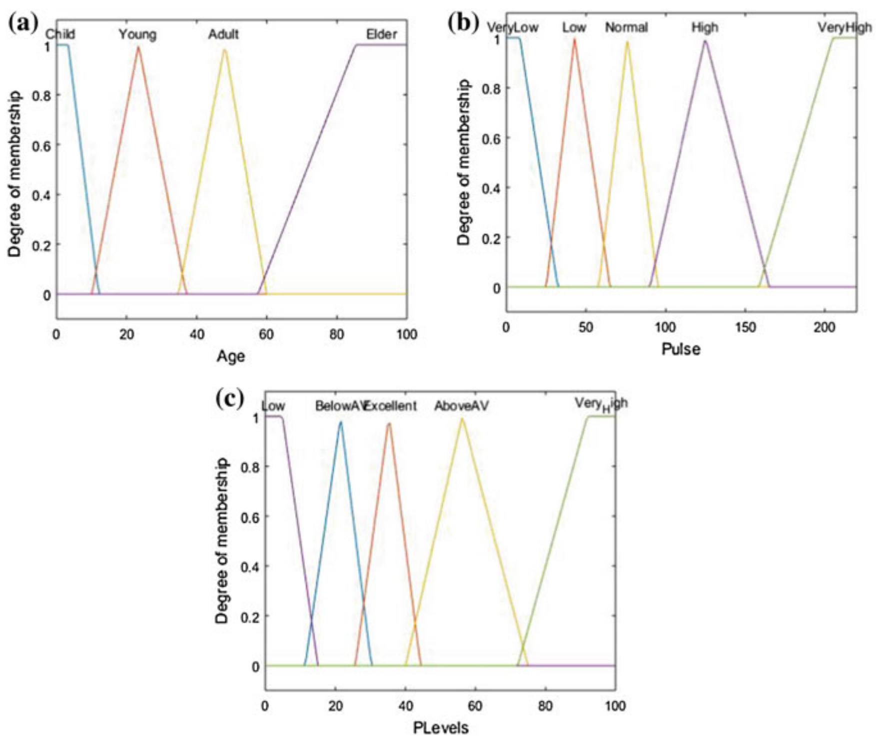

Fig. 6.4 **a** Input for age. **b** Input for pulse. **c** Output for pulse level

Table 6.2 Fuzzy rules set

Age/Pulse	VeryLow	Low	Normal	High	VeryHigh
Child	Low	Low	Excellent	Excellent	AboveAV
Young	Low	BelowAV	Excellent	AboveAV	VeryHigh
Adult	Low	BelowAV	Excellent	AboveAV	VeryHigh
Elder	Low	BelowAV	Excellent	VeryHigh	VeryHigh

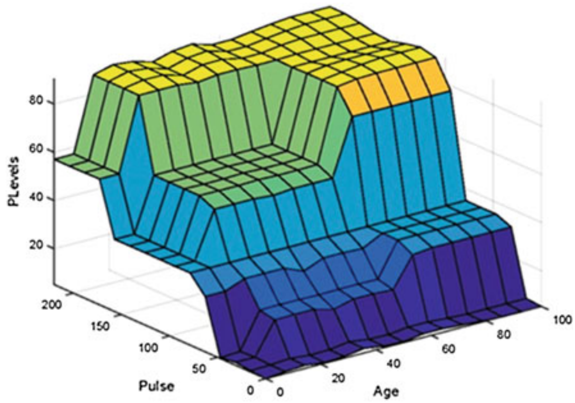

Fig. 6.5 Surface of the fuzzy model

6.3.1 *Graphical User Interface*

A graphical user interface for the diagnosis of cardiovascular risk was designed, and is shown in Fig. 6.6, for which the final user can search for the appropriate file where they have saved the patient's measures, the interface plots the behavior of the pressure and pulse obtained by ABPM device and shows the patient information as name and age.

The medical doctor can make questions about risk factors, and this will be evaluated together with the records of ABPM device in the fuzzy rules.

When the final user presses the evaluate button it will display the results obtained by the fuzzy inference systems and the result of the traditional system rules for cardiovascular risk diagnosis that the patient may have.

6.4 Results and Discussion

The modular neural network was trained with different architectures to observe the data behaviour and find the better results. In Table 6.3 we show some experiments, can be noted the training methods, which were the Levenberg-Marquardt (LM) and Gradient descent with momentum and adaptive learning rate backpropagation

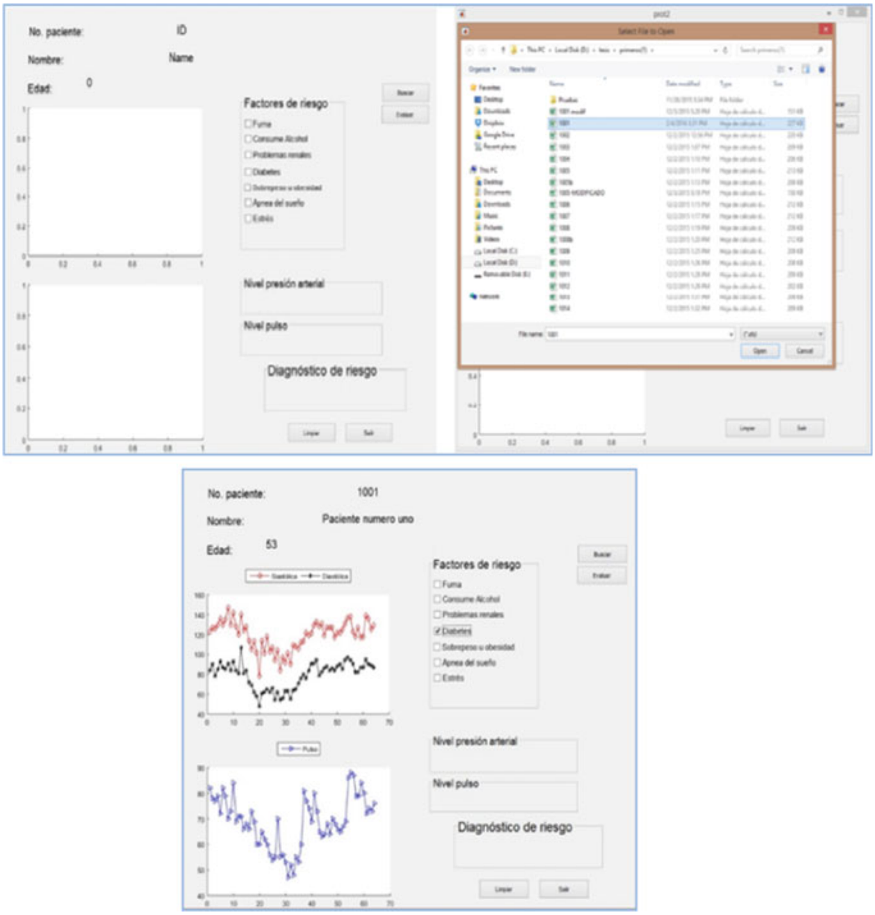

Fig. 6.6 Graphical user interface

(GDX), with different layers and neurons. There is a slight improvement in the training of LM method but is not significant.

Each training time was between 1 and 3 s and in the first 20 experiment we used 300 epochs, and in the last 10, was used 500 epochs. The error goal is 1.00 E^{-5}. We need to perform more tests to the neural network, try with another hidden layer, and maybe use delays for improving and obtain better results.

The pulse fuzzy system was tested with 15 patients obtaining good results, which are shown in Table 6.4.

In the same way, the fuzzy system for obtain the blood pressure classification was tested with 15 patients, showing the results in Table 6.5.

Table 6.3 Neural network training

				Errors					
				Systolic		Diastolic		Pulse	
No.	Train	Layers	Neurons	Train	Test	Train	Test	Train	Test
1	LM	1	25	0.0134	0.0101	0.0151	0.0159	0.009	0.0136
2	LM	1	30	0.013	0.0121	0.015	0.024	0.013	0.0121
3	LM	2	30,16	0.013	0.0119	0.0151	0.0261	0.009	0.0413
4	LM	2	25,12	0.0132	0.0337	0.0152	0.0024	0.009	0.4389
5	LM	1	18	0.0132	0.1036	0.0152	0.0142	0.009	0.0136
6	GDX	1	25	0.0104	0.0083	0.0166	0.0228	0.0057	0.0083
7	GDX	1	30	0.0118	0.0166	0.0131	0.0641	0.0079	0.0057
8	GDX	2	30,16	0.0099	0.0153	0.0139	0.0124	0.0062	0.0074
9	GDX	2	25,12	0.0122	0.0069	0.0138	0.0093	0.0065	0.0042
10	GDX	1	18	0.0105	0.0036	0.012	0.0344	0.008	0.0115
11	LM	1	35	0.0132	0.026	0.0151	0.1798	0.0091	0.0063
12	LM	1	12	0.013	0.0164	0.0152	0.0218	0.091	0.0108
13	LM	2	20,12	0.0133	0.0153	0.0152	0.247	0.0089	0.2576
14	LM	3	28,16,12	0.0131	0.151	0.0151	0.0649	0.0065	0.009
15	LM	3	32,18,13	0.0131	0.0128	0.0152	0.0315	0.0078	0.0073
16	GDX	1	35	0.0109	0.0045	0.0131	0.0484	0.0071	0.0151
17	GDX	1	12	0.0107	0.0045	0.0136	0.0138	0.0071	0.0095
18	GDX	2	20,12	0.0114	0.0032	0.0142	0.0154	0.0074	0.0078
19	GDX	3	28,16,12	0.0112	0.0104	0.0147	0.0058	0.006	0.0092
20	GDX	3	32,18,13	0.0113	0.0099	0.0155	0.0249	0.0081	0.0148
21	LM	1	33	0.0131	0.0245	0.015	0.0296	0.09	0.0081
22	LM	2	25,15	0.0131	0.0039	0.0151	0.3142	0.009	0.0273
23	LM	2	28,14	0.0132	0.0134	0.0152	0.3132	0.009	0.1519
24	LM	3	32,18,14	0.0131	0.018	0.0154	0.0746	0.0089	0.0486
25	LM	3	33,21,17	0.0132	0.0224	0.0157	0.0732	0.009	0.0864
26	GDX	1	33	0.0109	0.0149	0.014	0.0152	0.064	0.0226
27	GDX	2	25,15	0.0123	0.0109	0.0132	0.0182	0.0087	0.0136
28	GDX	2	28,14	0.0112	0.0083	0.0162	0.0336	0.0068	0.0048
29	GDX	3	32,18,14	0.012	0.0139	0.013	0.0244	0.0074	0.0042
30	GDX	3	33,21,17	0.0104	0.0152	0.0142	0.0169	0.0077	0.0067

Table 6.4 Pulse fuzzy system results

ABPM	Age/Pulse	Fuzzy model results	
1001	53/66.55	35.1	Excellent
1002	53/73.61	35.1	Excellent
1003	55/83.74	35.1	Excellent
1004	59/70	35	Excellent
1005b	27/74.61	35.1	Excellent
1005	45/95	48.1	AboveAV
1006	26/88	35.1	Excellent
1007	29/69.3	35.1	Excellent
1008	31/59	32.5	Excellent
1008b	73/60	35	Excellent
1009	71/71.70	35.1	Excellent
1010	58/72.4	35	Excellent
1011	31/80	35.1	Excellent
1012	53/76.44	35.1	Excellent
1013	69/70.73	35.1	Excellent

Table 6.5 Results of fuzzy system for blood pressure classification

ABPM	Syst	Diast	Fuzzy BP
1001	117	76	Optimal
1002	107	74	Optimal
1003	122	75	Normal
1004	114	66	Optimal
1005	141	81	ISH Grade 1
1005b	106	62	Optimal
1006	120	81	Normal
1007	107	61	Optimal
1008	130	74	High Normal
1008b	116	73	Optimal
1009	134	62	High Normal
1010	135	81	High Normal
1011	121	77	Optimal
1012	109	63	Optimal
1013	123	71	Normal

6.5 Conclusions and Future Work

This research work has presented a hybrid intelligent system for providing a risk diagnosis in patients with hypertension, this type of system can be helpful for reducing the complexity of the problem to be solved. We used a modular neural network with a fuzzy response integrator to provide an accurate result. So far, we have good results, but more experiments will be conducted and other factors will be added to the model to make improvements, such as more risk factors to give a final risk diagnosis more accurate.

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Chapter 7
Conclusions

Abstract We present in this book a novel model for classification, diagnosis and risk evaluation of high blood pressure or arterial hypertension using new hybrid intelligent systems, combining Modular Neural Networks, Fuzzy Logic and Genetic Algorithms. The motivation of this research work is based on the importance of developing new methods using Computational Intelligence for application in medicine, particularly in the area of cardiology to diagnose cardiovascular diseases. In this particular case to help medical doctors diagnose, classify and determine the possible risk of developing high blood pressure.

The book has presented a novel model for classification, diagnosis and risk evaluation of high blood pressure or arterial hypertension using new hybrid intelligent systems, combining Modular Neural Networks, Fuzzy Logic and Genetic Algorithms. This book focused on the development of hybrid intelligent systems; first for the classification of blood pressure levels using the experience of cardiologists and the guidelines of European Society of Cardiology (ESC), for constructing a fuzzy logic classification method based on patient's Blood pressure. The second model developed was for classification based on a fuzzy rule base optimization using a hierarchical genetic algorithm, reducing the number of rules used in the final system to give more accurate results for the classification of levels of hypertension. The third part was the complete architecture of the hybrid system based on Modular Neural Networks and Fuzzy Inference Systems for classification, diagnosis and risk evaluation of HBP. The Modular Neural Network is used for modeling the trend of the blood pressure during the period of 24 h using the information of the ambulatory blood pressure monitoring readings, and this trend is given to the classification module, in parallel a module of fuzzy inference systems is used for providing the risk of hypertension depending on variables of the patients and the trend of the blood pressure. At the end, the Model produces the classification level of blood pressure and the estimation risk of develop hypertension.

P. Melin and G. Prado-Arechiga, *New Hybrid Intelligent Systems for Diagnosis and Risk Evaluation of Arterial Hypertension*, SpringerBriefs in Computational Intelligence, DOI 10.1007/978-3-319-61149-5_7

The motivation of this research work is based on the importance of developing new methods using Computational Intelligence for application in medicine, particularly in the area of cardiology to diagnose cardiovascular diseases. In this particular case to help medical doctors diagnose, classify and determine the possible risk of developing high blood pressure.

Future research work could include the following. First, other types of hybrid models could be considered, such as ensembles instead of modular neural networks. Second, other optimization meta-heuristics could be applied to improve the architectures or the accuracy. Third, fuzzy logic models are mainly of type-1, and could be extended to be type-2 or intuitionistic fuzzy systems.

Appendix A

In the first part of the research for developing the initial classifier the data base of 30 patients monitoring during 5 days with 4 readings at day was created for use in the model. The measures were taking with a Microlife Blood pressure monitor with model Premium Touch Screen. In the second part of the study, for the design of the Hybrid Intelligent models we developed a data base from the results of the Ambulatory Blood Pressure Monitor (ABPM) to obtain information about patient's blood pressure for 24 h. These measurements were obtained from master and doctoral students in computer science at Tijuana Institute of Technology and in addition the Cardiodiagnostico of the Excel Medical Center in Tijuana, Mexico, provided us with measurements of their patients. The measurements were taking with two different ABPM devices, one is the Spacelab 90217A ABPM monitor, and the other one is the Microlife Watch BP03 ABPM monitor. With all this information a database is created which is organized according to the systolic, diastolic and pulse blood pressure respectively for use in the models. The age's ranges of the people were from 15 to 95 years, and were taking from November 13 of 2014 to February 24 of 2017. Up to now we have a database of more than 250 ABPM studies. In the following images we show the repository of the data base Fig. A.1 are the files taking direct for the ABPM monitor, and Fig. A.2 shows the processed information of the ABPM that are used in the hybrid intelligent systems to build a model of classification.

Figures A.3, A.4 and A.5 shows the example of the report that we have on the studies of ABPM of a particular patient taking with the Microlife WatchBP03 ABPM device, which shows the readings of blood pressure, and the graph in the time of readings, with this study the cardiologist diagnoses the possible arterial hypertension of a person. In Figs. A.6 and A.7 we show reports of the ABPM monitor of Spacelab 90217A. On the other hand our new model is fed with this information to learn to model the behavior and later to classify and to diagnose the possible hypertension. At the end of the study, validation tests of the diagnosis of the cardiologist against the diagnosis of the prototype were done.

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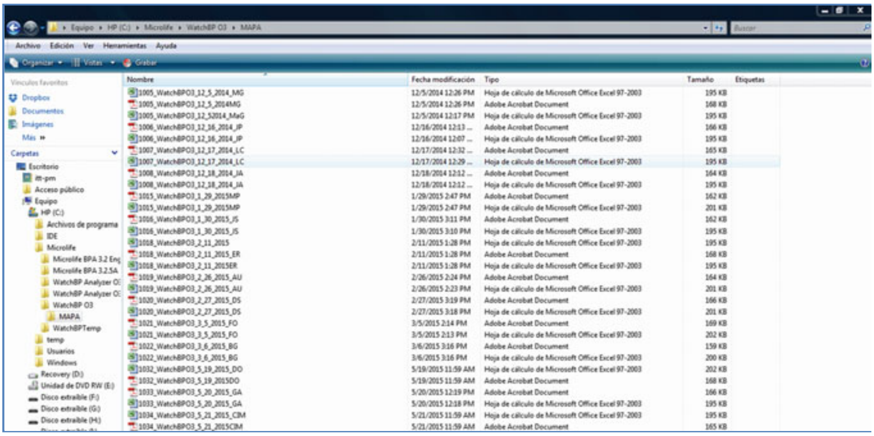


Fig. A.1 Repository of ABPM information containing measurements of the BP

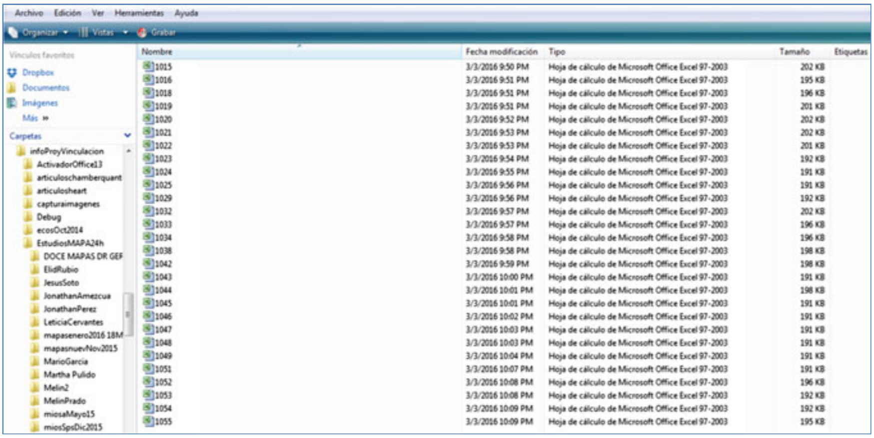


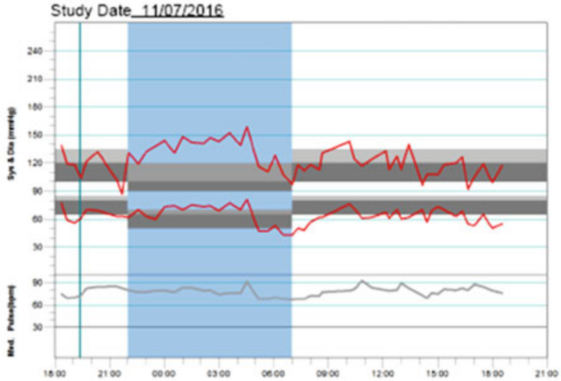
Fig. A.2 Processed files that will be used for the neural network training and modeling

Ambulatory Blood Pressure Measurement Report

Physician : DR. O G PRADO

Patient ID : 1104	
Name : R A M	
Sex : Female	
Age : 63	
DOB : 26/07/1952	
Day and Night Period	
Time	**Interval**
Day : 07 ~ 22	20 min
Night : 22 ~ 07	30 min
Actual Awake / Asleep	
Awake : 07 ~ 22 h	
Asleep : 22 ~ 07 h	
BP Threshold	
Day : 135/85 mmHg	
Night : 120/70 mmHg	

Study Date 11/07/2016



Readings
Total Readings : 63
Successful : 53 (84.1%)

BP Load
Day readings ≥ 135/85 **8.6%**
Night readings ≥ 120/70 **83.3%**

Average Blood Pressure (SD)

	Sys	Dia	HR	MAP	PP
24-hr	124 (14)	64 (8)	78 (6)	84	60
Awake	117 (11)	63 (6)	79 (6)	81	54
Asleep	135 (13)	66 (11)	77 (5)	89	69

White Coat Window

	Sys	Dia	HR
Readings	3	3	3
1st hr Max	139	77	75

Night-time Dip%

	Sys	Dia
Dip%	-15.5	-4.9

Date / Time	Sys	Dia	HR	Date / Time	Sys	Dia	HR	Date / Time	Sys	Dia	HR
11/07/2016				05:41	111	47	68	16:41	92	55	80
18:23	139	77	75	06:05	128	53	70	17:01	105	53	87
18:41	119	59	69	06:31	108	43	68	17:30	119	65	84
19:05	118	56	70	07:01	97	43	67	18:01	99	50	79
19:25	104	61	73	07:21	118	50	68	18:31	117	55	76
19:45	122	70	82	07:41	112	48	68				
20:21	132	69	84	08:01	118	57	72				
21:24	102	63	85	08:31	113	62	72				
21:41	87	63	82	08:41	131	62	77				
22:04	131	62	80	10:10	143	76	79				
22:35	119	70	77	10:25	124	71	81				
23:01	132	63	77	10:51	117	61	92				
23:31	138	60	79	11:24	124	62	83				
12/07/2016				12:10	133	67	80				
00:01	144	73	79	12:21	113	61	79				
00:35	131	74	77	12:45	127	70	80				
01:01	148	70	83	13:01	113	60	89				
01:31	142	75	83	13:25	140	62	82				
02:10	141	73	79	14:10	96	70	73				
02:31	147	74	80	14:25	108	57	69				
03:01	143	69	74	14:41	108	69	76				
03:35	152	77	76	15:01	108	73	75				
04:11	139	70	76	15:21	118	70	81				
04:31	159	81	91	16:01	120	63	80				
05:11	116	47	68	16:20	126	68	82				

Comments:

Fig. A.3 Results of the ABPM monitoring for a patient with the Microlife WatchBP03 ABPM monitor showing some of the readings with high pressure level

Ambulatory Blood Pressure Measurement Report

Physician : DR. O G PRADO

Study Date 29/01/2016

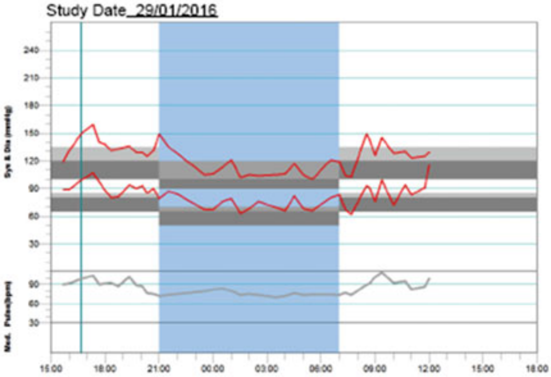
Patient ID : 1079
Name : R O B C
Sex : Female
Age : 39
DOB : 04/08/1976

Day and Night Period

	Time	Interval
Day :	07 ~ 21	20 min
Night :	21 ~ 07	30 min

Actual Awake / Asleep
Awake : 07 ~ 21 h
Asleep : 21 ~ 07 h

BP Threshold
Day : 135/85 mmHg
Night : 120/70 mmHg



Readings
Total Readings : 42
Successful : 41 (97.6%)

BP Load
Day readings ≥ 135/85 **68.0%**
Night readings ≥ 120/70 **50.0%**

Average Blood Pressure (SD)

	Sys	Dia	HR	MAP	PP
24-hr	124 (15)	83 (12)	84 (10)	97	41
Awake	131 (11)	90 (11)	91 (8)	104	41
Asleep	114 (13)	74 (6)	75 (4)	87	40

White Coat Window

	Sys	Dia	HR
Readings	2	2	2
1st hr Max	131	89	91

Night-time Dip%

	Sys	Dia
Dip%	13.2	18.3

Date / Time	Sys	Dia	HR
29/01/2016			
15:41	119	89	90
16:00	131	89	91
16:45	151	100	99
17:20	159	107	103
17:41	140	97	90
18:00	138	88	91
18:21	131	80	92
18:45	133	81	87
19:21	136	94	102
19:45	129	90	88
20:05	129	93	87
20:21	125	85	76
20:41	131	90	75
21:01	149	79	72
21:31	135	87	73
22:01	128	84	75
23:31	105	67	79
30/01/2016			
00:01	106	67	82
00:31	113	76	83
01:01	121	79	80
01:31	102	63	73
02:01	105	68	75
02:31	104	76	73

Date / Time	Sys	Dia	HR
03:31	105	69	70
04:01	106	66	72
04:31	117	82	76
05:01	105	68	73
05:31	100	66	74
06:31	121	80	74
07:01	119	83	73
07:21	104	67	77
07:41	103	62	73
08:31	149	93	89
08:41	143	91	91
09:01	126	76	101
09:22	145	99	108
10:02	128	72	92
10:41	130	94	95
11:01	123	83	82
11:46	125	91	86
12:00	129	115	98

Comments:
Isolated 24-h Diastolic Hypertension, Isolated Daytime Diastolic Hypertension, Isolated Nighttime Diastolic Hypertension.

Fig. A.4 Results of the ABPM monitoring with the Microlife WatchBP03 ABPM monitor for a patient showing readings with isolated diastolic hypertension

Ambulatory Blood Pressure Measurement Report

Physician : DR. PRADO

Patient ID : 1083
Name : V C A
Sex : Male
Age : 31
DOB : 11/11/1984

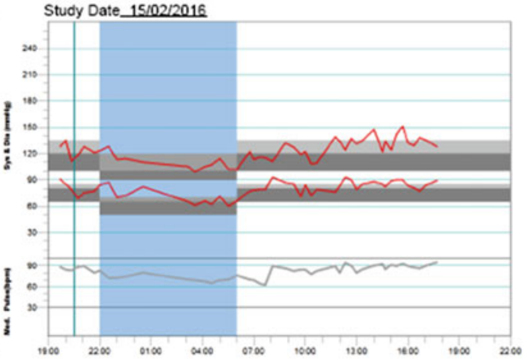
Day and Night Period

	Time	Interval
Day :	06 ~ 22	20 min
Night :	22 ~ 06	30 min

Actual Awake / Asleep
Awake : 06 ~ 22 h
Asleep : 22 ~ 06 h

BP Threshold
Day : 135/85 mmHg
Night : 120/70 mmHg

Study Date 15/02/2016



Readings
Total Readings : 56
Successful : 46 (82.1%)

BP Load
Day readings ≥ 135/85 48.6%
Night readings ≥ 120/70 54.5%

Average Blood Pressure (SD)

	Sys	Dia	HR	MAP	PP
24-hr	122 (11)	79 (8)	81 (9)	93	43
Awake	127 (9)	82 (6)	84 (7)	97	45
Asleep	111 (8)	72 (10)	73 (5)	85	39

White Coat Window

	Sys	Dia	HR
Readings	3	3	3
1st hr Max	135	91	88

Night-time Dip%

	Sys	Dia
Dip%	12.5	12.4

Date / Time	Sys	Dia	HR	Date / Time	Sys	Dia	HR
15/02/2016				08:50	132	87	86
19:43	128	91	88	09:21	127	85	82
20:00	135	85	84	09:44	119	71	84
20:20	111	79	83	10:01	122	84	84
20:44	118	69	88	10:20	108	72	78
21:05	128	75	89	10:41	109	79	82
21:41	121	77	80	11:45	139	76	89
22:01	123	84	83	12:01	134	83	80
22:31	128	87	72	12:20	124	93	94
23:01	113	70	72	12:41	137	90	90
23:31	114	72	74	13:01	131	79	80
16/02/2016				13:21	135	85	85
00:31	110	82	80	14:01	147	88	90
03:11	105	65	70	14:31	122	85	92
03:33	99	61	69	14:40	134	82	85
04:10	105	66	67	15:01	124	89	91
04:31	107	62	65	15:20	142	90	89
05:01	114	71	69	15:41	151	90	93
05:31	102	60	70	16:00	132	83	89
06:01	102	66	76	16:21	129	81	87
06:45	122	77	70	16:41	138	77	86
07:00	113	78	69	17:04	135	84	90
07:21	116	79	64	17:41	128	89	95
07:41	115	79	62				
08:05	111	93	89				

Comments:

24-h Normotension, Daytime Normotension, Isolated Nighttime Diastolic Hypertension, White Coat Hypertension, Dipper

Fig. A.5 Results of the ABPM monitoring for a patient with Microlife WatchBP03 ABPM monitor, showing readings with daytime normotension, isolated nighttime diastolic hypertension and with white coat hypertension

Date of Birth: 6/28/1971 (44 Years)
Height: 5' 6"
BMI: 23.3
Physician:

Gender: Male
Weight: 143lbs 5oz
BSA: 1.7

Medications

Indications

Recording Information

Start: 12/15/2015 5:34:00 PM
End: 12/16/2015 5:34:00 PM
Number of Readings: 51
Duration: 1.00:00:00

Successful: 61.45%
Systolic > Limits: 35.29%
Diastolic > Limits: 23.53%
AASI: 0.35
MSI: 14.25

Overall Summary

	AVG	STD	MIN	MAX	Dipping
Systolic (mmHg)	127	14.75	100 (5:44 AM Wed)	170 (10:17 AM Wed)	17.68 %
Diastolic (mmHg)	76	11.25	53 (1:14 AM Wed)	101 (10:17 AM Wed)	22.93 %
MAP (mmHg)	90	11.1	68	116	19.15 %
Pulse Pressure (mmHg)	51	8	31	69	
Heart Rate (BPM)	69	7.89	56	91	

SBP > Limits : 35.29% DBP > Limits : 23.53% AASI: 0.35 MSI: 14.25

Daytime Summary

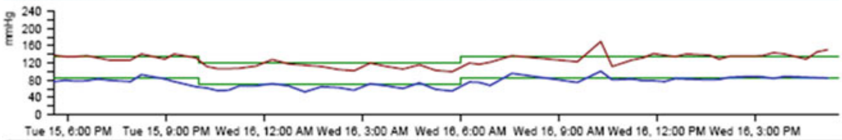
	AVG	STD	MIN	MAX
Systolic (mmHg)	135	10.49	112 (10:38 AM Wed)	170 (10:17 AM Wed)
Diastolic (mmHg)	82	7.12	65 (9:54 PM Tue)	101 (10:17 AM Wed)
MAP (mmHg)	96	7.11	84	116
Pulse Pressure (mmHg)	53	8.62	31	69
Heart Rate (BPM)	72	7.64	56	91

SBP > 135 mmHg: 50% DBP > 85 mmHg: 26.47%

Nighttime Summary

	AVG	STD	MIN	MAX
Systolic (mmHg)	111	7.22	100 (5:44 AM Wed)	128 (12:14 AM Wed)
Diastolic (mmHg)	63	6.41	53 (1:14 AM Wed)	74 (4:44 AM Wed)
MAP (mmHg)	78	6.25	68	89
Pulse Pressure (mmHg)	48	5.37	41	62
Heart Rate (BPM)	63	4.55	57	73

SBP > 120 mmHg: 5.88% DBP > 70 mmHg: 17.65%



Interpretations

Fig. A.6 Report results of the ABPM monitoring for a patient with Spacelab 90217A ABPM monitor, showing readings with daytime hypertension and with white coat hypertension

Date of Birth: 11/26/1985 (31 Years) Gender: Female
Height: 5' 7" Weight: 152lbs 2oz
BMI: 23.9 BSA: 1.8
Physician:

Medications

Indications

Recording Information

Start: 2/23/2017 2:53:00 PM
End: 2/24/2017 2:13:00 PM
Number of Readings: 62
Duration: 23:20:00

Successful: 88.57%
Systolic > Limits: 27.42%
Diastolic > Limits: 29.03%
AASI: 0.24
MSI: 10.43

Overall Summary

	AVG	STD	MIN	MAX	Dipping
Systolic (mmHg)	126	14.48	100 (2:43 AM Fri)	161 (11:53 AM Fri)	15.75 %
Diastolic (mmHg)	76	12.44	53 (2:43 AM Fri)	100 (8:13 AM Fri)	22.84 %
MAP (mmHg)	93	14.31	69	133	20.66 %
Pulse Pressure (mmHg)	50	7.28	36	75	
Heart Rate (BPM)	74	19.54	51	146	

SBP > Limits : 27.42% DBP > Limits : 29.03% AASI: 0.24 MSI: 10.43

Daytime Summary

	AVG	STD	MIN	MAX
Systolic (mmHg)	131	12.54	106 (7:56 AM Fri)	161 (11:53 AM Fri)
Diastolic (mmHg)	81	10.26	56 (9:53 PM Thu)	100 (8:13 AM Fri)
MAP (mmHg)	99	12.63	71	133
Pulse Pressure (mmHg)	51	7.79	36	75
Heart Rate (BPM)	80	19.12	55	146

SBP > 135 mmHg: 36.96% DBP > 85 mmHg: 36.96%

Nighttime Summary

	AVG	STD	MIN	MAX
Systolic (mmHg)	111	6.4	100 (2:43 AM Fri)	119 (11:13 PM Thu)
Diastolic (mmHg)	62	6.66	53 (2:43 AM Fri)	74 (12:43 AM Fri)
MAP (mmHg)	78	5.05	69	86
Pulse Pressure (mmHg)	48	5.42	36	56
Heart Rate (BPM)	56	2.88	51	61

SBP > 120 mmHg: 0% DBP > 70 mmHg: 6.25%

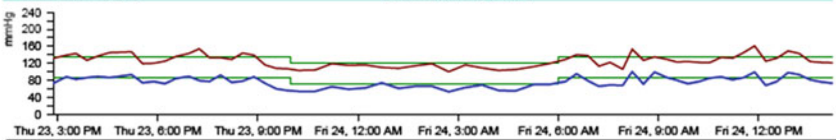


Fig. A.7 Report of the ABPM monitoring results for a patient with Spacelab 90217A ABPM monitor, showing readings with daytime hypertension

Index

P. Melin and G. Prado-Arechiga, *New Hybrid Intelligent Systems for Diagnosis and Risk Evaluation of Arterial Hypertension*, SpringerBriefs in Computational Intelligence, DOI 10.1007/978-3-319-61149-5