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Modelling an Integrated Fuzzy Based Decision Support System for an Anaesthetist during Pre-Operative Clinical Assessment

[1]Etuk Akaninyene U., [2]Harmony Nwobodo-Nzeribe and [1]Okoye Francis A.

[1]Department of Computer Engineering Enugu State University of Science and Technology (ESUT) Nigeria.
[2]Dir. Research and Innovation Enugu State University of Science and Technology (ESUT) Nigeria.
Corresponding Author Email: ibomatai1970@gmail.com

ABSTRACT

Pre-operative clinical assessment is a crucial responsibility for every anaesthetist before any major medical procedure. This assessment evaluates a patient's suitability for anaesthesia and their overall physical condition to endure the stresses of surgery. This is especially vital given recent data linking many surgical deaths to improper anaesthesia administration, with a mortality rate of 20 deaths per 10,000 anaesthetics in developed countries. This paper proposes an integrated fuzzy-based decision support system to assist anaesthetists during pre-operative clinical assessments. The approach combines neural network algorithms to classify and normalize input data, which then feeds into a fuzzy logic system for multi-variable decision-making analysis. To evaluate this decision support system, patient anaesthesia assessment datasheets were sourced from Ibom Multi Specialist Hospital in Akwa Ibom State, along with an online dataset from electronic anaesthesia records (MetaVision, 1MDsoft) of adult patients undergoing surgery at a major academic medical center. The study focused on patients over 18 years old undergoing non-cardiac surgeries, taking into account factors such as urgency and type of anaesthesia. The next step involves a decision-making process that assesses patient suitability for surgical anaesthesia based on established rules and membership functions developed through the fuzzy inference system. The results from this integrated decision support system were found to be reliable and consistent with anaesthetists' assessments. The system achieved an accuracy of 91.46%, as indicated by a ROC curve comparing sensitivity and specificity, demonstrating its effectiveness in evaluating patients for medical procedures. To enhance the training of future anaesthesiologists, the introduction of artificial intelligence into the curriculum is recommended, along with the application of evolutionary algorithms like genetic algorithms and programming. These strategies aim to significantly enrich the decision-making processes employed by anaesthetists.

Keywords: Fuzzy logic, neural network, anaesthesia, artificial intelligence

INTRODUCTION

Technological advancements have significantly enhanced the safety, scalability, and efficiency of anaesthesia practices. With the exponential growth of electronic medical data, artificial intelligence (AI) algorithms have enabled the development of clinical decision support systems, which facilitate appropriate interventions to reduce errors, deficiencies, and incidents in the operating theatre [1]. According to a global survey, surgery ranks as one of the most expensive aspects of clinical management [2]. However, managing an operating department is complex, involving multidisciplinary teams of healthcare professionals and instrumentation, along with a certain degree of unpredictability inherent in medicine [3]. Medicine is a continually evolving field, and most medical data are inherently imprecise. Therefore, Boolean or conventional logic, which uses sharp distinctions (0 for false and 1 for true), is often unsuitable for analysing medical data. Fuzzy logic, popularized by Lofti Zadeh, employs continuous set membership functions ranging from 0 to 1, making it well-suited for medical applications. Fuzzy logic (FL) allows for ambiguity and is thus particularly effective in medical data handling. FL systems are frequently used due to their capacity to manage imprecision in their reasoning schemes

[4]. Consequently, an integrated support system using fuzzy classification in its decision-making strategy is recommended, which supports the broader acceptance of AI in healthcare. Artificial Intelligence (AI) encompasses techniques that enable computers to mimic human intelligence. It relies on algorithms that equip machines with the ability to reason and perform functions such as problem-solving, object and word recognition, inference, and decision-making [5]. In healthcare, AI's purposes include precision medicine, resource optimization, and reduction of inequalities [6]. The application of AI across various medical fields—such as diagnosis, treatment, drug production, clinical management, and medical education—yields excellent results. For instance, machine learning (ML) algorithms have been used in managing osteoporosis and Paget's disease to identify the best therapeutic combinations and reduce drug-drug interactions [7]. Anaesthesia, which can induce physiological changes leading to morbidity or mortality, is considered a high-risk activity with issues such as airway management, cardio circulatory events, and drug administration related to anaesthesia. The continuous monitoring of anaesthesia-related mortality data from surgeries, such as cardiac, thoracic, vascular, gastroenterological, paediatric, and orthopaedic procedures, has made anaesthesia a favourable field for applying a new integrated support system [8 9]. These systems are crucial in managing and developing preventive strategies for anaesthesia-related mortality [10]. Developing an intelligent decision support system for anaesthetists and modelling their knowledge for evaluating patients during surgical assessment and management is crucial. This effort aims to further reduce the frequency of anaesthesia-related mortality, which has already decreased from 6.4 per 10,000 in 1940 to 0.4 per 10,000 today [11]. This significant improvement is largely due to the introduction of safety standards, improved training, modern practice guidelines, advanced monitoring techniques, and especially the integration of artificial intelligence technology [9]. During the preoperative assessment, anaesthetists evaluate a patient's suitability for anaesthesia before surgery. They determine if the patient's general physical condition can withstand the stresses of operating room management, which includes monitoring blood pressure, pulse oximetry, lung function, body weight, and particularly cardiac and respiratory competence [12]. Preoperative risk assessment is a critical task for every anaesthetist. A thorough assessment of the patient's cardiac and respiratory systems is essential, as these are the primary systems anaesthetists manage during surgery and operating room procedures [13]. This study recommends using an integrated fuzzy decision support system to achieve optimal results. Such a system, trained from two existing models, would be computationally efficient and facilitate an easier understanding of its decisions. This is particularly important as recent data attribute most surgical deaths to improper anaesthesia administration, with a mortality rate of 20 deaths per 10,000 anaesthetics in developed countries [11].Therefore, developing an integrated fuzzy-based system is essential to support anaesthetists in making intelligent clinical decisions during surgery.

Literature Review

[14] Developed SENTINEL, a system for identifying faults and assisting clinicians in assessing aesthetic patients by analysing physiological signals. The system achieved sensitivity and specificity above 90% for assessing seven common or serious anesthesia-related conditions.

[15] Developed a fuzzy logic-based algorithm to detect malignant hyperpyrexia, achieving early detection compared to clinical observations.

[16] Designed a fuzzy rule-based system integrating EEG features to estimate depth of anaesthesia (DoA) using statistical analysis and an adaptive network-based fuzzy inference system (ANFIS).

[17] Developed a Madman-type fuzzy model using aesthetic knowledge to construct patient models and employ ANFIS for signal modelling.

[18] Developed an anaesthesia alarm system using statistical tools to detect changes in SAP, aiming for clinically useful alarm timing.

[19] Developed a multivariable fuzzy temporal profile (MFTP) model for monitoring physiological variables, achieving a low false alarm rate.

using a medical information bus (MIB) to collect and validate bedside monitor data.

[12] developed a machine learning model for pre-operative risk assessment of heart rate, pulse, airways, and blood pressure complications.

[20] Developed a deep learning model from facial images to identify difficult intubation patients with improved sensitivity but lower specificity compared to conventional tests.

[21] Proposed a predictive model for difficult laryngoscopy (Grade 3 and 4 by Cormack-Lehane classification) using the Balanced Random Forest (BRF) algorithm, achieving an AUROC of 0.79 (0.72 – 0.86).

[22] developed a convolutional neural network (CNN) algorithm for evaluating intubation difficulty, achieving an excellent AUC of 0.864 by analysing patient facial pictures.

Materials Used

Collected dataset from electronic health records

Celeron – quad – core Intel N3450

Windows Professional X64 edition

Neural Network Architecture Software – Apache 2.0-(Neuroph)

Regression Analyzer

Matlab (mathworks, version 2.3.1 R2018.) computing environment that through the FL toolbox provides the tool for analysing, designing and simulating system based on fuzzy logic.

Analysis of the Proposed System

Understanding the concept of pre-operative assessment is crucial for ensuring high-quality clinical decision-making in surgical patients. Each patient presents with unique risk factors and comorbidities [12]. Apart from the general risks associated with surgery and anesthesia, each specific surgical procedure carries its own set of management challenges and potential complications. While this model cannot encompass all risks across all procedures, it provides an essential framework for anaesthesiologists to optimize pre-operative assessments. The researcher aims to achieve this through integrating a fuzzy logic system with neural networks. Such systems have been widely applied across various fields to address challenges using classification and regression approaches. Artificial Intelligence (AI) mimics human behaviour by collecting and learning from case study data, thereby making accurate predictions with high precision [5]. In this model, patient datasets will be collected to train neural networks, which will generate reference outputs. These outputs will then serve as inputs for the fuzzy system to conduct pre-operative assessments in real-time. This approach facilitates intelligent clinical decision-making by anaesthesiologists before surgery, enabling estimation of morbidity and mortality risks, identifying patients needing further evaluation, and guiding discussions on informed consent [12].The inference process is developed using a Mamdani-type fuzzy inference system, leveraging its intuitive rule-based nature to enhance decision-making capabilities.

Dataset Collection and Sources

This study aims to enhance clinical decision-making by anaesthetists during pre-operative assessments. A fuzzy-based system integrates offline and online data collected from 100 patients prior to surgery. Patient anaesthesia assessment data sheets were sourced from Ibom Multi Specialist Hospital in Akwa Ibom State, with approval from the hospital's chief medical director. Additionally, online data was gathered from the electronic anaesthesia records (Meta Vision, 1 MDsoft) of adult patients undergoing surgery over a three-year period, from December 2019 to April 2022, at a major academic medical centre. [2] The study focused on patients over 18 years old undergoing non-cardiac surgeries, excluding cases of cardiac surgeries or organ transplants, and patients lacking anaesthesia information. Surgical details included the emergency status and type of anaesthesia (general or regional).

Data Set Classification and Normalization

The data set collected was prepared and normalized for suitable input data set to be used with neural network because of the variety of some data type with such parameter as (text, integer, real) etc as well as the value interval. One of the value intervals that is possible to use as an input in neutral networks is (0,1) and this is the reason why it is necessary to standardize the data collected by linear transformation; [23].

$$x_{1(0,1)} \quad \frac{x_1 - x_{\min}}{x_{\max} - x_{\min}} \quad \ldots\ldots\ldots\ldots \quad (1)$$

Where:

x_1 – Value of data i

$x_{\min}$ – Minimum data value in observed set

$x_{\max}$ – Maximum data value in observed set

$x_{1(0,1)}$ – Value of data I after normalization in (0.1) interval

Table 1: Values Provided to Integrated Fuzzy Based System during Normal Assessment

S/N	Input Variables	Unit	Minimum Value	Maximum Value	Linguistic Label	Membership Function
1.	Cardiac sound classification	N/A	0	1	Low Medium High	Triangular
2.	Respiratory sound classification	N/A	0	1	Low Medium High	Triangular
3.	Blood pressure systolic	mmHg	40	200	Low Medium High	Triangular
4.	Blood pressure diastolic	mmHg	30	150	Low Medium High	Triangular
5.	Heart rate	Bpm	25	130	Low Medium High	Triangular
6.	Patient age	years	18	110		Triangular
7.	Patient gender	N/A	0 (female)	1 (male)		Triangular
8.	SPo_2	%	1	100	Low Medium High	Triangular
9.	Blood sugar	N/A	140	458	Low Medium High	Triangular
10.	Smoker	N/A	Binary	Encoded		Triangular
11.	Warfarin inhaler, HRT	N/A	Binary	Encoded		Triangular
12.	Peak expiratory flow rate	L/min	50	500		Triangular
13.	Forced expiratory volume (1s)	L	0.1	10		Triangular
14.	Steroids, Aspirin, Diuretics	N/A	Binary	Encoded		Triangular
15.	Female Contraceptive Pill	N/A				Triangular
16.	Hepatitis B, Hepatitis C	N/A	1: true	Positive		Triangular
17.	MRSA, Active TB, HIV	N/A	0: false	Negative		Triangular
18.	Afro-Carribbean origin	N/A				Triangular
19.	Excessive alcohol intake	N/A				Triangular
20.	Infection	N/A				Triangular
21.	Blood disorders/anaemia	N/A	Binary	Encoded		Triangular
22.	Diabetic	N/A	0: false	Negative		Triangular
23.	Kidney/urinary problems	N/A	1: true	Positive		Triangular
24.	Bleeding disorders	N/A	0: false	Negative		Triangular
25.	Thyroid disease	N/A				Triangular
26.	Malignancy	N/A				Triangular
27.	Open wound	N/A				Triangular
28.	Cardiovascular disease history	N/A				Triangular
29.	Varicose veins	N/A	1: true	Positive		Triangular
30.	Smoker	N/A				Triangular
31.	Pneumonia/chronic bronchitis	N/A				Triangular
32.	Asthma (well controlled)	N/A				Triangular
33.	Asthma (hospitalized)	N/A	Binary	Encoded		Triangular
34.	Shortness of breath at rest	N/A	1: true	Positive		Triangular
35.	Respiratory disease history	N/A	0: false	Negative		Triangular
36.	Productive cough	N/A				Triangular

Data normalization transforms each parameter value to fit within the interval (0,1) and adjusts qualitative values accordingly. This normalization process followed Equation 1.

Dataset Processing and Consideration

The Decision Support System (DSS) integrates inputs from Neural Network outputs, the Neural Network outputs were 1-in-N encoded and normalized to enhance classification accuracy. The normalized outputs represented probabilistic assertions aiding anaesthetist assessments. The Neural Network's outputs, bounded between 0 and 1, reflect classification probabilities. Table 1 summarizes variables used as inputs to the Neural Network in this model. Patient clinical history and medication were encoded as shown in Table 1, focusing on five categories: haemodynamic, cardiac (including circulatory), respiratory, bio-hazard, and medication. Each category further details relevant conditions from the patient's history. Data collected from 100 patients were classified by a consulting anaesthetist into three categories: 'approved for surgical anaesthesia', 'partially approved for surgical anaesthesia (refer patient)', and 'not approved for surgical anaesthesia'.

Modelling an Integrated Fuzzy-Based Decision Support System

Fuzzy systems effectively handle problems that defy conventional approaches. However, identifying suitable fuzzy rules and membership functions from available datasets remains challenging, often requiring trial and error [24]. This model addresses this challenge by integrating fuzzy systems with neural networks. Neural network learning algorithms are employed to determine parameters of the fuzzy system, creating a neuro-fuzzy system that combines the strengths of both methodologies while overcoming their individual limitations [24].The integrated fuzzy-based decision support system for anaesthetists, described in this section, aims to model the anaesthetist's decision-making process. It integrates the Neural Network classifications with a fuzzy rule-base system to enhance decision strategies [25].

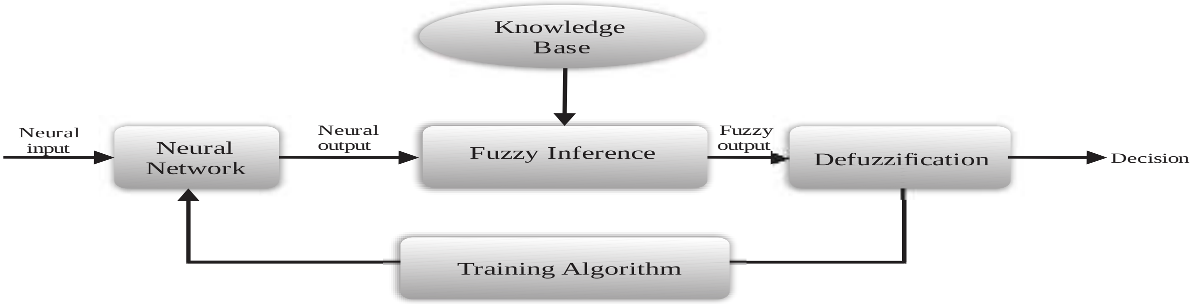


Figure 1: Model Architecture design of the integrated fuzzy based decision support system

Neural networks excel in generalizing solutions to domain classification problems but struggle to provide linguistic interpretations of their decisions, [26]. Their responses are typically weighted sums of successive linear and non-linear transformations, lacking inductive reasoning that could explain their decision-making process using classification based on inductive reasoning. In contrast, fuzzy classifiers have the ability to linguistically demonstrate the reasoning chain leading to their classifications [24]. For this model, fuzzy rules will be considered as linguistic statements indicating variable X's membership of class C to degree μc(x) (the fuzzy membership function). The membership function's boundary and inclusion values for input variables are defined as follows:

$$\mu(x) = wtr\mu tr(x) + wg\mu g(x) + wb\mu b(x) + wt\mu t(x), \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (2)$$

Where wtr, wg, wb, and wt are weight terms summing to unity. These weights are determined by triangular membership functions governed by a mixture coefficient m ($0 \leq m \leq 100$). Equation 2 represents μ(x) as a linear mixture of two function systems (Neural Network and fuzzy system).

Training and Development of Neural Networks

The Neural Network was trained using Gradient Descent Training Algorithm to classify, analyse, and identify various attributes of the dataset shown in Table 1. Additionally, it learned to recognize patterns and characteristics to predict the anaesthesia performance status based on patient-related input parameters. Notably, each patient underwent a unique set of tests such as demographics (e.g., age, sex), medical history (e.g., Charlson comorbidity index, smoking, heart failure), physiological measurements (e.g., blood pressure, pulse rate), anaesthesia type, and laboratory measurements (e.g., albumin, white blood cells, glucose). The purpose of training is to make the system able to learn on how to classify the input parameters into desired controlled classification [5]. This process is achieved using the Gradient Descent Training Algorithm. The neural network tool and architecture for the training process is shown in figure 2.

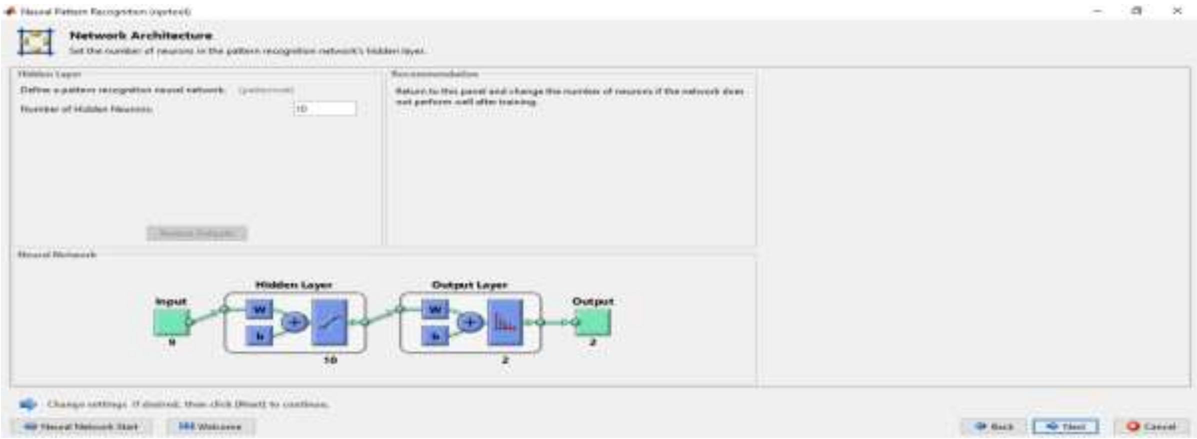


Figure 2: Neural Network Architecture

The training algorithm automatically splits the dataset into training testing and validation sets before training. The training process using Gradient Descent Training Algorithm automatically adjust the weights of each neurons while simultaneously checking the epoch values until the best training result is achieved and the classification model is generated which formed the input for the fuzzy based logic system. The dataset was split into training and validation sets for testing the Neural Network's performance. During training, data was utilized iteratively to adjust parameters, and the number of neurons was optimized to achieve the desired performance of the Neural Network.

System Implementation

Rule selection involves a fuzzy rule-base comprising 3 rules, each corresponding to a classification output. These rules vary in complexity, with each rule term containing an operator (AND X, OR +, AND NOT – X, OR NOT - +), a fuzzy variable, and a linguistic expression (low, medium, high). This approach mirrors the decision-making strategy of an anaesthetist, focusing on predicting surgical anaesthesia according to clinical decisions [25]. The integrated fuzzy system generated the following rule-base, as referenced in Table 2:"

Table 2 Variable Description for the Integrated Fuzzy Rule Base

Variable	Variable description
x(1)	Gender
x(2)	Age
x(3)	Systolic blood pressure
x(4)	Diastolic blood pressure
x(5)	Heart rate
x(6)	SpO2
x(7)	Peak expiratory flow rate
x(8)	Forced Expiratory volume (1 second)
x(9)	Medication indicator
x(10)	Biohazard indicator
x(11)	Haemodynamic indicator
x(12)	Cardoivascular indicator
x(13)	Respiratory indicator
x(14) – x(30)	Heart sound classification (1-17)
x(31) – x(44)	Lung sound classification (1-14)

Rule #1: (Approved for surgical anaesthesia)
IF (X(4) IS NOT high) THEN (Y IS class_1)
Rule #2: (Partially approved for surgical anaesthesia)
IF (X(11) IS high) AND (X(5) IS low) AND (X(3) IS NOT high) AND (X(9) IS high OR (X(10) IS low) AND (X(11) IS high)AND
(X(3) IS high) OR (X(5) IS low) AND (X(12) IS NOT low) AND
(X(2) IS NOT medium) OR (X(4) IS high) THEN (Y IS class_2)
Rule #3: (Not approved for surgical anaesthesia)
IF (X(2) IS low) AND (X(7) IS high) AND (X(8) IS NOT high) THEN (Y IS class_3)

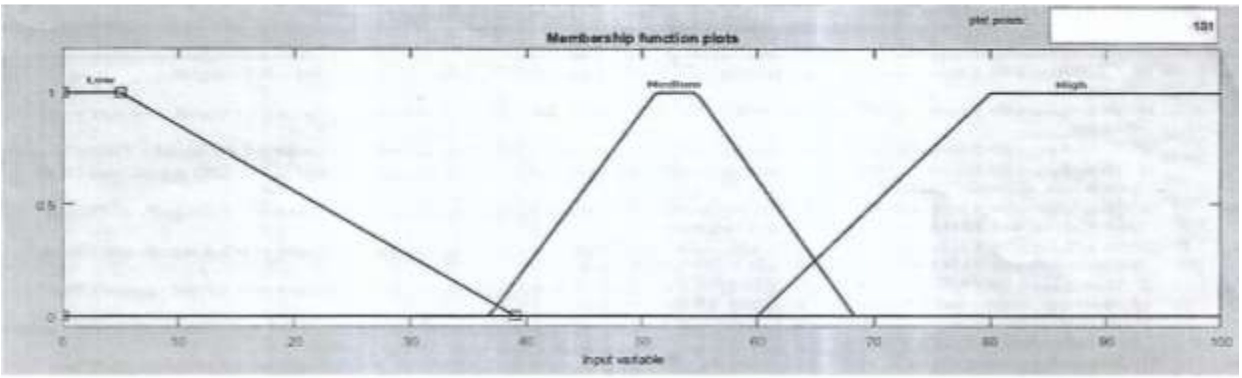
The rule-base outlined in the rule section illustrates that each rule's complexity can be regarded as trivial [24]. To illustrate this, the Mamdani fuzzy controller algorithm was employed to develop an integrated fuzzy-based model capable of effectively modelling the decision-making strategy of an anaesthetist. The integrated fuzzy-based system aims to amalgamate the classifications performed by the neural network components, with other relevant data to form a complementary decision strategy. Following the pruning of contradictory terms, the rule-base generated by the integrated fuzzy model is presented in the rule section, with reference to Table 2. This integrated approach leverages the Mamdani fuzzy controller algorithm to construct a robust model that encapsulates the nuanced decision-making process employed by anaesthetists. By integrating fuzzy logic with neural network classifications and additional pertinent data, the system enhances decision-making capabilities through a synergistic fusion of diverse information sources [24]. The decision to prune contradictory terms from the rule-base underscores a meticulous refinement process aimed at enhancing the model's accuracy and applicability. This refinement ensures that the rules governing the integrated fuzzy model remain coherent and aligned with the desired decision-making objectives. Table 2 provides a detailed reference point for understanding the structure and content of the pruned rule-base within the integrated fuzzy model. By delineating the rules in this manner, the model achieves clarity and precision in its representation of the anaesthetist's decision-making strategy. In summary, the utilization of the Mamdani fuzzy controller algorithm within the integrated fuzzy-based model signifies a significant advancement in the field of decision support systems for healthcare professionals [25]. This approach not only synthesizes diverse data inputs but also refines them through a systematic process of rule-base pruning, thereby optimizing the model's efficacy and relevance in real-world applications. By elucidating the role of integrated fuzzy systems in decision support, this model contributes to the broader discourse on computational intelligence and its application in medical decision-making contexts. The integration of fuzzy logic with neural network classifications represents a promising avenue for future research, offering potential enhancements in decision-making accuracy and efficiency across various domains of healthcare practice. Overall, the integrated fuzzy-based model stands as a testament to the synergistic potential of computational methodologies in augmenting decision support frameworks. Through its nuanced approach to rule-base development and refinement, this model exemplifies a forward-thinking paradigm in leveraging artificial intelligence for enhanced clinical decision-making outcomes.

Fuzzification

Fuzzification involves the process of transforming crisp sets of rules generated by Mamdani-type algorithms into fuzzy sets using fuzzy logic, [25]. Unlike traditional binary logic, which operates with values of strictly 0 or 1, fuzzy logic allows for values across the continuous range from 0 to 1. This characteristic earns fuzzy logic the designation of multi-valued logic, in contrast to the strict membership or non-membership of elements in conventional set theory. In the framework of fuzzy theory, a fuzzy set A in the universe X is defined as a collection of ordered pairs where $\mu A(x)$ denotes the membership function of set A. The membership function $\mu A(x): X \rightarrow [0, 1]$ determines the degree to which an element x belongs to set A. Specifically, $\mu A(x) = 1$ signifies complete membership of x in A, $\mu A(x) = 0$ indicates no membership, and $0 < \mu A(x) < 1$ reflects partial membership. Fuzzy sets accommodate gradations of membership, offering a continuum of possible choices. For any element x in the universe X, the membership function $\mu A(x)$ signifies the extent of x's membership in set A, a value bounded between 0 and 1 termed the membership grade or membership value. Fuzzy logic thereby serves as a tool to model and manage uncertainty and ambiguity, permitting sets to overlap and avoiding the rigidity of sharp boundaries. In the domain of clinical decision-making for anaesthesia patients, fuzzification of dataset attributes—comprising system inputs and outputs—is essential to address inherent inaccuracies, ambiguities, and uncertainties associated with clinical assessments, [27]. System input parameters encompass patient demographics, pre-operative laboratory tests, surgical details, and data extracted from hospital electronic medical records. Demographic data typically includes age, sex, height, weight, body mass index, blood pressure, glucose levels, cholesterol, triglycerides, cardiovascular, and respiratory indicators. Pre-operative laboratory tests encompass parameters such as white blood cell count, [28]. The output variable in this context is categorized into fuzzy linguistic values: approved, partially approved, and not approved. These linguistic categories encapsulate the classification output derived from neural networks. It's noteworthy that while fuzzy variables allow for ambiguity and overlap in their membership across sets, anaesthesia classification inherently demands a clear, singular assessment for each patient. The value of a fuzzy variable is dictated by its membership grade, determined by the choice of membership function. For input variables, a trapezoidal membership function was adopted, while the output variable employed a triangular membership function. The trapezoidal membership function, defined as Trapezoidal (x; a, b, c, d), assigns membership values of 0.0 at x = a and x = d, and 1.0 at x = b and x = c, thus providing a smooth transition between full and no membership [29]. Conversely, the triangular membership function, denoted as Triangle (x; a, b, c), allocates membership values of 0.0 at x = a and x = c, and 1.0 at x = b, facilitating a simpler triangular distribution of membership grades [25, 29,30]. These functions are essential tools in transforming crisp data into fuzzy sets, allowing for a more nuanced representation of uncertainty and variability in clinical decision support systems. Fuzzification via fuzzy logic is instrumental in refining clinical decision-making processes by accommodating uncertainties and ambiguities inherent in medical data. By employing fuzzy sets and appropriate membership functions, the approach enhances the accuracy and reliability of anaesthesia assessment systems, ultimately contributing to improved patient care outcomes as shown in equation 3 [29].

$$\mu_A(x) = \begin{cases} 0 & \text{If } x \le \alpha \min \\ \dfrac{x - \alpha \min}{\beta - \alpha \min} & \text{If } x \,\varepsilon\, (\alpha \min^1 \beta) \\ \dfrac{\alpha \max - x}{\alpha \max - \beta} & \text{If } x \,\varepsilon\, (\beta, \alpha \max) \\ 0 & \text{If } x \ge \alpha \max \end{cases} \qquad \ldots\ldots\ldots\ldots\ldots\ldots 3$$

The linguistic variables and membership function each attribute of the dataset is determined, calculated and visualized using MATLAB. Thus, each crisp value has been transformed or converted into a fuzzy value. As such, all the crisp set rules generated using madman-type algorithm were transformed into the corresponding fuzzy set rules. Moreover, after determining each attribute's linguistic variable and converting crisp value into fuzzy values, the crisp set rules generated earlier were converted into a fuzzy set of rules.



Membership functions of the Linguistic variables

Figure 3 Membership functions of pre-operative assessment

Fuzzy Based Integrated System

The integrated fuzzy based system for anaesthesia has three major components which include knowledge base, inference engine, and defuzzication (user interface).

Knowledge base

The knowledge base has been developed based on the input data and the experience of consultant anaesthetist consulted and involved in the stages of data collection, cleaning, interpretation and knowledge generation. Consultant anaesthetist verified each rule generated with the madman-type algorithm, and all the conflicts were resolved. The system employed a production technique written in the format of < IF (condition) THEN (conclusion>. In the present fuzzy system, condition and conclusion are fuzzy variables. These rules are pre-operative clinical assessment rules and are selected by the inference engine of the system. MATLAB is used to implement the system, which has three rules.

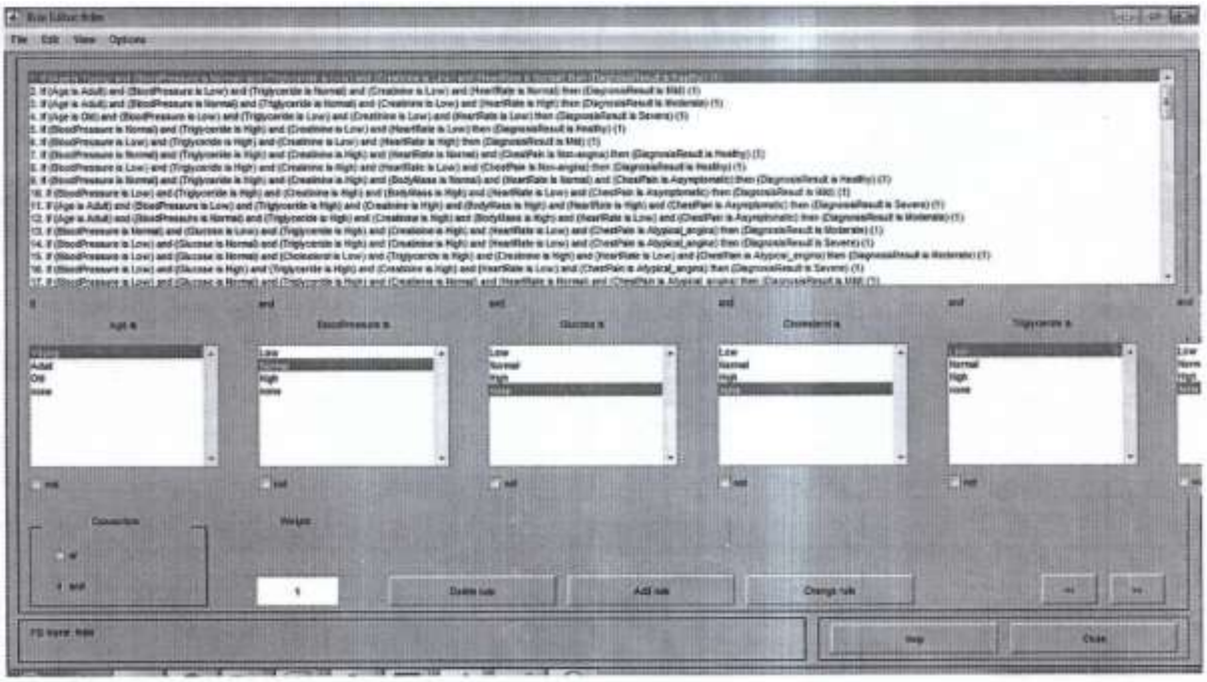


Figure 4: Knowledge Based Rules

Knowledge Inference Engine

Knowledge is a mechanism behind inferring new knowledge from existing fuzzy rules available in the system knowledge base [30]. Therefore, new information and conclusions would be deduced from it. Mamdani inference technique is used to stimulate expert anaesthetist reasoning in assessing a patient in this model. Mamdani Fuzzy Inference System is widely used because it provides good results with a relatively simple structure [25]. Mamdani is used to create a control system synthesizing a set of linguistic production rules obtained from experienced human operators. Therefore, the Minimum operator, the conjunction operator is MIN, the t-norm from the compositional rule is Min, and the MAX operator is used to aggregate the rules [25]. Figure 5 show the Graphical User Interface (GUI) of System Inference with Mamdani technique.

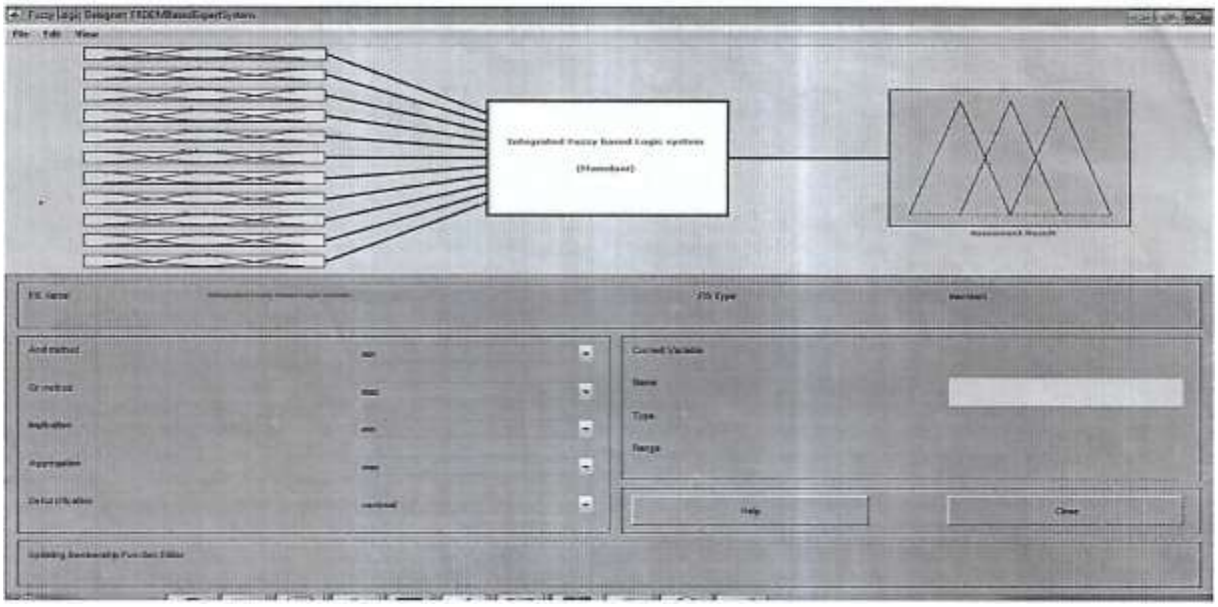


Figure 5: The Graphical User Interface (GUI) of System Inference with Mamdani technique

Defuzzification

Defuzzification involves transforming the output of the inference engine (fuzzy values) into crisp values. A centroid is employed in this work for defuzzification, called the center of area or centre of gravity, where y^1 is the output variable, and (B^I) is the membership function of the aggregated fuzzy set referring to y. The Centroid method de-fuzziest the system's assessment result's undefined values, which is the output of the system to crisp values.

$$y^I = \frac{y\mu B^I ydy}{\mu B^I ydy} \quad \text{---} 4$$

Figure 6 shows the model flowchart description of the integrated fuzzy based decision support system of the study.

Figure 6 Model Flow-chat of the Integrated Fuzzy Based Decision Support System

Integrated Fuzzy Based Logic System

This section presented the results of the Integrated Fuzzy Based Logic System which demonstrates the fuzzy sets as it relates to the linguistic variables based on the domain knowledge and the members of membership function as defined by the expert's anaesthetist. The output results were evaluated using outputs such as regression analysis, confusion matrix among others.

Table 3: Output Classification Result Summary during Pre-Operative Assessment

CLASSIFICATION	TOTAL NUMBER OF PATIENTS	NUMBER OF REFER PATIENTS	NUMBER OF WRONG ASSESSMENT
Approved for surgical anesthesia	45	05	05
Partially approved for surgical anesthesia	20	02	02
Not approved for surgical anesthesia	35	35	NIL
Total	100	42	07

Performance Evaluation

To evaluate the performance of the developed Integrated Fuzzy Based Logic System. A total of 100 dataset of patients undergoing pre-operative clinical assessment at Ibom Multi Specialist Hospital between December 2019 – April 2022 was collected and was approved by the chief medical director. All data processing procedures relating to the study was co-examined by a consultant anaesthetist. And due to lack of uniform medical records concerning all the assigned variable in this study, the sample of patient's dataset for evaluating the model was restricted to 100 patients. With reference to table 3. All patient's dataset were analysed to determine the outcome of the developed model. The result as recorded as showed in Table 4. Finally, based on the analysed data, the accuracy, specificity and sensitivity of the developed model was determined as follows with reference to the following:

Where: (i) TP: True Positive is 40
(ii) FN: False Negative is 02
(iii) FP: False positive is 05
(iv) TN: True Negative is 35

The Integrated Fuzzy Based System was used to access the dataset of 100 patients undergoing pre-operative clinical assessment with (45% approved for surgical procedure, 20% partially approved for surgical procedure and 35% not approved for surgical procedure.

For model evaluation, information based on the input variable as shown in Table 3 was taken about the patients and labelled by the consultant anaesthetist which is used to compare with the predicted output given by the Integrated Fuzzy Logic System as shown in Table 4.

Table 4: A Sample of Pre-Operative Assessment Performed with Integrated Fuzzy Based System and Consultant Anaesthsist

Test	Blood Sugar	DBP	SBP	Age	PAFEA	PAFIFS	Class Outcome
1	142.6	115.2	129.8	40	Partly Approved	Partly Approved	2
2	170	119	144	66	Not Approved	Not Approved	3
3	290	121	220	28	Not Approved	Not Approved	3
4	85.47	90.62	124.2	22	Approved	Approved	1
5	166.2	102.2	142.8	60	Approved	Approved	1
6	91.14	126	170.8	27	Partly Approved	Approved	1
7	146.7	112.3	155.8	30	Partly Approved	Approved	1
8	305.6	122.4	187.2	49	Not Approved	Not Approved	3
9	76.79	96.33	140.5	55	Not Approved	Partly Approved	2
10	122.9	126	197.8	28	Partly Approved	Not Approved	2
11	96.29	105.4	129.5	65	Approved	Approved	1
12	209.4	116.5	170.8	58	Approved	Approved	1
13	320.6	113	174.2	26	Partly Approved	Partly Approved	2
14	166.5	107.7	156.8	62	Approved	Approved	1
15	127.8	116.5	146.2	26	Not Approved	Not Approved	3
16	188	123.3	186.8	63	Partly Approved	Partly Approved	2
17	91.20	126	186.8	27	Partly Approved	Partly Approved	2
18	144.4	106.8	155	50	Partly Approved	Partly Approved	2
19	184.9	120.2	164.6	42	Approved	Approved	1
20	158.8	86.73	126.8	36	Not Approved	Not Approved	3
21	96.89	90.89	144.3	68	Partly Approved	Partly Approved	2
22	140.5	88.20	138.7	92	Approved	Approved	1
23	122.2	87.04	138.7	30	Partly Approved	Partly Approved	2
24	150.1	106.7	152.7	56	Approved	Approved	1
25	91.13	86.20	124.6	44	Not Approved	Not Approved	3
26	161.8	99.54	112.6	33	Partly Approved	Not Approved	2
27	144.2	106.8	112.6	29	Partly Approved	Partly Approved	2
28	169.2	122.8	191.6	26	Approved	Approved	1
29	144.6	122.8	183	62	Approved	Partly Approved	2
30	101.9	108.7	173.8	38	Approved	Approved	1
31	101.9	108.7	166.2	35	Not Approved	Not Approved	3
32	132.2	118.9	166.2	33	Approved	Approved	1

Note: DBP – Diastolic Blood Pressure, SBP – Systolic Blood Pressure, PAFA – Patient Assessment From Consultant Anesthetist, PAFIF - Patient Assessment From Integrated Fuzzy Based System. Class outcome: 1 – Approved for surgical procedure, 2 – Partly Approved or refer for further medical examination, 3 – Not Approved for medical procedure.

The Integrated Fuzzy Based System was used to access the patient's pre-clinical status before medical procedure with the following metrics. Accuracy: is used to evaluate the percentage of pre-clinical patients who were approved and cleared for surgical procedure. Sensitivity is used to evaluate the percentage of pre-clinical patients who were not approved but were referred for further pre-clinical assessment. Specificity is used to evaluate the percentage of pre-clinical patients who were partially approved for surgical procedure but referred for further examination and needed for further medical procedure. Receiver operating characteristic curve (ROC) is used to show the relationship between the specificity and sensitivity of the integrated system.

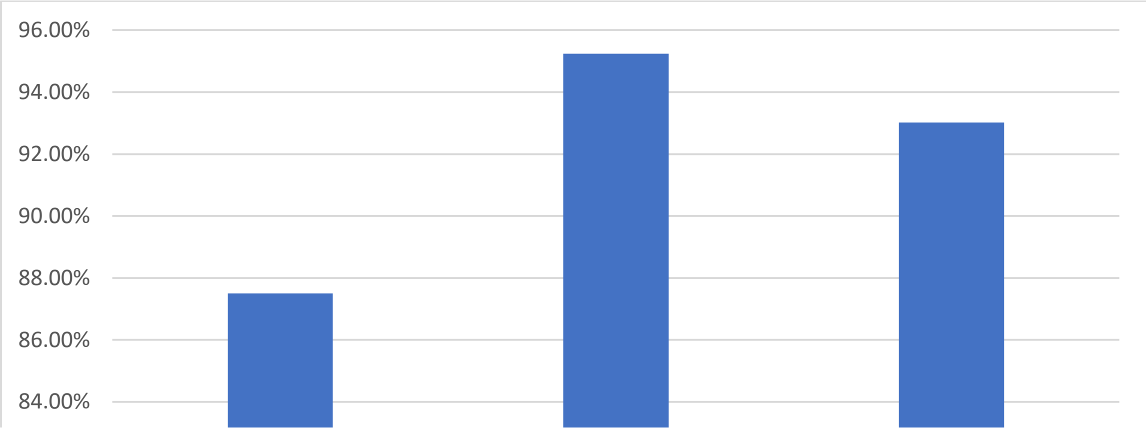


Figure 7 Model Performance Evaluation

Table 7 and figure 8 shows the system performance evaluation result based on sensitivity, accuracy and specificity of 95.24%, 91.46% and 87.50% respectively. ROC shows the relationship between the specificity and sensitivity of the system. The result indicates that the system is reliable and can access pre-operative patient effectively. The X-axis of ROC is showing specificity while Y-axis showing sensitivity as shown in figure 8. The curve shows that the relationship between the specificity and sensitivity and it indicates the pre-operative clinical assessment capacity of the system as it determines the suitability of the patients for surgical procedure. The curve shows that the integrated system can perform pre-operative assessment of patients efficiently.

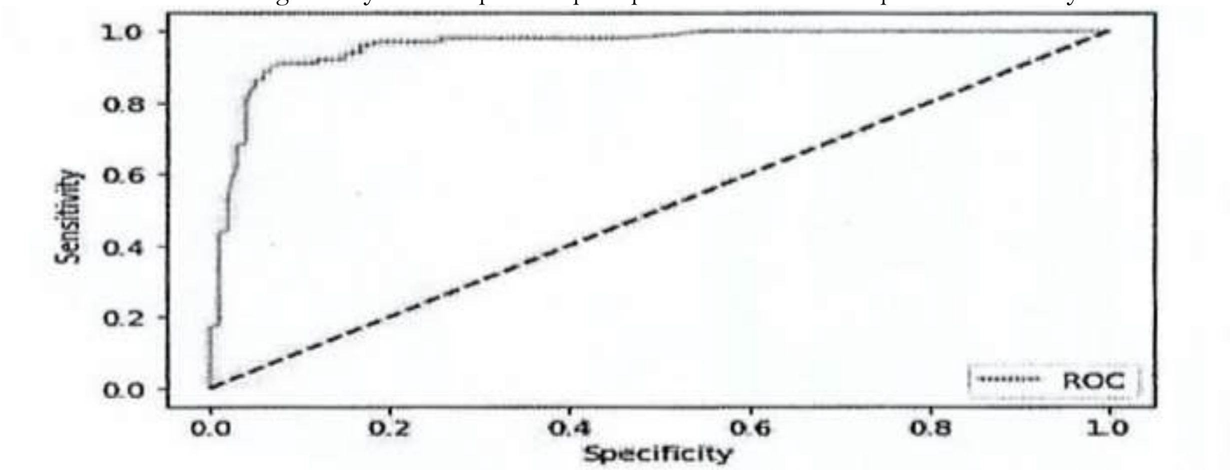


Figure 8: Receiver Operating Characteristic Curve

RESULTS

In order to evaluate the Integrated Fuzzy Based Logic System, the performance measures such as precision, specificity, sensitivity, F1 – measure and accuracy have been used which are calculated as:

Therefore Sensitivity = $\frac{(TP)}{(TP + FN)}$ $\frac{40}{(40 + 02)}$

Specificity = $\frac{(TN)}{(TN + FP)}$ $\frac{35}{35 + 05}$ %

Precision = $\frac{(TP)}{(TP + FP)}$ $\frac{40}{40 + 03}$ %

Classification accuracy = $\frac{(TP + TN)}{(TP + FP + TN + FN)}$

= $\frac{(40 + 35)}{(40 + 05 + 35 + 02)}$ = 91.46%

Where TP, FN, FP and TN are true positive, false negative, false positive and true negative respectively. The "approved for surgical anaesthesia category is taken as a default assessment used as a potential mode of accuracy. Figure 8 shows the output bar chart classification of the Integrated Fuzzy Based Decision Model. It is observed that the developed model performance is good in accessing patients' suitability for surgical anaesthesia effectively. Confusion matrix includes information concerning the output classification of the developed model. Due to the n classes, a confusion matrix is an n x m matrix. Performance of the classification output is usually evaluated using the dataset in the results summary. The confusion matrix of the Integrated Fuzzy Based Logic System is displayed in Table 7 which elaborates the strengths and the weaknesses of the model. For confusion, true positives for patients approved for anaesthesia = 45 while false positive is 05 while 35 is for true negative and false negative is 02. Therefore, diagonal elements of matrix 45 + 35 = 80 represent the right classified and element 5 + 2 shows the wrong classified refer for reassessment. Regarding the model performance in terms of all five metrics including sensitivity, specificity, precision, accuracy. It is observed that sensitivity had the maximum rate wise about 0.9524 and specificity had the minimum rate with a bit more than 0.0476, while F1 – measure, precision and accuracy were respectively 0.9146. Figure 8 shows Roc curve comparing the sensitivity and specificity of the integrated model. (AUC = Area Under Curve).

Discussion on the Developed Model

The Integrated Fuzzy Based Logic System is a supporting tool in decision-making about anaesthesia practice. Consultant anaesthetist decision would be considered as final, the developed model can also make decision as the consultant anaesthetist based on the knowledge-based of the system. Hence it is a very useful tool for assisting medical personnel for the robust decision regarding the pre-operative clinical assessment. The accuracy obtained from the developed model is 91.46%., which means the system is successful in assessing patient considered for medical procedure.

CONCLUSION

The primary objective of this study was to model the expert knowledge of anaesthetists and develop a robust decision support system for pre-operative clinical assessments. Divided into distinct objectives, this study aimed to establish a sound decision-making strategy rooted in expert knowledge and technological integration. From the findings presented, it is evident that integrated fuzzy-based systems can effectively classify patients in pre-operative contexts. This conclusion is substantiated by the system's design and performance metrics, showcasing its capability to encapsulate and leverage anaesthetists' expertise for optimal decision-making. Furthermore, the integrated fuzzy-based system excels not only in individual applications but also in collective contexts, where collaborative decision-making processes benefit from its comprehensive approach. By consolidating the knowledge of anaesthetists into a rule-based system, this study underscores the computational efficiency and clarity afforded by such approaches. These systems minimize complexity while maximizing understanding, facilitating informed decisions that uphold patient safety and procedural efficacy. The integration of fuzzy-based decision support systems represents a significant advancement in healthcare technology. By encapsulating anaesthetists' knowledge, these systems empower medical practitioners to make informed decisions regarding surgical anaesthesia administration. This study demonstrates the feasibility and effectiveness of integrating intelligent systems like neural networks and fuzzy logic into healthcare practices, enhancing the quality and precision of medical assessments.

Recommendation for Future Work

In this model, the focus was on an integrated fuzzy-based system designed to enhance the decision-making strategies of anaesthetists during pre-operative clinical assessment. The future directions of this research should aim to enhance and incorporate additional variables that could aid anaesthetists in intra-operative assessment within the context of operating room management. Given the multi-variable nature of the assessment process, exploring evolutionary algorithms such as Genetic Algorithms (GAs) and Genetic Programming (GPs) could significantly enrich the decision support strategies employed by anaesthetists. Collaborative research with manufacturers would provide valuable insights into the comprehensive application of the integrated fuzzy system in supporting anaesthetists. Such joint efforts could lead to a deeper characterization of the system's outcomes and its practical implications. Moreover, integrating artificial intelligence into the training curriculum for future anaesthesiologists is imperative. This inclusion would equip them with both technical and non-technical skills necessary to stay abreast of current trends in the digital revolution affecting medical practices.

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