Fuzzy Intelligent System for Supporting Preeclampsia Diagnosis from the Patient Biosignals

Macarena Espinilla[1(✉)], Sixto Campaña[2], Jorge Londoño[3], and Ángel-Luis García-Fernández[4]

[1] Computer Science Department, University of Jaén, Jaén, Spain
mestevez@ujaen.es
[2] Universidad Nacional Abierta y a Distancia - UNAD, ECBTI, Pasto, Colombia
sixto.campana@unad.edu.co
[3] Universidad Pontificia Bolivariana - UPB, Medellín, Colombia
jorge.londono@upb.edu.co
[4] Computer Science Department, University of Jaén, Jaén, Spain
algarcia@ujaen.es

Abstract. This contribution presents a proposal for generating linguistic reports based on the study of biomedical signals of human patients. Although this topic is dealt in many previous works, there are challenges still open for the scientific community, such as the development of systems to produce reports and alerts using a human-friendly language. We present a brief review of some relevant previous works, as well as our proposal of a system based on fuzzy linguistic approach applied to the diagnosis of the preeclampsia disease that may affect pregnant women. Our system transforms numerical values of biomedical signals into linguistic values that are understandable information for the patients and the medical staff. The dataset used for testing the system contains real data from a study carried out by the Davinci UNAD Group (Colombia) on patients that suffer from preeclampsia.

Keywords: Fuzzy logic · Fuzzy linguistic intelligent systems · Biomedical systems · Preeclampsia

1 Introduction

We live in the era of data. Our everyday lives are surrounded by sensors that capture information associated to objects, humans or environments, such as vision sensors, motion sensors, light sensors, medical sensors, etc. The so-called Internet of Things (IoT) is all around us, producing a huge amount of data that needs to be automatically organized and processed in order to produce easy to understand reports for the users, as trying to deal with this data directly is far from the human capabilities.

Data analysis is at the core of a relevant amount of recently published works, many of them focusing on data mining techniques to extract useful knowledge

C.R. García et al. (Eds.): UCAmI 2016, Part I, LNCS 10069, pp. 3–14, 2016.
DOI: 10.1007/978-3-319-48746-5_1

from the data and shape it so that the users understand what is happening and act accordingly. The research on methods to communicate this knowledge in a user-friendly way has led to the concept of linguistic descriptions [1], which allow to abstract useful data into different levels and dimensions, therefore providing interpretability.

Our work considers a case study in the health care area, given its relevance nowadays [2], although the presented techniques could be applied in other areas as well.

Modern health care systems make use of many technological advances to measure biomedical signals that produce large amounts of raw data. The development of methods for analysing this data relies mostly on *soft computing techniques* whose results in most cases still require some level of expertise to understand and use them properly. This is the motivation for the development of linguistic report techniques, which rely on fuzzy logic principles to communicate important information obtained from the analysis of the data. In our work, biomedical signals will be used to identify risk conditions and generate linguistic reports for the medical staff.

Submitting user-friendly reports to support the diagnosis and monitoring of a given disease is a problem that has not been completely solved yet, as sometimes a rigid interpretation of the data can lead to misdiagnosis. Therefore we propose in this paper a new system based on fuzzy linguistic approach focused on this process.

This work is structured as follows: Sect. 2 describes a series of related works; Sects. 3 and 4 introduce a fuzzy intelligent system that is used in our proposal; Sect. 5 presents the result of applying the fuzzy intelligent system to a preeclampsia case study, and finally, Sect. 6 summarizes our conclusions and future work.

2 Related Works

Nowadays data mining is one of the major topics in the research on data analysis. The work from Karahoca et al. [3] presents a scientific review of the needs that have motivated many researchers to study new ways of organizing and interpreting data in order to find out and/or understand the activity that is monitored and notify the users about it, so that they can use that information for any further action.

The search for new ways to understand the data generated in different contexts has resulted in the development of intelligent systems and linguistic descriptions [1]. These descriptions allow to abstract easy to understand information from raw data, organize it into different levels and dimensions and shape it into a useful format for the users who demand it.

Other interesting works related to this topic include the one from Bhunia et al. [4] who present the design of a system for health surveillance and remote monitoring of patients, able to detect any abnormal situation by applying fuzzy rules; this system is also able to produce alerts for the health care staff when necessary. Although the system from Bhunia et al. produces technical reports, it lacks the capacity of producing a linguistic description of its results.

Baig et al. [5] give a thorough review of the research works related to the application of intelligent environments to health monitoring. In their work, the application of fuzzy logic to the identification of abnormal conditions and the generation of linguistic descriptions for the medical staff is said to be a still open topic, as very little has been done on it up to now.

Different reviews have been published on the application of fuzzy systems [6], health care systems [7] and data mining on medical sensor data [8]. All these works make patent the need of having systems able to generate linguistic descriptions easy to read and interpret.

The application of fuzzy logic systems to health care has been dealt in a series of already published works: Yuan et al. [9] propose a fuzzy reasoning system for remotely monitoring chronic patients which generates reports on their behaviour; Latifi et al. [10] present an expert system that applies fuzzy logic to assist in diagnosing leukemia in children; Sen et al. [11] introduces a data mining system that makes use of fuzzy logic for predicting coronary heart disease; Ekong et al. [12] focus their system on the diagnosis of depression; Nnamoko et al. [13] present a fuzzy expert system for monitoring diabetes mellitus; and finally, Dennis et al. [14] propose an adaptive genetic fuzzy system for classifying medical data.

The generation of linguistic summaries in order to generate health alerts has been studied by Jain et al. [15]; Wilbik et al. [16] also worked on a system to linguistically summarize sensor data related to eldercare. An expert system to support a preeclampsia prevention program was also presented by Matamoros et al. [17], but to the best of our knowledge, it is the only published work linking fuzzy systems and preeclampsia; moreover, that work does not deal with the generation of linguistic reports in the way that we propose.

According to Acampora et al. [18], there are still many challenges to face, especially those related to the generation of user-friendly reports on data from sensors that monitor medical variables that affect humans. This task requires intelligent systems to manage and process the data, and generate the expected results.

3 Previous Concepts

Fuzzy linguistic modelling makes possible the representation of qualitative descriptions that describe words or statements in natural or artificial language by means of linguistic variables [19]. These variables take numerical values such as measurements and can be transformed into statements more understandable to the end user. The elements of an intelligent fuzzy system [20] are the fuzzy rules, the knowledge base and finally, the inference engine. All of them are briefly described in this section.

3.1 Fuzzy Rules

Fuzzy rules are statements of the form "IF - THEN". These rules allow the identification of actions to be performed when a certain condition is met. For example, if the temperature is high, then send the alert "high temperature". In our case, the rules take the form "If x is A then y is B", given a set of input and output pairs [21] in which the output is an alert or an action that is performed in response to the variation of a monitored variable.

The input-output pairs are part of the fuzzy universe of the intelligent fuzzy system. It is common in fuzzy logic the combination of one or more input fuzzy sets (Antecedent), which in turn generate an output fuzzy set (Consequent) [22]. For the case of two fuzzy input sets the rule is as follows

$$\text{IF } x \textit{ is } \mathbf{A} \text{ AND } y \textit{ is } \mathbf{B} \text{ THEN } z \textit{ is } \mathbf{C} \tag{1}$$

Where x, y and z are linguistic variables and A, B and C are fuzzy sets defined in the universe of x, y and z.

3.2 Knowledge Base

The knowledge base supports the set of fuzzy rules [20]. It may include facts and expert opinions on the subject. In some cases the facts are absolute and certain (a body temperature above 37.5 °C corresponds to fever). In other cases it may depend on the opinion of the expert who advises or assists the system (given their high body temperature, the patient may go into convulsions). There are clinical protocols [23] which determine certain actions to be taken given the diagnosis and/or the medical condition of a patient. These protocols are also part of the knowledge base for the intelligent system. In this work, we have also received medical expert advice on the selected topic.

3.3 Inference Engine

The inference engine uses the knowledge base to draw conclusions from the inputs, and produces proper responses. In the case of biomedical signal monitoring, the inference engine links the changes in the monitored variables to the alerts or reports that are generated in the process. There are different inference engine models, the ones from Mamdani and Takagi-Sugeno being the most popular [24]. In this work, the inference engine by Mamdani is used.

The rules in the Mamdani fuzzy model are represented as follows:

$$R^i : \text{IF } x_1 \textit{ is } \mathbf{A}_1^i \text{ AND } x_2 \textit{ is } \mathbf{A}_2^i \text{ ... AND } x_n \textit{ is } \mathbf{A}_n^i \text{ THEN } y \textit{ is } \mathbf{B}^i \tag{2}$$

Where x_i and y are linguistic variables, and $\mathbf{A}_j^i$ and $\mathbf{B}$ represent linguistic values that the variables can take.

According to the above, we propose a set of fuzzy rules for monitoring patients and supporting the diagnosis of the preeclampsia disease from the biosignal values of the patient. This rules are the model of the fuzzy intelligent system that runs a standard inference engine.

4 Fuzzy Intelligent System for Supporting Preeclampsia Diagnosis

Preeclampsia (PE) is a medical condition that is mainly characterized by high blood pressure (BP) and proteinuria, which refers to the excess of proteins in the urine, and to a lesser extent, by high body temperature (T). This condition may be mild or severe [25] and occurs usually after 20 weeks of pregnancy. The protocol that applies in this type of pathology is as follows [26]:

Protocol diagnostic phase of preeclampsia (PE):

1. Measure the patient blood pressure (BP) twice, and compute the average of the two measurements. The BP consists of two values: the systolic blood pressure (SBP) and the diastolic blood pressure (DBP). Measure other vital signs of the patient, like the body temperature.
2. If either SBP or DBP are high, proceed to perform a urine test.
3. Perform a physical examination on the patient to search for oedemas or reddened body parts.
4. If the results of the above tests are abnormal, the patient may suffer from preeclampsia. The seriousness of the illness has to be evaluated:
   (a) Mild PE if: SBP between 140 and 160 mmHg and DBP between 90 and 110 mmHg; proteinuria is between 2 g/24 h y 5 g/24 h; no oedema
   (b) Severe PE if: SBP is greater than 160 and DBP is greater than 110; proteinuria is greater than 5 g/24 h; presence of oedema; T greater than 36.5 °C.
5. According to the type of preeclampsia, the doctor determines the procedure to be followed.

In the following subsection we propose the linguistic variables (SBP, DBP and T) and their linguistic terms that will be used by our proposed system.

4.1 Measured Variables and Linguistic Terms

As stated above, Our contribution will work with only three linguistic variables: systolic and diastolic blood pressure and body temperature, as these three values can be easily measured at home. Regarding blood pressure, there exist a series of portable, non-invasive sensors that may be used together with smartphones, like the ones from iHealth Labs, that provide the systolic pressure (SBP) and diastolic blood pressure (DBP) values [27], both measured in mmHg. Body temperature (T) can be measured in different ways [28]; temperature sensors have been considered in the literature [29,30] and are now commercially available [31].

Our system has a single linguistic output that is the proposal of diagnosis for the patient: DP $\in$ {Absence of PE, Possible mild PE, Possible severe PE}. Table 1 shows the relationship between the type of PE and the value ranges of SBP and DBP, and Table 2 shows the relationship between PE and the T value.

The linguistic variables associated to the three measured values are described as follows:

Table 1. Classification of blood pressure ranges [32]

Variable	Normal	Abnormal (mild)	Abnormal (severe)
SBP	120–140	141–160	>160
DBP	80–90	91–105	>110

Table 2. Classification of body temperature ranges

Variable	Normal	High	Low
Temperature	36 °C–36.5 °C	>36.5 °C	<36 °C

- *Systolic Blood Pressure (SBP)*: universe of discourse: [120, 220] mmHg; linguistic term sets: SBP $\in$ {normal, abnormal (mild), abnormal (severe)}. (Figure 1)
  SBP values below 120 mmHg are not a preeclampsia symptom, and therefore they will not be taken into account in this study.
- *Diastolic Blood Pressure (DBP)*: universe of discourse: [80, 120] mmHg; linguistic term set: DBP $\in$ {normal, abnormal (mild), abnormal (severe)}. (Figure 2)
  DBP values below 80 mmHg are not a preeclampsia symptom, and therefore they will not be taken into account in this study.
- *Temperature (T)*: universe of discourse: [35, 45] °C; linguistic term set: T $\in$ {normal, high, low}. (Figure 3)

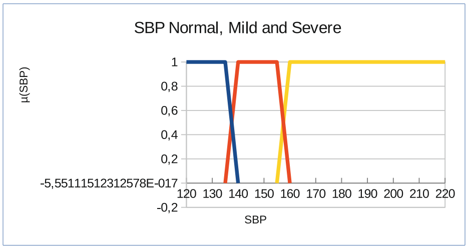

Fig. 1. SBP fuzzy membership functions: normal, abnormal (mild) and abnormal (severe)

4.2 Fuzzy Rules

For the case of preeclampsia, we have defined the fuzzy rules that are shown in Table 3.

Table 3. Fuzzy rule set connecting preeclampsia with blood pressure and body temperature

Rule	Antecedent	Consequent
1	IF ((SBP is normal) OR (DBP is normal) OR (T is normal))	THEN (DP is absence of PE)
2	IF ((SBP is normal) OR (DBP is normal) OR (T is high))	THEN (DP is absence of PE)
3	IF ((SBP is normal) OR (DBP is normal) OR (T is Low))	THEN (DP is absence of PE)
4	IF ((SBP is abnormal (mild)) OR (DBP is normal))	THEN (DP is possible mild PE)
5	IF ((SBP is normal) OR (DBP is abnormal (mild)))	THEN (DP is possible mild PE)
6	IF ((SBP is abnormal (mild)) OR (DBP is abnormal (mild)))	THEN (DP is possible mild PE)
7	IF ((SBP is abnormal (severe)) OR (DBP is abnormal (mild)) OR (T is high))	THEN (DP is possible severe PE)
8	IF ((SBP is abnormal (mild)) OR (DBP is abnormal (severe)) OR (T is high))	THEN (DP is possible severe PE)
9	IF ((SBP is normal) OR (DBP is abnormal (severe)) OR (T is high))	THEN (DP is possible severe PE)
10	IF ((SBP is abnormal (severe)) OR (DBP is normal))	THEN (DP is possible severe PE)
11	IF ((SBP is abnormal (severe)) OR (DBP is normal))	THEN (DP is possible severe PE)
12	IF ((SBP is normal) OR (DBP is abnormal (severe)))	THEN (DP is possible severe PE)
13	IF ((SBP is abnormal (severe)) OR (DBP is abnormal (severe)) OR (T is high))	THEN (DP is possible severe PE)

4.3 Inference Engine

The inference engine of our system is based on the Mamdani model [24], and applies the rules from Table 3 using the OR operator.

The trapezoidal-shaped membership functions of the engine are shown in Eq. 3. In these functions, x represent the value of the measured variable, a and d correspond to the "feet" of the trapezoid (the limits of the membership range for the variable), and b and c correspond to the "shoulders" of the trapezoid (the limits of the range for which the membership function takes its maximum value).

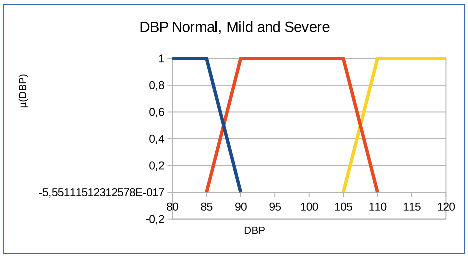

Fig. 2. DBP fuzzy membership functions: normal, abnormal (mild) and abnormal (severe)

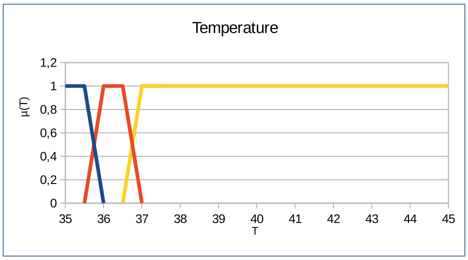

Fig. 3. T fuzzy membership functions: low, normal and high

$$A(x) = \begin{cases} 0 & \text{IF} \quad ((x \leq a) \text{ OR } (x \geq d)) \\ (x-a)/(b-a) & \text{IF} \quad x \in (a,b) \\ 1 & \text{IF} \quad x \in [b,c] \\ (d-x)/(d-c) & \text{IF} \quad x \in (b,d) \end{cases} \tag{3}$$

In Sect. 5 we will show the application of this engine to some example data.

5 Results

In order to prove the effectiveness of the proposed system, we have applied it to a series of real data from patients with preeclampsia that attended the University Hospital of the Nariño department in Colombia. Here we present three example cases:

– **Case 1:** Table 4 shows the SBP, DBP and T values of the patient.
The results of the inference engine for this case are the following: Rule 1 (Table 3) produces the highest degree of membership, due to the fact that the values of SBP, DBP and T are labeled as *normal*, all of them with a degree of membership equal to 1. Rules 2 and 3 could also be partially considered, given the values of the monitored variables. The final proposal of diagnosis is "absence of PE" with a degree of membership equal to 1.

Table 4. Measured values of the patient from Case 1

Variable	Value
SBP	130 mmHg
DBP	84 mmHg
Temperature	36.5 °C

Table 5. Measured values of the patient from Case 2

Variable	Value
SBP	137 mmHg
DBP	89 mmHg
Temperature	36.2 °C

- **Case 2:** Table 5 shows the SBP, DBP and T values of the patient. The results of the inference engine for this case are the following: Rule 5 (Table 3) produces the highest degree of membership, due to the fact that the value of SBP is labeled as *normal* with a degree of membership of 0.6 and the value of DBP is labeled as $abnormal(mild)$ with a degree of membership of 0.8. Rules 4 and 6 could also be partially considered, given the values of the monitored variables. The final proposal of diagnosis is "Possible mild PE", with a degree of membership equal to 0.8.
- **Case 3:** Table 6 shows the SBP, DBP and T values of the patient.

Table 6. Measured values of the patient from Case 3

Variable	Value
SBP	158 mmHg
DBP	88 mmHg
Temperature	36.8 °C

The results of the inference engine for this case are the following: the value of SBP is labeled as $abnormal(mild)$ with a degree of membership equal to 0.4, and as $abnormal(severe)$ with a degree of 0.6; the value of DBP is labeled as *normal* with a degree of membership equal to 0.4, and as $abnormal(mild)$ with a degree of membership equal to 0.6; finally, the value of T is labeled as *normal* with a degree of membership equal to 0.4, and as *high* with a degree of membership equal to 0.6.

Given the labels for the measured biosignals, Rule 10 (Table 3) produces the highest degree of membership, while Rules 7, 8, 9, 11, 12 and 13 could also be partially considered. The final proposal of diagnosis is "Possible severe PE", with a degree of membership equal to 0.6.

6 Conclusions and Future Work

One of the most important tasks in medicine is the interpretation of the results of the different tests that are performed on the patients, as the choice of one or the other treatment depends on it. Fuzzy models can give support to this task, as fuzzy logic is a well-known technique that can be adapted to many application areas. However, the creation of a general model for creating linguistic descriptions of the fuzzy system results is still an unsolved problem.

In this work we have presented a model for the analysis of biomedical signals that applies fuzzy logic principles as a step towards the development of an intelligent system that allows the generation of user-friendly linguistic descriptions. Our aim for future works is the development of a system able to monitor biomedical signals over the time and identify possible pathologies using pattern matching techniques. For this purpose, we will have support by medical experts for defining the fuzzy sets and rules for the system.

References

1. Ramos-Soto, A., Bugarin, A.J., Barro, S., Taboada, J.: Linguistic descriptions for automatic generation of textual short-term weather forecasts on real prediction data. IEEE Trans. Fuzzy Syst. **23**(1), 44–57 (2015)
2. Uribe, T.M.: El autocuidado y su papel en la promoción de la salud. Investigación y Educación en Enfermería, vol. 17, no. 2 (2013)
3. Karahoca, A., Karahoca, D., Şanver, M.: Survey of Data Mining and Applications (Review from 1996 to Now) (2012)
4. Bhunia, S.S., Dhar, S.K., Mukherjee, N.: iHealth: a fuzzy approach for provisioning intelligent health-care system in smart city. In: 2014 IEEE 10th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), pp. 187–193 (2014)
5. Baig, M.M., Gholamhosseini, H.: Smart health monitoring systems: an overview of design and modeling. J. Med. Syst. **37**(2), 1–14 (2013)
6. Kar, S., Das, S., Ghosh, P.K.: Applications of neuro fuzzy systems: a brief review and future outline. Appl. Soft Comput. **15**, 243–259 (2015)
7. Touati, F., Tabish, R.: U-healthcare system: state-of-the-art review and challenges. J. Med. Syst. **37**(3), 1–20 (2013)
8. Banaee, H., Ahmed, M.U., Loutfi, A.: Data mining for wearable sensors in health monitoring systems: a review of recent trends and challenges. J. Sens. **13**(12), 17472–17500 (2013)
9. Yuan, B., Herbert, J.: Fuzzy cara-a fuzzy-based context reasoning system for pervasive healthcare. Procedia Comput. Sci. **10**, 357–365 (2012)
10. Latifi, F., Hosseini, R., Mazinai, M.: A fuzzy expert system for diagnosis of acute lymphocytic leukemia in children. Int. J. Inf. Secur. Syst. Manage. **4**(2), 424–429 (2015)
11. Sen, A.K., Patel, S., Shukla, D.P.: A data mining technique for prediction of coronary heart disease using neuro-fuzzy integrated approach two level. Int. J. Eng. Comput. Sci. ISSN 2319-7242 (2013)
12. Ekong, V.E., Inyang, U.G., Onibere, E.A.: Intelligent decision support system for depression diagnosis based on neuro-fuzzy-CBR hybrid. Modern Appl. Sci. **6**(7), 79 (2012)

13. Nnamoko, N.A., Arshad, F.N., England, D., Vora, J.: Fuzzy expert system for Type 2 Diabetes Mellitus (T2DM) management using dual inference mechanism. In: AAAI Spring Symposium: Data Driven Wellness (2013)
14. Dennis, B., Muthukrishnan, S.: AGFS: Adaptive Genetic Fuzzy System for medical data classification. Appl. Soft Comput. **25**, 242–252 (2014)
15. Jain, A., Keller, J.M.: Textual summarization of events leading to health alerts. In: 2015 37th Annual International Conference of the IEEE on Engineering in Medicine and Biology Society (EMBC), pp. 7634–7637 (2015)
16. Wilbik, A., Keller, J.M., Alexander, G.L.: Linguistic summarization of sensor data for eldercare. In: 2011 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 2595–2599 (2011)
17. Matamoros, A., Torrealba, A., Rivas, F., González, S., Sánchez, R., Molina, L., Rivas-Echeverría, C.: Expert system for the preeclampsia prevention program. In: Proceedings of the 4th WSEAS International Conference on Computational Intelligence, Man-machine Systems and Cybernetics, (MSC 2005), Miami, USA, pp. 146–149 (2005)
18. Acampora, G., Cook, D.J., Rashidi, P., Vasilakos, A.V.: A survey on ambient intelligence in healthcare. Proc. IEEE **101**(12), 2470–2494 (2013)
19. Zadeh, L.A.: The concept of a linguistic variable and its applications to approximate reasoning, pp. 43–80 (1975)
20. Ortiz, F., Liu, W.Y.: Modelado y control PD-difuso en tiempo real para el sistema barra-esfera, México DF (2004)
21. Rodríguez, F.O., Liu, W.Y.: Modelado y control PD-difuso em tiempo real para el sistema barraesfera. Master's thesis, Universidad de Mexico (2004)
22. Díaz, B., Morillas, A., et al.: Minería de datos y lógica difusa. Una aplicación al estudio de la rentabilidad económica de las empresas agroalimentarias en Andalucía. Estadística Española **46**(157), 409–430 (2004)
23. PARA, EPIDEMIOLOGÍA: Los protocolos clínicos. Med Clin (Barc), vol. 95, pp. 309–316 (1990)
24. Llano, L., Zapata, G., Ovalle, D.: Sistema de Inferencia Difuso para Identificar Eventos de Falla en Tiempo Real del STE usando Registros SOE [Fuzzy Inference System for Identifying Fault Events in STE Real Time Using SOE Registries]. Revista Avances en Sistemas e Informática [Advances in Systems and Informatics Journal] Escuela de Sistemas [School of Systems] de la Universidad Nacional de Colombia Sede Medellín **4**(2) (2007). Special Edition. ISSN: 1657-7663
25. Soli, S.B.: Presentación y evolución de las pacientes ingresadas en la Unidad de Cuidados Intensivos con diagnóstico de Preeclampsia-Eclampsia (2013)
26. Gutiérrez, A., Herráiz, M.A., Bellón, M., Martell, N., Escudero, M.: Protocolo de actuación ante la preeclampsia. Nuestra experiencia (2002)
27. Pérez, J.H., Unanua, A.P.: Hipertensión arterial (2002)
28. Padilla-Raygoza, N., Ruiz-Paloalto, M.L., Díaz-Guerrero, R., Olvera-Villanueva, G., Maldonado, A., del Pilar Raygoza-Mendoza, M.: Correlación de mediciones de temperatura corporal con 3 termómetros: ótico, cutáneo y digital, en niños mexicanos. Enfermería Clínica 4(3), 175–182 (2014)
29. Ng, K.-G., Wong, S.-T., Lim, S.-M., Goh, Z.: Evaluation of the cadi thermosensor wireless skin-contact thermometer against ear and axillary temperatures in children. J. Pediatr. Nurs. **25**(3), 176–186 (2010)
30. Ávila, D., Cervantes, H., Hipólito, J.I., Nieto, L., de Dios, J., Sánchez, R., Martınez, M.E., Calvo, A.H.: Arquitectura de e-Salud basada en Redes Inalámbricas de Sensores. DIFU100ci@, vol. 6, no. 2, pp. 54–61 (2012)

31. Beurer, G.: Body temperature from Beurer. Soeflinger Strasse, Alemania. Recuperado de: https://www.beurer.com/web/es/products/body_temperature/body_temperature.php (2016)
32. Sanchez, R.A., Ayala, M., Baglivo, H.: otros: Guias Latinoamericanas de Hipertension Arterial. Revista chilena de cardiologia 29 (2010)