Implementation of a Clinical Decision Support Systems-Based Neonatal Monitoring System Framework

Sobowale A. A[1], Olaniyan O. M[2]*, Adetan. O[3], Adanigbo. O[4]
Esan. A[5], Olusesi. A.T[6], Wahab. W.B[7], Adewumi. O. A[8]
Department of Computer Engineering, Federal University Oye-Ekiti, Nigeria[1, 2, 4, 5]
Department of Electrical and Electronic Engineering, Ekiti State University Ado-Ekiti, Nigeria[3]
Department of Electrical, Electronics & Computer Engineering, Bells University of Technology Ota, Nigeria[6]
Department of Computer Engineering, Ladoke Akintola University of Technology Ogbomoso, Nigeria[7]
Department of Computer Science and Information Technology, Bells University of Technology Ota, Nigeria[8]

Abstract*—A Clinical Decision Support-based information systems to monitor the vital signs of the neonate's conditions in prematurely born babies placed in infant incubators of Neonatal Intensive Care Unit (NICU) is developed in this work. A DMS was developed consisting of a supervisory microcomputer and sensitive sensors for measuring the vital signs. The Conventional Monitoring System (CMS) was used simultaneously with the DMS to collect the vital sign readings of thirty (30) neonates, over a period of one week. 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 (R2014a). The FIS-CDSS maps the THR to an output status (Normal, Abnormal and Critical). The performance of the FIS-CDSS was evaluated using confusion matrix. The results showed that the system yielded sensitivity ranges of 90 - 100, 80 - 89, 70 - 79, 60 - 69 and 50 - 59% for five, eleven, seven, six and one neonates, respectively with an average sensitivity of 77.92%. The specificity of the system ranged from 5.00 to 66.67% with an associated average specificity of 35.10%. The accuracy of the FIS-CDSS ranged from 70 to 100, 60 to 69, 50 to 59 and 0 to 49% for nine, nine, eight and four neonates, respectively with an average accuracy of 60.94%. The developed system 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.

General Terms: Neonatal Monitoring

Keywords*—*Clinical Decision Supports Systems (CDSS); Fuzzy Inference System (FIS); Neonatal Intensive Care Unit (NICU); vital signs; neonates

I. Introduction

Decision Support Systems (DSS) are increasing in coverage of different sections of life which includes academic, engineering, business, military and medicine [1]. Any automated program that helps specialists in settling on clinical choice is categorized as Clinical Decision Support Systems (CDSS) [2]. CDSS provide clinicians, staff, patients and other individuals with knowledge and person-specific information, wisely separated and displayed at proper times, to upgrade wellbeing, medicinal services and reduce medical errors [3][4][5]. CDSS does not decide; It just gives direction to provide current and pertinent knowledge to clinicians to aid patient care at the exact time of care delivery [6][7] It is a major technology application to make the right decision at the right time which aids in building an intelligent system for monitoring neonatal vital parameters [8]. The CDS Systems 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). [19].

Neonates born before thirty-seven (37) weeks gestation are considered premature and are usually in a fragile condition and may be at risk of complications, such babies therefore require special monitoring and intensive care involving treatment in an incubator at an NICU [9][10][11]. Neonatal monitoring refers to the monitoring of vital physiological parameters of premature infants [12]. The survival rate of premature infants is dependent on the continuous monitoring of vital signs; this provides a lot of information about a baby's state of health [18].

In the last decades the advances in sensor technologies and wireless communications technologies have resulted in the possibility of developing intelligent systems for monitoring neonatal vital parameters [13]. Technology therefore provides easy data collection from the neonates monitoring system and aids the neonatologists' in taking appropriate decision.

However, the quality of neonatal care provided by Nigerian hospitals is not uniform and mostly manual, which creates difficulty of interpretation for inexperienced staff [14][15][16] More so, despite the impact of CDSS applications in various sectors of the health system, its application to monitoring of vital signs of preterm babies in the NICU is limited [5], [17].

This paper therefore developed a CDSS that can be used to efficiently monitor the neonate's condition in the incubators of NICU. The paper has five (5) sections in all. Section I is the introduction to the work. Section II gives the architectural framework of CDS systems. The methodology adopted in this work is discussed under Section III. Results obtained in this work are discussed under Section IV while the conclusion is given under Section VI.

*Corresponding Author

II. The CDSS-based Architecural Framework

The CDSS architectural framework is made up of three components (knowledge base, inference engine and interface) as shown in Fig. 1. 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.

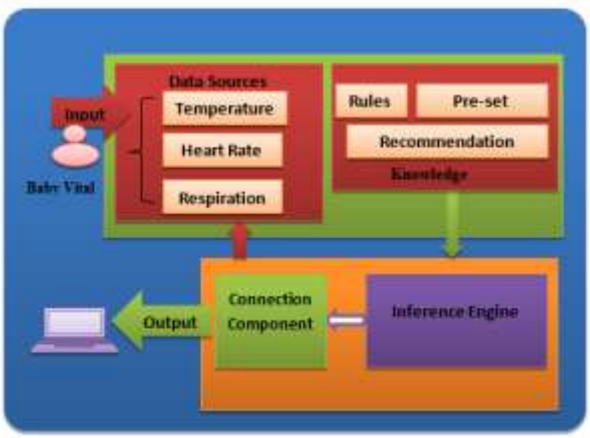

Fig. 1. The CDSS Architecture of the Developed Monitoring System.

III. Methodology

The Fuzzy Inference System (FIS) was developed using MATLAB R2014a to implement the CDSS architectural framework. The FIS uses fuzzy logic to map the vital signals Temperature, Heart rate and Respiration rate (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 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 Fig. 2.

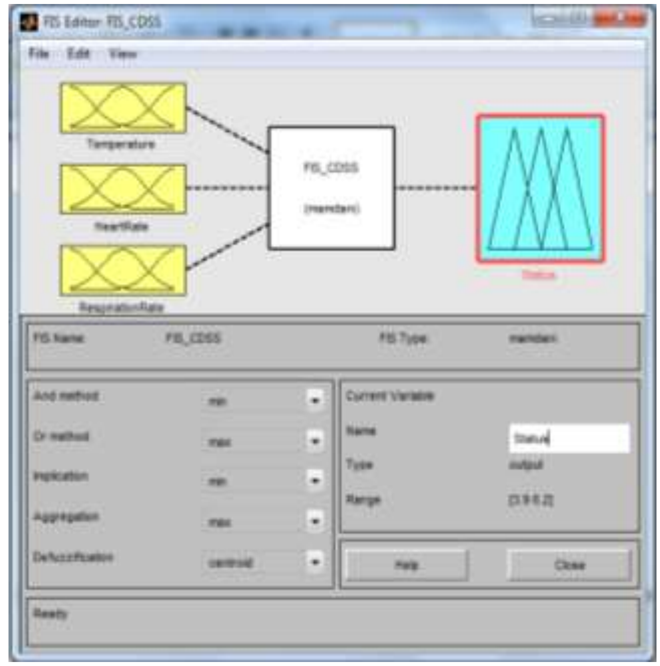

Fig. 2. GUI of the Developed Fuzzy Inference System in MATLAB Environment.

A. 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).

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°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 I(A). The MF for the fuzzy set for Temperature (Tmp) is defined as:

$$Low\ (Tmp) = \left\{ \begin{array}{ll} 1 & Tmp \le 32.5 \\ \dfrac{38 - Tmp}{1} & 32.5 < Tmp < 36.5 \end{array} \right\} \quad 1a)$$

$$Medium\ (Tmp) = \left\{ \begin{array}{ll} \dfrac{Tmp - 32.5}{2} & 35 \le Tmp < 37.5 \\ 1 & Tmp = 37 \\ \dfrac{38 - Tmp}{1} & 37 < Tmp < 38 \end{array} \right\} \quad 1b)$$

$$High\ (Tmp) = \begin{cases} \frac{Tmp - 37.5}{2} & 37.5 \le Tmp < 39.5 \\ 1 & Tmp \ge 39.5 \end{cases} \quad (1c)$$

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 I(B). The MF for the fuzzy set for heart rate is:

$$Low\ (H_r) = \begin{cases} 1 & H_r < 125 \\ \frac{132 - H_r}{7} & 125 < H_r < 132 \end{cases} \quad 2a)$$

$$Medium\ (H_r) = \begin{cases} \frac{H_r - 128}{17} & 128 \le H_r < 145 \\ 1 & H_r = 145 \\ \frac{162 - H_r}{17} & 145 < H_r < 162 \end{cases} \quad 2b)$$

$$High\ (H_r) = \begin{cases} \frac{H_r - 158}{12} & 158 \le H_r < 170 \\ 1 & H_r \ge 170 \end{cases} \quad (2c)$$

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 I(C). The MF for the fuzzy set for respiration is:

$$Low\ (R_r) = \begin{cases} 1 & R_r \le 35 \\ \frac{42 - R_r}{7} & 35 < R_r < 42 \end{cases} \quad 3a)$$

$$Medium\ (R_r) = \begin{cases} \frac{R_r - 38}{12} & 38 \le R_r < 50 \\ 1 & R_r = 50 \\ \frac{62 - R_r}{12} & 50 < R_r < 62 \end{cases} \quad 3b)$$

$$High\ (R_r) = \begin{cases} \frac{R_r - 60}{10} & 60 \le R_r < 70 \\ 1 & R_r \ge 70 \end{cases} \quad (3c)$$

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 I(D).

$$Abnormal\ (Out) = \begin{cases} 1 & Out \le 3.5 \\ \frac{4 - Out}{0.5} & 0.5 < Out < 5 \end{cases} \quad 4a)$$

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

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

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

TABLE I. A: CLASSIFICATION OF TEMPERATURE

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

TABLE I (B): CLASSIFICATION OF HEART RATE

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

TABLE I (C): CLASSIFICATION OF RESPIRATION RATE

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

TABLE 1D: CLASSIFICATION OF STATUS

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

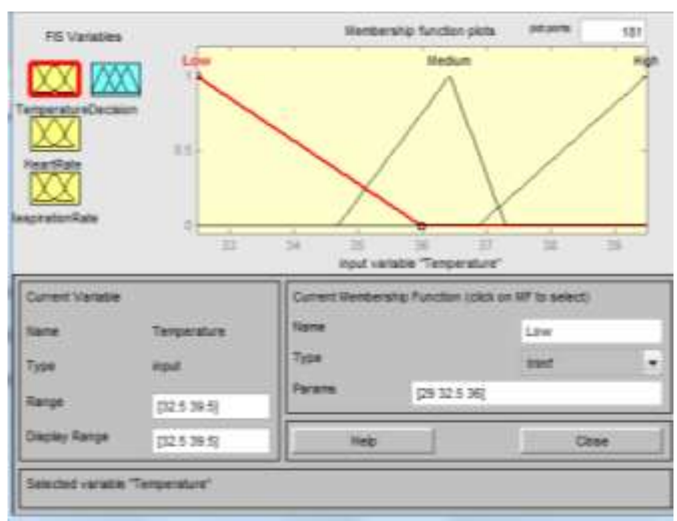

Fig. 3. Membership Functions for Temperature.

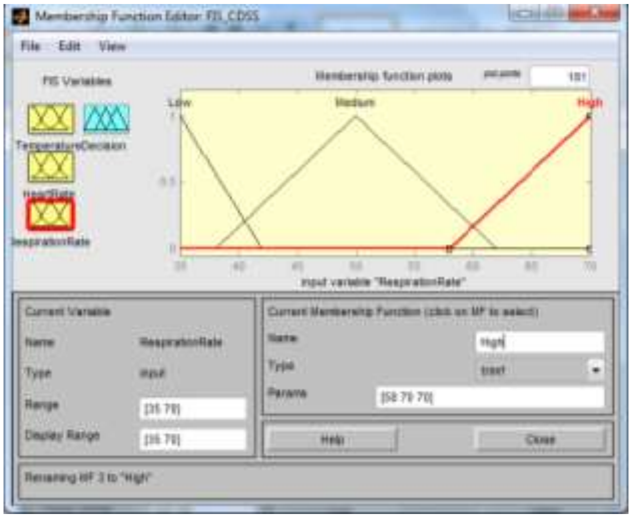

Fig. 4. Membership Functions for Respiration Rate.

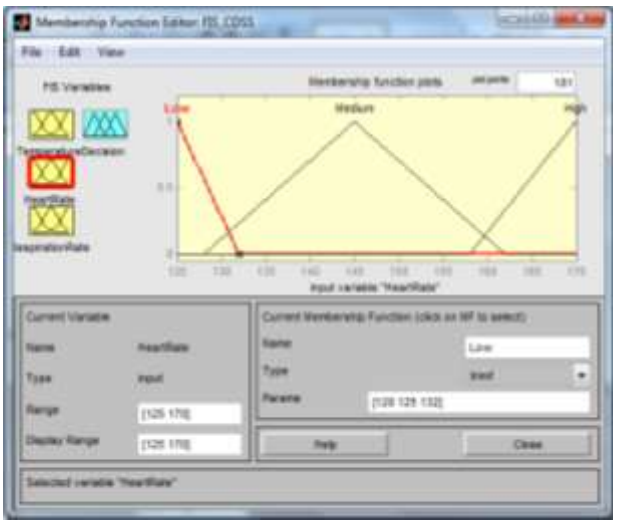

Fig. 5. Membership Functions for Heart Rate.

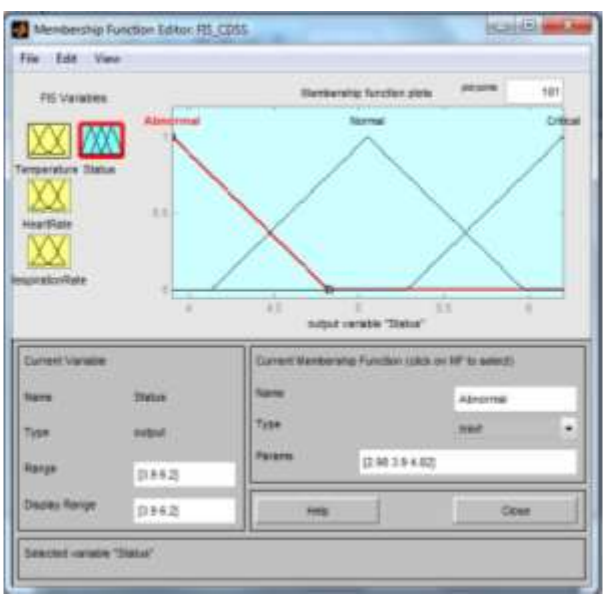

Fig. 6. Membership Functions for Status.

IV. 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. 7) 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. 8. The loaded readings were run through the FIS-CDSS for classification as shown in Fig. 9 and Fig. 10. 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. 11, the developed system's prediction can be saved into the CDS as shown in Fig. 12.

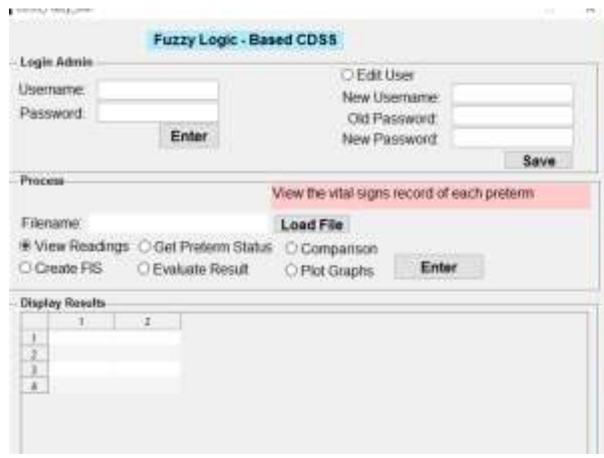

Fig. 7. The Developed FIS-CDSS Window.

Fig. 8. Viewing of the Recorded Vital Signs on the GUI.

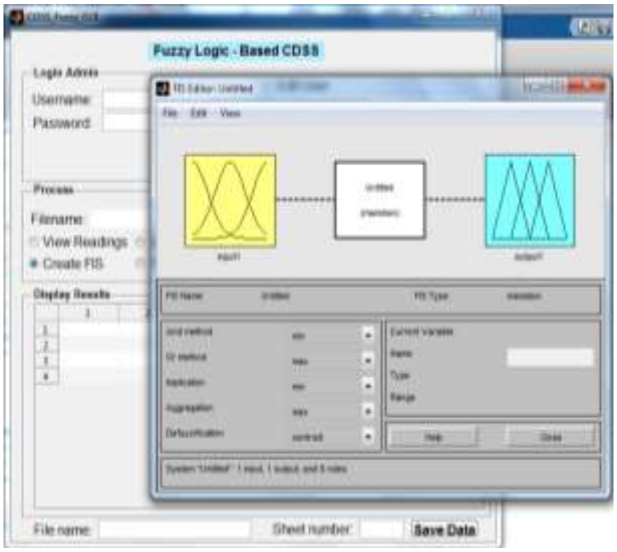

Fig. 9. Creation of a Fuzzy Inference System (FIS) Model for the CDSS.

Fig. 10. Acquisition of the Recorded Vital Signs for the FIS Classification.

Fig. 11. Display of the FIS Classification Results.

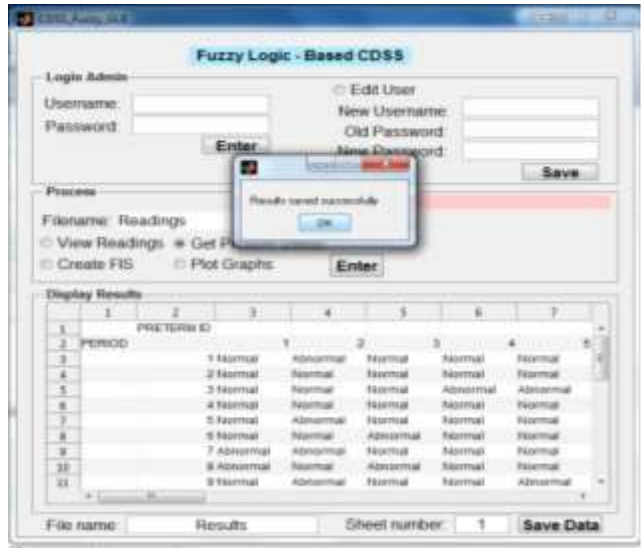

Fig. 12. Saving of the FIS Classification Results.

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 II.

TABLE II. 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

V. Conclusion and Further Work

In this research, a CDSS based architecture for monitoring neonates in the NICU has been implemented. The developed system collects readings of the vital signs of neonates from measuring sensors attached to the wrist of the neonates. 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.

The research work could be extended to measure or include more factors than the three basic vital signs temperature, heart beat rate and respiration. Other factors being observed by the specialist nurses such as transient clinical death, feeding rate and wavering weather could be included. The research work could also be extended to cover adults and other areas of health could be monitored and remotely reported to the physicians anywhere, anytime.

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