DEVELOPMENT OF FUZZY RULES FOR CDSS BASED NEONATAL MONITORING SYSTEM

Supported by tetfund

A. A. Sobowale[1], O. M. Olaniyan[1]*, O. Adetan[2], J. B. Oladosu[3], S. O. Olabiyisi[3] and E. O. Omidiora[3]
[1]Department. of Computer Engineering, Federal University Oye-Ekiti, Ekiti State, Nigeria
[2]Department. of Electrical and Electronic Engineering, Ekiti State University, Nigeria
[3]Department of Computer Science & Engineering, Ladoke Akintola University of Technology, Ogbomosho, Nigeria
*Corresponding author: olatayo.olaniyan@fuoye.edu.ng

Received: July 30, 2020 **Accepted:** October 14, 2020

Abstract: Clinical Decision Support Systems (CDSS) Fuzzy model helps medical diagnosis, monitoring and classifications of the vital signs of Intensive Care Unit (ICU) patients which provide support for decision-making in patient care. A category of such patients is the prematurely born babies, which are placed in infant incubators of Neonatal Intensive Care Unit (NICU) for continuous monitoring of their body vital signs (temperature, heart rate and respiration). However, the development of Fuzzy rule based CDSS for classification of neonates' health status is limited and still manually monitored in many developing countries like Nigeria. This work developed Fuzzy Inference System-CDSS rules that can be used to efficiently classify the neonate's condition in the incubators of NICU. A Fuzzy Inference System CDSS (FIS-CDSS) was developed for the three inputs: Temperature, Heart rate and Respiration rate (THR) based on their membership functions' value (low, medium, high) and twenty-seven (27) IF-THEN fuzzy rules using fuzzy logic toolbox in Matrix Laboratory 8.1 (R2013a). The FIS-CDSS maps the THR to an output status (Normal, Abnormal and Critical). The vital signs' readings were fed into the FIS-CDSS, which fuzzifies them and classifies the health status of the neonates. This work developed a Fuzzy-rule based system that can efficiently classify neonates' health status which provides adequate and accurate information for on-the-spot assessment of neonates for decision making that improves the mortality rate and recovery period of neonates. Also, the system could provide baseline information for other researchers in developing fuzzy rule based CDSS for other categories of patients.

Keywords: CDSS, fuzzy inference system, NICU, vital signs, neonates

Introduction

Clinical Decision Support Systems (CDSS) are computer-based information systems used to integrate clinical and patient information to provide support for decision-making in patient care. A category of such patients are the prematurely born babies, which are placed in infant incubators of Neonatal Intensive Care Unit (NICU) for continuous monitoring of their body vital signs (temperature, heart rate and respiration) (Prabhu *et al.*, 2014). Premature neonates are babies born before thirty-seven (37) weeks gestation; their condition is usually delicate and may be at risk of complications. Special monitoring is required involving treatment in an incubator at an NICU to enhance their survival (Quinn, 2007; Nicklin *et al.*, 2004; STELLA, 2010). This neonatal monitoring is the monitoring of premature infants' body vital signs which are Temperature, Heart rate and Respiration rate (THR); this provides a lot of information about a baby's state of health (Suresh *et al*., 2014). However, the quality of neonatal care provided by Nigerian hospitals is not uniform and mostly manual, which creates difficulty of interpretation for inexperienced staff (Okonkwo *et al.*, 2016; Sobowale *et al.*, 2011; Mednax, 2011).

A major technology application needed in neonatal healthcare to make the right decision at the right time is the CDSS. The CDSS aims to benefit the clinical decision making process which aids in building an intelligent systems for monitoring neonatal vital parameters. CDSS are being used to enhance decision making and improve efficiency in diverse health care environments, from acute care to ambulatory practice (Ball *et al.*, 2001; Bouwstra *et al.*, 2009; Seoane *et al.*, 2012). CDSSis basically categorized into two; Knowledge based CDSS and Non-knowledge based CDSS as shown in Fig. 1 (Abbasi and Kashiyarndi, 2011; Prasath *et al.*, 2013).

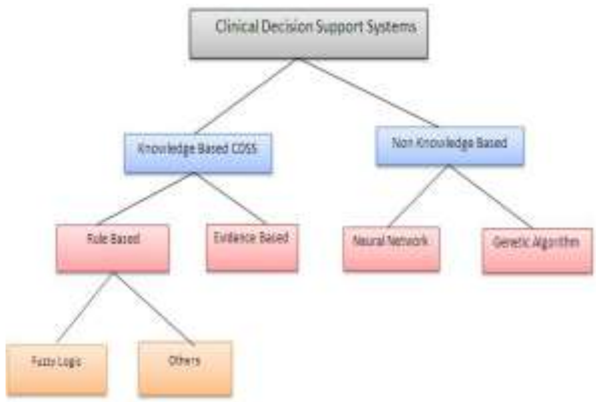

Fig. 1: Categorization of the clinical decision support systems (Abbasi *et al.*, 2013)

Knowledge based CDSS

This CDSS comprises of rules mostly in the form of IF-Then statements. The data is usually connected with these rules. The knowledge based CDSS is basically composed of three main parts; Knowledge base, Inference rules and a means or mechanism to communicate. The knowledge base contains the rules, the inference engine joins rules with the patient data and the communication mechanism is used to display the result to the users and additionally to provide input to the system. They are the commonest type of CDSS used in clinics and hospitals implemented by use of UML techniques and handling of variance through the construction of generalized fuzzy rules (Ali and Chia, 1999; Ye and Tong, 2009). There are two types Fuzzy Logic Rule and Evidence based; the Fuzzy logic is employed in this work.

The pattern recognition technique can help medical personnel in measuring the pain which is an augmentation of Vector machine algorithm (Jäkeland *et al.*, 2010). The Fuzzy Logic Rule based classifier is very effective in high degree of positive predictive value and diagnostic accuracy. For example in diseases like appendicitis, the results predicted by fuzzy logic rule based classifier have an accuracy rate of 95% on average (Sivasankar and Rajesh, 2010). For enhancing the adequacy of fuzzy set theory, the Rough set theory can be proposed to supplement fuzzy set and to manage ambiguity and uncertainty. The major advantage is that it does not require data such as basic probability assignment and distribution in statistics as well as grade of membership of value in fuzzy set theory (Pawlak *et al.*, 1995). Clinical rules give advantages to health results and are practical yet they have certain characteristics that are difficult to manage such as vagueness and ambiguity. Fuzzy logic equips us for treatment of vagueness in decision support system. Fuzzy logic method can be a very helpful means for describing vagueness and imprecision in precise mathematical language, clearly representing clinical vagueness (Warren *et al.*, 2000).

The CDSS-based architectural framework

The CDSS architectural framework is made up of three components (knowledge base, inference engine and interface) as shown in Fig. 2. This is made up of a set of functional and informational units. The functional unit is divided into the reasoning engine and the connection component. The informational unit comprises the data source and the knowledge base. The knowledge base consists of decision rules, low, medium and high boundary values, diagnosis terms, and clinical recommendation contents. The reasoning engine takes the readings of the vital signs as its data source. After the execution of the decision rules on the data source, the reasoning engine generates the output result, which is displayed on the monitor of the CDSS system and printed from the CDS located at the nursing stand. The clinicians take informed, on the spot decision based on the printed results. This enhances decision making and general performance as the manual routine checks by the nurses is no more the only basis of attending to neonates.

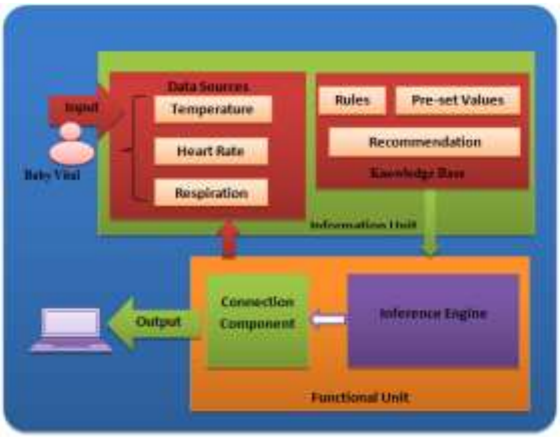

Fig. 2: The CDSS architecture of the developed monitoring system (Abbasi *et al.*, 2013)

Methodology

The Fuzzy Inference System (FIS) was developed using MATLAB R2014a to implement the developed architectural framework. The FIS uses fuzzy logic to map the vital signals THR to a status (*Normal, Abnormal and Critical*). The output is used to decide on the appropriate treatment for a particular preterm. The FIS decisions are made by the use of membership function and If-Then fuzzy rules. FIS performs fuzzification on the inputs and defuzzification of the result of fuzzy logic rule to determine the output. Aggregation is used to combine the output of all the rules into a single fuzzy set. The developed FIS takes the vital signs as the inputs and gives "*Normal", "Abnormal" or "Critical*" as the output. It also consists of the membership functions (MF), antecedents (or premise), consequents (conclusion), weight and connective. A membership function defines the degree to which the value of a vital sign falls within a boundary (or degree of membership). Antecedents are the MF values of the inputs while the consequents are the MF values of the output. A weight determines the level of importance of a rule relative to the others, and the maximum weight a rule can take is 1. A connective takes either "AND" or "OR". The connective "AND" implies that the values of two antecedents determine the consequents while the connective "OR" implies that any of the antecedents can determine the consequents. The Graphics User Interface (GUI) of the developed FIS is shown in Figures below

Design of the membership function

Three linguistic terms (Low, Medium and High) were used to define the membership function of each of the input variables Temperature, Heart Rate and Respiration rate (THR).

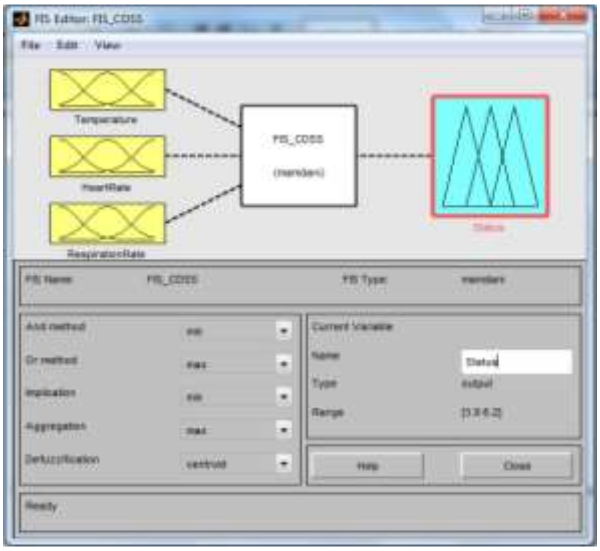

Fig. 3: Showing developed fuzzy inference system in MATLAB environment

Similarly, three linguistic values Normal (N), Abnormal (A) and Critical (C) were used to define the membership function of the Status or Output (Out) of the inference engine. The value range of the vital signs readings used in the Children Intensive Care Unit (CICU) of Ladoke Akintola Teaching Hospital (LAUTECH) Osogbo, were used to set the range used in the FIS and were classified as Low for readings below the normal range, medium for normal range and high for readings above the normal range, this is discussed below.

Temperature: The normal range for Temperature is 36.5-37.5^{o}C; if the input temperature value is more than this range then its MF is High, and if it is below this range, then its MF is Low. The classification of Temperature is presented in Table 1a. The MF for the fuzzy set for Temperature (Tmp.) is defined as:

$$\text{Low}(Tmp) = \begin{Bmatrix} 1 & Tmp \leq 32.5 \\ \frac{36.5-Tmp}{4} & 32.5 < Tmp < 36.5 \end{Bmatrix} \quad (1a)$$

$$\text{Medium}(Tmp) = \begin{Bmatrix} \frac{Tmp-35}{2} & 35 \leq Tmp < 37 \\ 1 & Tmp = 37 \\ \frac{38-Tmp}{1} & 37 < Tmp < 38 \end{Bmatrix} \quad (1b)$$

$$\text{High}(Tmp) = \begin{Bmatrix} \frac{Tmp-37.5}{2} & 37.5 \leq Tmp < 39.5 \\ 1 & Tmp \geq 39.5 \end{Bmatrix} \quad (1c)$$

Heart rate: The normal range for Heart Rate (Hr) is 130-160 bpm; if the input heartbeat rate value is more than this range then its MF is High, and if it is below this range then its MF is Low. The classification of Heart Rate is presented in Table 1b. The MF for the fuzzy set for heart rate is:

$$\mathrm{Low}(Hr) = \begin{Bmatrix} 1 & Hr < 125 \\ \frac{132-Hr}{7} & 125 \le Hr < 132 \end{Bmatrix} \qquad (2a)$$

$$\mathrm{Medium}(Hr) = \begin{Bmatrix} \frac{Hr-128}{17} & 128 \le Hr < 145 \\ 1 & Hr = 145 \\ \frac{162-Hr}{17} & 145 < Hr < 162 \end{Bmatrix} \qquad (2b)$$

$$\mathrm{High}(Hr) = \begin{Bmatrix} \frac{Hr-158}{12} & 158 \le Hr < 170 \\ 1 & Hr \ge 170 \end{Bmatrix} \qquad (2b)$$

Respiration rate: The normal range for Respiration Rate (Rr) is 40-60 cm; if the input heartbeat rate value is more than this range then its MF is High, and if it is below this range then its MF is Low. The classification of Heart Rate is presented in Table 1c. The MF for the fuzzy set for respiration is:

$$\mathrm{Low}(Rr) = \begin{Bmatrix} 1 & Rr \le 35 \\ \frac{42-Rr}{7} & 35 < Rr < 42 \end{Bmatrix} \qquad (3a)$$

$$\mathrm{Medium}(Rr) = \begin{Bmatrix} \frac{Rr-38}{12} & 38 \le Rr < 50 \\ 1 & Rr = 50 \\ \frac{62-Rr}{12} & 50 < Rr < 62 \end{Bmatrix} \qquad (3b)$$

$$\mathrm{High}(Rr) = \begin{Bmatrix} \frac{Rr-60}{10} & 60 \le Rr < 70 \\ 1 & Rr \ge 70 \end{Bmatrix} \qquad (3c)$$

Status: This is the output variable of the FIS. The normal range for Status (Out) is 4-6; if the output value is more than this range then its MF is Critical, and if it is below this range then its MF is Abnormal. The classification of Status is presented in Table 1d.

$$\mathrm{Abnormal}(Out) = \begin{Bmatrix} 1 & Out \le 3.5 \\ \frac{4-Out}{0.5} & 3.5 < Out < 4 \end{Bmatrix} \qquad (4a)$$

$$\mathrm{Normal}\ (Out) = \begin{Bmatrix} \frac{Out-3.8}{1.2} & 3.8 \le Out < 5 \\ 1 & Out = 5 \\ \frac{6.2-Out}{1.2} & 5 < Out < 6.2 \end{Bmatrix} \qquad (4b)$$

$$\mathrm{Critical}(Out) = \begin{Bmatrix} \frac{Out-6}{0.2} & 6 \le Out < 6.2 \\ 1 & Out \ge 6.2 \end{Bmatrix} \qquad (4c)$$

The MF plots for Temperature, Respiration rate, Heart rate and Status are shown in Figs. 3 to 6.

Table 1a: Showing result of classification of temperature

Vital Sign	Range	Linguistic Term
Temperature	< 36.5	Low
	36.5 – 37.5	Medium
	> 37.5	High

Table 1b: Showing result of classification of heart rate

Vital Sign	Range	Linguistic Term
Heart Rate	< 130	Low
	130 – 160	Medium
	> 160	High

Table 1c: Showing result of classification of respiration rate

Vital Sign	Range	Linguistic Term
Respiration Rate	< 40	Low
	40 – 60	Medium
	> 60	High

Table 1d: Showing classification of status result

Output	Range	Linguistic Term
Status	< 4	Abnormal
	4 – 6	Normal
	> 6	Critical

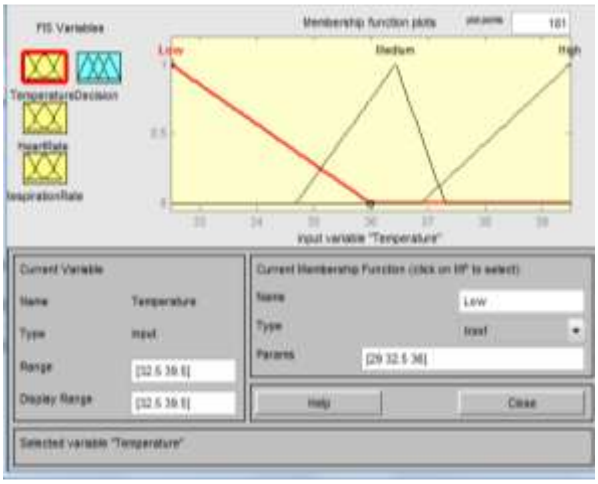

Fig. 4: Showing membership functions for temperature result

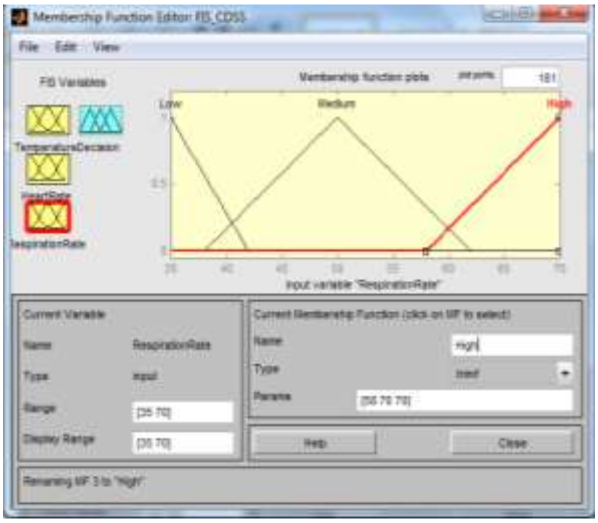

Fig. 5: Showing membership functions for respiration rate

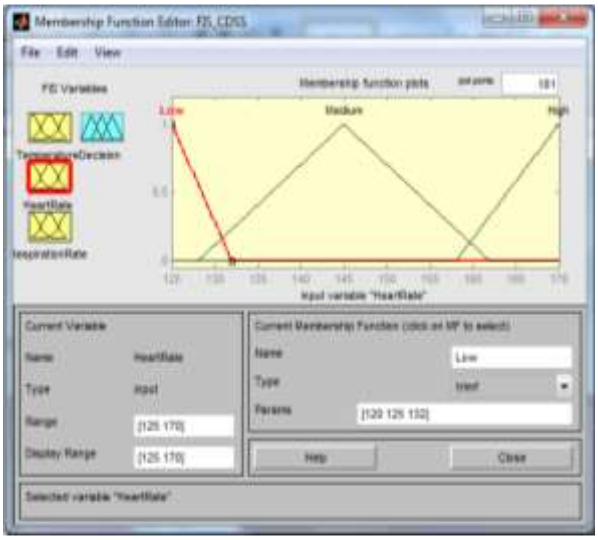

Fig. 6: Showing membership functions for heart rate

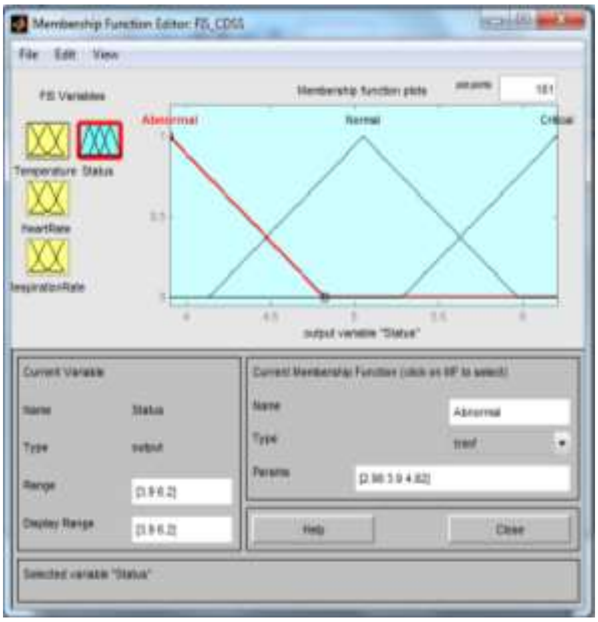

Fig. 7: Showing membership functions for status

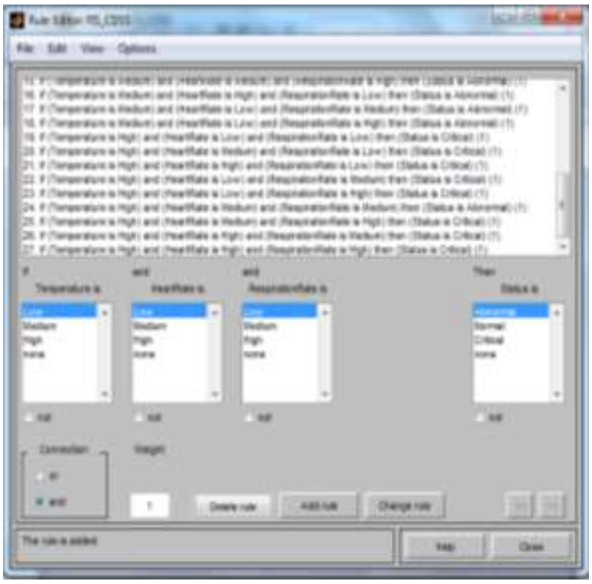

Fig. 8: Showing GUI of the Fuzzy rule list for the CDSS

Fuzzy rule base for the CDSS

The rule list was created from the combination of the MFs of the variables for each data sample. The developed FIS-CDSS makes use of fuzzy rule base to classify the preterm's health status. The rules were generated from the knowledge base - the data gathered from the expert. Every possible rule for the system was generated in the Rule Editor of MATLAB, and 27 possible rules were formed as shown in Fig. 7. Below are some of the rules:

Rule 1: IF (Temperature is Low) AND (HeartRate is Low) AND (RespirationRate is Low) THEN (Status is Critical)
Rule 2: IF (Temperature is Low) AND (HeartRate is Low) AND (RespirationRate is Medium) THEN (Status is Critical)
Rule 3: IF (Temperature is Low) AND (HeartRate is Medium) AND (RespirationRate is Medium) THEN (Status is Abnormal)
Rule 4: IF (Temperature is Medium) AND (HeartRate is Low) AND (RespirationRate is Low) THEN (Status is Critical)
Rule 5: IF (Temperature is Medium) AND (HeartRate is Medium) AND (RespirationRate is Low) THEN (Status is Abnormal)
Rule 6: IF (Temperature is Medium) AND (HeartRate is High) AND (RespirationRate is High) THEN (Status is Critical)
Rule 7: IF (Temperature is High) AND (HeartRate is High) AND (RespirationRate is High) THEN (Status is Critical)
Rule 8: IF (Temperature is Medium) AND (HeartRate is Medium) AND (RespirationRate is Medium) THEN (Status is Normal) …….

Fig. 9: Showing developed FIS-CDSS window

Results and Discussion

An interactive Graphic User Interface (GUI) application was developed using MATLAB R2014a as the frontend and MYSQL 5.1 as the backend to implement the CDSS architectural framework. The developed system named Fuzzy Inference System Clinical Decision Support System (FIS-CDSS) was copied in a folder into the Clinical Database Server (CDS) with a Matlab file (FIS-CDSS_gui.m); the CDS contains database of the vital signs readings collected from the measuring sensors attached to each neonate. The FIS-CDSS GUI window (Fig. 8) appeared as the filename was executed. The vital signs (Temperature, Heart rate and Respiration) readings from the DMS were loaded into the developed FIS-CDSS as shown in Fig. 9.

Fig. 10: Result viewing of the recorded vital signs on the GUI

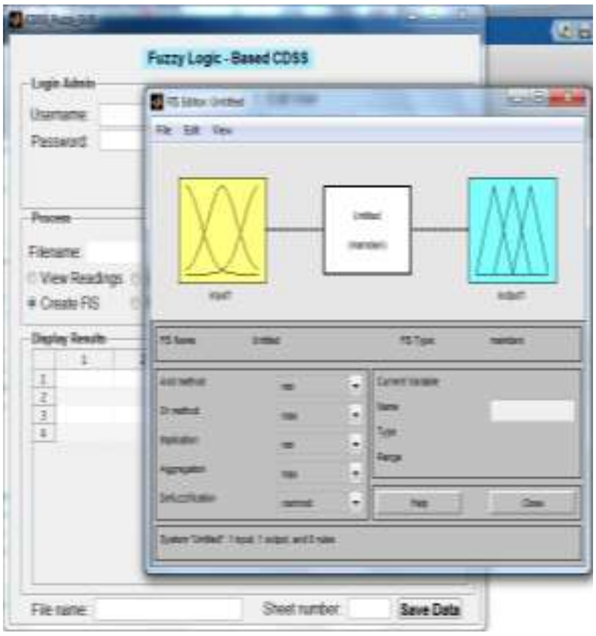

Fig. 11: Result showing creation of a fuzzy inference system (FIS) model for the CDSS

The loaded readings were run through the FIS-CDSS for classification as shown in Figs. 10 and 11. The CDSS_FIS classified the status of the baby (developed system prediction) as *Normal*, *Abnormal* or *Critical* based on the readings and the fuzzy logic rules in the knowledge base of the system; this is shown in Fig. 12, the developed system's classification can be saved into the CDS as shown in Fig. 13.

Fig. 12: Acquisition of the recorded vital signs for the FIS classification result

Fig. 13: Display of the FIS classification results

Table 2: Predictions made for a neonate by the developed system (FIS-CDSS)

PERIOD	FIS-CDSS Prediction
1	Normal
2	Abnormal
3	Normal
4	Normal
5	Normal
6	Abnormal
7	Normal
8	Normal
9	Normal
10	Normal
11	Normal
12	Normal
13	Normal
14	Normal
15	Normal
16	Normal
17	Abnormal
18	Normal
19	Normal
20	Normal
21	Normal
22	Normal
23	Normal
24	Abnormal
25	Abnormal
26	Normal
27	Normal
28	Abnormal

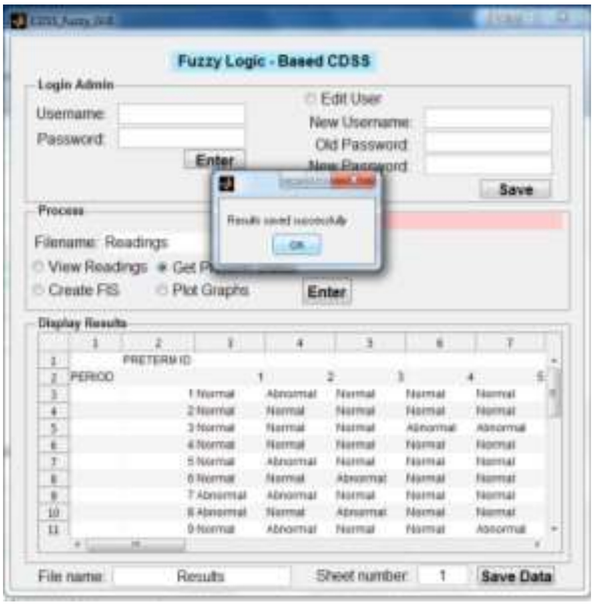

Fig. 14: Saving of the FIS classification results

The predictions of the developed system for the thirty (30) neonates was Taken 4 times daily (6:00am, 10:00am, 2:00pm and 6:00pm) for seven (7) days, giving a total of twenty-eight (28) predictions per neonate as shown in Table 2. The complete classification for the thirty babies over a week each is shown in Table 3.

Conclusion

In this research, a CDSS based architecture for monitoring neonates in the NICU has been implemented. Fuzzy Inference System CDSS (FIS-CDSS) was developed for the three inputs: Temperature, Heart rate and Respiration rate (THR) based on their membership functions' value (low, medium, high) and twenty-seven (27) IF-THEN fuzzy rules using fuzzy logic toolbox. The FIS-CDSS maps the THR to an output status (Normal, Abnormal and Critical). The vital signs' readings were fed into the FIS-CDSS, which fuzzifies them and outputs the health status of the neonates.

Conflict of Interest

Authors have declared that there is no conflict of interest reported in this work.

References

Abbasi MM & Kashiyarndi S 2011. Clinical Decision Support Systems: A Discussion on Different Methodologies used in Health Care; Proceedings of the International Conference on Frontiers of Intelligent Systems 1-15 accessed 20th April, 2015.

Ali S & Chia KO 1999. Graphical knowledge-based protocols for chest pain management. *Computer in Cardiology, IEEE*, 309 -312.

Ball MJ, Douglas JV & Lillis J 2001. Health informatics: Managing information to deliver value. PubMed Indexed for MEDINE: *Stud. Health Techn. Infor.*, 84(Pt 1): 305-308. http://www.ncbi.nlm.nih.gov/pubmed/11604752 accessed on 20th December, 2015.

Bouwstra S, Chen W, Feijs L & Bambang S 2009. Smart Jacket Design for Neonatal Monitoring with Wearable Sensors. A paper presented at IEEE Body Sensor Networks.

Gholami B, Hadda WM & Tannenbaum AR 2010. Relevance vector machine learning for neonate pain intensity assessment using digital imaging. *IEEE Transac. on Biomed. Engr.*, 1457 -1466.

Jäkel J & Bretthauer G 2016. Fuzzy System Applications. Control Systems, Robotics and Automation – Vol. XVII Institute of Applied Computer Science, Forschungszentrum Karlsruhe, Germany. http://www.eolss.net/sample-chapters/c18/e6-43-23-04.pdf accessed on 6th July, 2016.

Mednax Services 2011. Pediatrix Medical Group: For Parents, Your Baby and The NICU. Important Information from Your Health Care providers through The Centre for Research, Education and Quality. www.pediatrix.com/forparents accessed on 24th March, 2016.

Nicklin S, Wickramasinghe YA & Spencer SA 2004. Neonatal intensive care monitoring *Current Paediatrics*, 14:1, 1-7 accessed on 20th February, 2016.

Okonkwo IR, Abhulimhen-Iyoha BI & Okolo AA 2016. Scope of neonatal care services in major Nigerian hospitals. *Niger. J. Paed.* 2016; 43 (1):8– 13, www.ajol.info/index.php/njp/article/download/127950/117501 accessed on 4th July, 2016.

Prabhu M, Senthil PN & Lakshmi K 2014. Clinical decision support systems. *Computer Sciences Corporation* (CSC), 1-19 accessed in June, 2016.

Prasath V, Lakshmi N, Nathiya M, Bharathan N & Neetha N 2013. A survey on the applications of fuzzy logic in medical diagnosis. *Int. J. Scient. & Engr. Res.*, 4(4).

Quinn JA 2007. Bayesian Condition Monitoring in Neonatal Intensive Care. PhD thesis submitted to Institute for Adaptive and Neural Computation School of Informatics University of Edinburgh.

Seoane F, Bouwstra S, Marquez JC, Löfhede J & Lindecrantz K 2012. Smart Textiles in Neonatal Monitoring: Enabling Unobtrusive Monitoring at the NICU. Chapter 3 of a book published by IGI Global, p. 4.

Sivasankar E. and Rajesh R. S. (2010):" Knowledge Discovery in Medical Datasets Using a Fuzzy Logic rule based Classifier. *Electr. Comp. Techn. Int. Conf.*, IEEE, pp. 208 - 213.

Sobowale AA, Olabiyisi SO & Abdul-Hameed TA 2011. Development of a framework for computerized health management information systems in Nigeria. *Int. J. Infor. and Commun. Techn. Res.*.

Stella Newsletter 2010. 2nd International Workshop on. Flexible and Stretchable Electronics. Content Issue No. 6: http://www.stella-research work.de/Portals/0/Stella_Newsletter_6.pdf accessed on 15th March, 2016.

Suresh L, Latha AN, Murthy RB, Alam KT & Babu JK 2014. Neonatal monitoring system. *Int. J. Engr. Res. and Applic.* www.ijera.com 4(7 Version 3): 12-15. Accessed on 4th July, 2016.

Stultz JS & Nahata MC 2012. Computerized clinical decision support for medication prescribing and in pediatrics. *J. Am. Med. Infor. Assoc.*, 19, accessed on 5th April, 2016.

Warren J, Beliakov G and Zwaag B. (2000): " Fuzzy logic in clinical practice decision support system. Proceedings of the 33rd Hawaii International Conference on System Sciences.

Ye Y & Tong SJ 2009. A Knowledge-Based Variance Management System for Supporting the Implementation of Clinical Pathways. *Management and Servicecience, 2009, IEEE*, pp. 1 – 4.