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Reliability Comparison of Fuzzy Logic and Analytic Hierarchy Process (AHP) as Engine for the Development of Intelligent Medical Diagnostic Systems

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Abstract: Medical diagnosis and therapy involve the determination of the nature of disease from observation of signs and symptoms and subsequent curative treatment of such a disease. It demands the state space search of medical knowledge of a particular disease, which includes patient's medical history, patient medical examination and drugs. A number of researchers have utilized the fuzzy or Analytical hierarchy process (AHP) methodology in developing intelligent systems that handle imprecise data in medical diagnosis and therapy. The fuzzy logic is able to handle vagueness and uncertainty management in decision making, while the AHP has the ability to carry out pairwise comparison of decision elements in order to determine their importance in the decision process. This study attempts to carry out a reliability comparison of the fuzzy and Analytical hierarchy process methods in the development of medical diagnosis system (intelligent system) in order to provide a framework for determining the appropriate backbone in a fuzzy-AHP hybrid system. Data collected from severe tuberculosis patients were used to diagnose using AHP and fuzzy logic independently. The results were compared and it indicates that fuzzy technology is relative significant superior over the AHP technology. It was also discovered from the results of fuzzy logic diagnosis co-vary a little bit more strongly to the conventional diagnosis results than that of AHP.

Key words: Tuberculosis · Fuzzy Logic · Analytical Hierarchy Process · Medical Diagnosis · Intelligent System

INTRODUCTION

The task of carrying out an effective and efficient disparity medical diagnosis is a complex one. It involves a state space search of medical knowledge, which could become unwieldy, especially when the variables involved are numerous [1]. It is recognized that a very important task in achieving hospital efficiency is to optimize the diagnostic process in terms of the number and duration of the patients' examinations, with accompanying accuracy, sensitivity and specificity [2]. The task of medical diagnosis like other diagnosis processes is made more complex because a lot of imprecision is involved. Patients cannot describe exactly what has happened to them or how they feel; doctors and nurses cannot tell exactly what they observe; laboratories report results with some degree of errors; medical researchers cannot precisely characterize how disease alter the normal functioning of the body [3]. A number of expert systems have attempted to address the subject of knowledge acquisition, representation and utilization in medical diagnosis. However, the problem of managing imprecise knowledge still exists.

The first attempts at creating decision support tools for medical diagnosis began with the application of statistical methods for medical diagnosis, initiated by the pioneering efforts of Lipkin, Hardy and Engle in the 1950s at the Cornell medical school. Logical and probabilistic approaches were explored to the diagnosis of haematological disorders. This era saw the applicability of Bayesian inference, utility theory, Boolean logic and discriminant analysis to medical diagnostic problems [4]. Bayesian inference is a popular statistical decision making process, which provides a paradigm for updating information by using Bayes theorem statement of conditional probabilities relating causes (states of nature) to outcomes. Utility theory allows decision makers to give formalized preference to a space defined by the

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alternatives and criteria. The scores for each alternative are combined with measures of each criterion's importance (i.e weight) to give a total utility for the alternative. Boolean logic is a form of algebra in which all values are reduced to either true or false, while discriminant analysis is a mathematical approach which tries to differentiate between classes, categories or clusters or groups. It partitions a sample into yes or No groups, positive and negative values [5].

By the early 1970s, it became evident that statistical tools were unable to deal with most complex clinical problems [6]. The first attempt at applying artificial intelligence (AI) principles in medical diagnosis started with the efforts made by Kulikowski in 1970, aimed at moving away from purely engineering approaches toward a deeper consideration of the "cognitive model" that the human physician uses in diagnosis. Pattern recognition methods were the focus of AI application in medical diagnosis until 1974 when short life published the first rule based approach for therapy advice in infectious diseases [7, 8]. Rule based programs use the "if -then - rule" in chains of deductions to reach a conclusion. Szolovits observed [9] that rule based system are good for narrow domains of medicine, but most serious diagnostic problems are so broad and complex that straightforward attempts to chain together larger sets of rules encounter major difficulties. Such system lacked the model of the diseases or clinical reasoning. In the absent of the models, the addition of new rules leads to unanticipated interactions between rules, resulting in serious degradation of program performance [10]. Furthermore, rule based systems attempt to represent different kinds of information (defining terms, expressing domain facts, supporting formalism. This compounding of different kind of knowledge results in poorly structured systems that are difficult to understand and maintain.

As research in medical diagnosis deepened, emphasis shifted to the representation and utilization of unstructured, imprecise and dynamic knowledge. Szolovits recognized [9] that uncertainty is the central and critical fact about medical reasoning. Uncertainty and imprecision characterize the sources of information available to medical expert systems. Such sources include the patient, physician and laboratory, technical methods of evaluation and mathematical models that simulate the diagnostic process [10]. Researchers in medical diagnostic systems in the past decade have attempted to find ways to manage uncertainty in medical diagnosis using soft computing methods [11]. One of the earliest efforts in this direction attempted to develop heuristic methods for imposing structure on ill-structured components of medical diagnosis, resulting in the "internist-1" diagnostic program. Evolutionary algorithm case-based reasoning and hypertext-based systems and knowledge base technology [12] have been applied in the management of imprecise and unstructured medical knowledge. [13], proposed a neuro-case rule based hybridization in medical diagnosis. The utilization of fuzzy logic and AHP became very popular in attempting to resolve the problems of imprecision and uncertainty in medical diagnosis. This is because of the ability of fuzzy logic to handle vague information and the ability of AHP to mathematically model unstructured information [14, 15].

The AHP has been proposed for the building of the kernel of medical decision support system in, while a framework for utilizing AHP in the diagnosis of fever has been reported as well Fuzzy models are discussed elsewhere [16, 17]. The AHP is a multi-criteria decision analysis method that uses mathematical algorithm to transform qualitative subjective judgements into quantitative data, which produces a computational model that serves as input into the evaluation of decision alternatives. It uses judgments from a group of decision makers along with hierarchical decomposition of a problem to derive a set of ratio-scaled measures for decision alternatives. With the AHP the analyst structures a problem hierarchically and then, through an associated measurement and decomposition process, determines the relative priorities consistent with overall objectives [18]. The AHP is based on four axioms: reciprocal judgements, homogeneous elements, hierarchic or feedback dependent structure and rank order expectations Fuzzy logic is a generalization of the conventional set theory as a mathematical way to represent vagueness of parameters [19]. The basic idea in fuzzy logic is that statements are not just true or false, but partial truth is also accepted. Fuzzy logic exhibits complementary characteristics by offering a very powerful framework for approximate reasoning. Fuzzy systems are capable of acquiring knowledge from domain experts and attempt to model the human reasoning process at a cognitive level [20].

Research Objective: The specific objective of the research is to compare the reliability of fuzzy logic and Analytic Hierarchy Process (AHP) to determine the best engine for the development of intelligent medical system for diagnosing tuberculosis.

Related Works: Fuzzy Logic (FL) which was introduced by Lofti Zadeh, a professor at the University California, in his paper "Fuzzy Sets'' in 1965, is a problem-solving control system methodology and one of the strongest tools to scheme the independent intelligent systems [21]. It is very useful for solving the problems that are not easy to model mathematically. FL can be operated on problem that is based on vague, imprecise and incomplete data and this is its very positive point. In a Fuzzy Logic process, a crisp set of input data congregates and transforms to a fuzzy set with a reliable set of inference rules during fuzzification step and then during the defuzzification process the generated outputs get converted into a crisp set using a membership function [22]. FL is well suited for many control system applications as it mimics human control logic. In fact, to control the problems imitates how a man makes decision, only speedier. In FL unlike classical logic, a statement can have a truth value between 1 and 0, all real numbers from 0 to 1, rather than having a truth value of either 1 for true or 0 for false. The article "A partly true story", which is written by Ian Stewart, is very helpful to get more about the Fuzzy Logic and its concepts [23]. Fuzzy Logic is one of strongest tools to develop autonomous intelligent systems and well suited to solve the problems which are hard to model mathematically. The most potency of fuzzy logic is upon its capability to pull out the outcome and produce responses in terms of vague, imprecise and defective qualitative data. Moreover, FL is capable to reach stable situation in a shorter time distance and less values, rules and decisions are required [24].

Furthermore, Fuzzy Logic (FL) is a form of many-valued logic which deals with reasoning that is approximate rather than fixed and exact. Compared to traditional binary sets (where variables may take on true or false values), fuzzy logic variables may have a truth value that ranges in degree between 0 and 1 [25]. Due to the flexibility of FL concept, Fuzzy Logic Systems (FLSs) have attracted growing interest in modern information technology, production technique, decision making, pattern recognition, data mining and medical diagnosis among others [26]. FL has found a variety of applications in industrial process control and securities trading [27]. It has equally been employed in the modelling of medical diagnosis systems [28]. A typical FLS is strongly based on the concepts of fuzzy sets, linguistic variables and approximate reasoning. The fuzzifer transforms crisp inputs into fuzzy values while the Fuzzy Rule Base makes up the Knowledge Base which stores relevant data and knowledge of human experts in a specific domain; the Decision-making unit combines all the red rules for a given case and makes inference; while the defuzzifier converts fuzzy results into a crisp value for easy analysis and interpretations. Generally, when a problem has dynamic behaviour and involves several variables, FL technique can be applied to solve such problem [29,30]. However, a major problem of the FLSs is the determination of its fuzzy sets and fuzzy rules which require deep knowledge of human experts in a particular domain [31]. The Membership Functions (MFs) of FLSs are arbitrarily chosen, therefore fixed in nature. Generally, the shape of the MFs depends on certain parameters that can be adjusted. Rather than choosing the MF parameters arbitrarily, the neural network learning and tuning techniques provides a method for the FLS to learn information about a given dataset in order to automatically compute its MF parameters. Some of the advantages of fuzzy logic are as follows: (1) Using linguistic descriptions, there is no need to mathematically model the controlled parameters. (2) System robustness can be achieved by addressing the lagged time-varying, non-linear and other complex problems. (3) It enables mathematical variables to be represented with linguistic variables and can describe expertise with fuzzy conditional statements. (4) By using linguistic rules and heuristic knowledge, an FL has the ability to simulate the people's way of thinking [32], which benefits its coping mechanism within the complex system.

The analytic hierarchy process (AHP), attempts to support multi criteria analysis of decision variables in order to determine the relative importance of each variable in the decision matrix on a pair wise basis [33]. The variables involved in tuberculosis diagnosis are numerous; as such, their combinatorial analysis may be come explosive and lead to a decay of the medical expert's preference. This is further complicated by the inability of the human mind to handle more than 7±2 pieces of information at the same time [34]. The AHP deals with dependence among variables or clusters of decision structures in order to combine statistical and judgmental information. The analytical hierarchy process is a very popular and classical method of evaluation where priorities are derived from Eigen values of the pairwise comparison matrix of a set of elements expressed on ratio scales. AHP falls into a class of techniques known under the name Multiple -Criteria Decision Aid (MCDA). An evaluation problem solved by MCDA can be modelled as a 7pole {A,T,D,M,E,G,R} where A is the set of alternatives under evaluation in the model, T is the type of evaluation, D is the tree of the evaluation attributes,

M is a set of associated measures, E is the set of scales associated to the attributes, G is the set of criteria constructed in order to represent the decision maker's preference and R is the preference aggregation procedure [35].

Other MCDA methods include: Preference Ranking Organization Method for Enrichment Evaluations [36], Technique for Order Preference by Similarity to Ideal Solution [36], Ordered Weighted Averaging and Fuzzy Ranking method [37].

The AHP is preferred to most of the MCDA methods for AHP is structured, it is suitable for group decision making [38] and it provides a systematic and comprehensive evaluation of the relative importance of the factors/variables (symptoms of tuberculosis) [39]. This approach is a way of getting around cognitive psychological problems that arise when an individual is asked to compare a large number of factors. The human mind becomes inefficient as the number of information increases. Thus, when the variables under consideration are so many, the expert's preference may decay and would not be able to make effective comparison, but with AHP, pairwise comparison reduces this problem associated with comparing many variables at the same time. Also, AHP meets the MCDA method properties of interaction, weighting, dominance and scaling [40], it has a demonstrable superiority over other MCDA methods. The AHP is based on four axioms: reciprocal judgments, homogeneous elements, hierarchic or feedback dependent structure and rank order expectations [41]. The application of the AHP to the complex problem usually involves four major steps [11]: Break down the complex problem into a number of small constituent elements and then structure the elements in a hierarchical form, Make a series of pair wise comparisons among the elements according to a ratio scale, Use the eigen value method to estimate the relative weights of the elements and Aggregate these relative weights and synthesize them for the final measurement of given decision alternatives.

The AHP is a powerful and flexible multi-criteria decision-making tool for dealing with complex problems where both qualitative and quantitative aspects need to be considered. The AHP helps analysts to organize the critical aspects of a problem into a hierarchy rather like a family tree [42]. Based on the survey conducted by [43], it was observed that AHP is the most popular method used for group decision making followed by PROMETHEE and ELECTRE. Moreover, AHP is a time-tried and tested method that has been applied in a number of decisions. The method has been exceptionally powerful in making confused, frequently irreversible decisions. Also, AHP is made up of suitable techniques for prioritizing critical management problems. Furthermore, AHP is intuitive appealing and flexible and many governments and corporations regularly apply the techniques for major policy decisions. analysed the performance of PART and PART based on K-Means Clustering classification rule algorithms on heart disease dataset collected from UCI Repository. The dataset contains 303 instances and 14 selected attributes. The pre-processed heart disease dataset was grouped using the K-means algorithm with the K=2 values on classes to cluster evaluation testing mode [44]. 10-fold cross validation method was used to measure the unbiased estimate of the prediction model. The accuracy of K-Means Clustering, PART and PART based on K-Means Clustering are 81.08%, 79.05% and 84.12% respectively. The PART algorithm generated 26 rules while PART through Simple K-Means Clustering generated 11 rules. The study deduced the best fit algorithm based on accuracy and the number of rules alone without considering their empirical risk function. Compared the behaviour of traditional classification algorithms with respect to leukaemia cancer dataset which contains 7130 attributes with 72 records. The results were analyzed using two benchmarks such as prediction accuracy and time. The evaluation was conducted using WEKA. Three Classifiers used were: Naïve Bayes Classifier, Decision Tree Classifier and Lazy Classifier (LC) to build a classification knowledge flow to get the time and accuracy results of the predictive models. From the results it is identified that Naïve Bayes classifier is able to build good prediction model with 91.17% with less time of 0.16 seconds. This study had successfully used accuracy and time of learning as benchmark for prediction, but nevertheless, the minimal risk of choosing Naïve Bayes classifier was not considered and the dataset is rather small for prediction [45].

Analysed the significant factors for dengue infection prognosis using the Random Forest classifier and develop a new computational intelligence-based methodology that predicts the diagnosis in real time, by minimizing the number of false positives and false negatives values. The model used Random Forest to investigate two classical issues of variable selection; the use of Dengue survivability data and viral particles for diagnosis. The system was able to use Random Forest for survival analysis. The weakness of this system is that investigation of the diversity of the number of classifiers was not done. Also, the possibility of using the RF algorithm in a larger dataset with scores of attributes was

not investigated to show the performance of the classifiers [46], review some subareas of medical diagnoses techniques like image processing, ECG with genetic algorithms and Artificial neural networks. It was illustrated that the field of medical diagnosis currently uses genetic algorithms and its application increases day by day. It also stated that improvement of genetic algorithms will definitely help to solve various complex medical diagnoses application and medical image processing tasks in the future which is applicable to rain tumour or any other tumour detection. Whoever, the work lack clearly application of the technique [4], developed enhanced Neuro-Fuzzy System Based on Genetic Algorithm for Medical Diagnosis of Typhoid fever patients. The system use Genetic Algorithm (GA) technique to automatically evolve optimum connection weights needed to efficiently train a built ANFIS model which is used for Typhoid fever diagnosis. The GA module computes the best set of connection weights, stores them and later supplies them to the corresponding hidden layer nodes for training the ANFIS. The medical record of 104 Typhoid fever patients aged 15 to 75 were used to evaluate the performance of the multi-technique decision support system. 70% of the dataset was used training data, 15% was used for validation while the remaining 15% was used to observe the performance of the proposed system. From the evaluation results, the proposed Genetic Adaptive Neuro Fuzzy Inference System (GANFIS) achieved an average diagnosis accuracy of 92.7% compared to 85.4% recorded by the ANFIS method. It was equally observed that the diagnosis time was much lower for the proposed method when compared to that of ANFIS. However, despite the strength of these two algorithms, the drawback is that the two algorithms where not implemented individual to identified their strength and weakness before hybrid [6] presented communication-efficient algorithms for statistical optimization whereby the algorithms achieve the best possible statistical accuracy and suffer the least possible computation overhead; proposed a distributed optimization algorithm using empirical risk minimization to determine the communication cost which is independent of the data size and is only weakly dependent on the number of machines and then designed and implemented a general framework for parallelizing sequential algorithms [5] introduced the local, global and distributed models for experiments and used two methods such as average and feature methods to analyse their privacy guarantee under the sense of differential privacy. The methods were tested in distributed model using the differential private empirical risk minimization and it was discovered that noise affect the final performance of these two methods [6] identified the different approaches to solve large-scale ERM problems and focused on incremental and stochastic methods which split the training samples into smaller sets across time to lower the computation burden of traditional descent algorithms. Consequently, convergent stochastic variants of quasi-Newton methods which do not require computation of the objective Hessian was developed and analysed to approximate the curvature using gradient information.

[33]demonstrated how Deep Learning and Bayesian optimization methods were used in predicting clinical outcomes from large scale cancer genomic profiles for survival analysis and described a framework for interpreting deep survival models using a risk back propagation technique. The framework was implemented in Python for training, evaluation and interpretation of deep survival models. It was illustrated that deep survival models can successfully transfer information across diseases to improve prognostic accuracy. In part A of the model, the molecular platforms produce data that can be used for precision prognostication with learning algorithms; in B, Deep survival models in neural networks was driven by a Cox survival model at the output layer and model likelihood was used to adaptively train the network to improve the statistical likelihood of the overall survival prediction. In C (1), the SurvivalNet framework enabled automatic design optimization and validation of deep survival models. Molecular profiles obtained from TCGA datasets were randomized for assigning patients to training, testing and validation sets; in C (2) Bayesian optimization searches the space of hyper-parameters like to optimize the model design, while in C (3) each selected design was trained and evaluated using validation samples to update the Bayesian optimizer. This model combined two algorithms for prediction and it was successful, however, despite the strength of these two algorithms, the drawback is that the two algorithms cannot work together because Bayesian networks deals with probabilistic problems while Deep learning does not [5].

MATERIAL AND METHODS

Data Collection: To achieve this reliability comparison of fuzzy logic and Analytic Hierarchy Process (AHP) as engines for the development of intelligent medical systems, data of tuberculosis patients were collected from the bed-tickets of three hundred and two (302) cases

Table 1: Conditions of Tuberculosis disorder

s/n	Category	Patients' attributes	Code Definition
	Physical symptoms (PS)	Weight loss	WL`
		Fatigue	FG
		fever	FR
		Coughing	CH
		Back pain	BP
		Chest pain	CP
		Night sweats	NS
		Blood in urine	BU
	Cognitive symptoms (CS)	Indecision	IN
		self-dislike	SL
		Worthlessness	WH
		Anxieties	AX
		Verbal comprehension	VC
		Working memory	WM
	Emotional symptoms (ES)	Loss of pleasure	LP
		Loss of appetite	LA
		Feel irritated	FI
		Cardiac Tamponade	CT
	Motivational symptoms (MS)	Loss of appetite	LA
		Loss of energy	LE
		Suicidal thought	ST
		feeling Irritated	FI
	Physiological symptoms (PHS)	Body mass index	BM
		Diastolic blood pressure	DP
		systolic blood pressure	SP
		Blood Glucose	BG
		Cerebrospinal fluid	CF
		Gray matter volume	GV

taking appropriate ethical measures. Choice of a case was irrespective of gender and age. All these cases were drug-naïve, i.e., they never took anti- Tuberculosis medications and reporting to the hospital for the first time. Cases presented with suicidal ideations were excluded as those require urgent treatment. Twenty- eight common symptoms as shown in Table 1 were considered for this work after consulting with three senior psychiatrists (with mean experience of 10.4 yrs.). The grade of each symptom (i.e mild, moderate and severe) and the corresponding probability of Tuberculosis were unanimously assigned [0, 1] by them.

Thereafter, fuzzy technique and analytic hierarchy process (AHP) was applied to the diagnosis of tuberculosis. These techniques use the appropriate human reasoning of fuzzy logic /Hierarchy Process to produce accurate medical report based on the patient complains to the physician and medical test carried out. These symptoms serve as inputs to the systems after scaled.

The AHP Methodology for Tuberculosis Diagnosis: The analytic hierarchy process (AHP), attempts to support multi-criteria analysis of decision variables in order to determine the relative importance of each variable in the decision matrix on a pair wise basis [31]. The variables involved in tuberculosis are numerous; as such their combinatorial analysis may become explosive and lead to a decay of the medical expert's preference. This is further complicated by the inability of the human mind to handle more than 7±2 pieces of information at the same time [25]. The AHP deals with dependence among variables or clusters of decision structure to combine statistical and judgemental information. AHP is built on three basic principle namely; decomposition, measurement of principles and synthesis.

Decomposition breaks down a problem into manageable elements that are treated individually. It begins with implicit description of the problems (the goal) and proceeds logically to the criteria (or state of nature) in terms of which outcomes are evaluated. The result of this phase is a hierarchical structure consisting of levels for grouping issues together as to their importance or influence with respect to the adjacent levels above. The decomposition of the tuberculosis diagnostic variable into hierarchy is presented in Table 2.

Table 2: Hierarchy of Basic Tuberculosis Diagnosis Criteria

LEVEL 1 (OBJECTIVE/GOAL)	LEVEL 2 (CRITERIA)	LEVEL 3 (Alternatives)
TUBERCULOSIS DIAGNOSIS	Physical symptoms (PS)	Weight loss (WL), Fatigue (FG), fever(FR), Coughing (CH), Back pain (BP), Chest pain (CP), Night sweats (NS), Blood in urine (BU)
	Cognitive symptoms (CS)	Indecision (IN), self-dislike (SL), Worthlessness(WH), Anxieties (AX), Verbal comprehension (VC), Working memory (WM)
	Emotional symptoms (ES)	Loss of pleasure(LP), Loss of appetite (LA), Feel irritated (FI), Cardiac Tamponade (CT)
	Motivational symptoms (MS)	Loss of appetite (LA), Loss of energy (LE), Suicidal thought (ST), feeling Irritated (FI)
	Physiological symptoms (PHS)	Body mass index(BM), Diastolic blood pressure(DP), systolic blood pressure (SP), Blood Glucose (BG), Cerebrospinal fluid (CF), Gray matter volume (GV)

Measurement of preferences involves a pair wise comparison of decision variables, which are verbal statements about the strength of importance of a variable over another, represented numerically on an absolute scale. The comparison is done from the top level of the hierarchy to the bottom level in order to establish the overall priority index. If two variables are of equal importance, the rating of the comparison is 1. If variable A is strongly more important than variable B, then the rating of the comparison could be 7. If it is weakly more important, the rating is 3. The values 2, 4, 6,8 represent intermediate judgement, while the reciprocal of the ratings show the converse of the relative importance.

Synthesis involves the computation of Eigen values and the Eigen vector. The Eigen values and eigenvectors present a means of obtaining linear relationships among the evaluation variables. This initial table of Eigen values and eigenvectors helps to establish priority model. It is important to note that the pair-wise comparisons are also carried out for elements of the sub-criteria (variables) of all evaluation criteria. The eigen vector is obtained as follows: (a) Obtain the column sum. (b) Divide the elements of the pair wise comparison (PWC) matrix by the column sum. (c) Finally to obtain the relative weight of each factor with respect to its controlling factor, average the elements of the corresponding row. This can be represented mathematically in the following [44]: The Eigen value for cell$\{a_{ij}\}$is derived as:

$$E_{ij} = \frac{V_{ij}}{T_j} \quad (1)$$

where,
E_{ij} is the eigenvalue of cell{aij}, V_{ij} is the value of the pairwise comparison matrix for cell $\{a_{ij}\}$, T_j is the sum of the values on column j.

The eigenvector for variable K is a vector given as:

$$\lambda_k = \frac{\sum_{j=1}^{n} E_{kj}}{n} \quad (2)$$

where,
λ_k is the eigenvector corresponding to variable k($\Sigma\, \lambda k = 1$), E_{kj} is the eigenvalue of cell$\{a_{ij}\}$, (j = 1,2 ..n). n is the number of evaluation variables.

The tables of eigen values and eigen vector for level 2 criteria and level 3 variables respectively were computed. The level 2 diagnostic criteria evaluation gives an eigen vector, $\square_1$, while the level 3 variables produce the eigen vector, $\square_2$. $\square_1$ combines with the column vector of level 2 factors to give the Diagnostic Factor Index for level 2 criteria (DFI_1), while $\square_2$ combines with the column vector of the level 3 variables to give the Diagnostic Factor Index for level 3 variables (DFI_2), as shown in (3) and (4).

$$DFI_{1=}0.506PS+0.238CS+0.048ES+0.065MS+0.026PHS \quad (3)$$

$DFI_2(PS) = 0.731WL + 0.188FG+0.081FR + 0.814CH + 0.231BP + 0.452CP + 0.557NS + 0.711BU$
$DFI_2(CS)= 0.667IN+0.111SL+0.111WH +0.121AX + 0.122VC + 0.341WM$
$DFI_2(ES)=0.272LP+0.293LA+0.032FI+0.244CT$
$DFI_2(MS)=0.106LOA+0.596LE+0.244ST+0.054FI$
$DFI_2(PHS)=0.143BM+0.857DP + 0.114SP + 0.223BG + 0.111CF + 0.212GV$ (4)

Combining (3) and (4)we have the Aggregate Diagnostic Factor Index (ADFI), given as:

$ADFI = 0.3699WL+ 0.0951FG + 0.0410FR+ 0.4119CH+0.1169BP +0.2287CP+0.2818NS+0.3598BU +0.1588IN+0.0264SL+0.0264WH+0.0288AX +0.0290VC+0.0812WM +0.0131LP+0.0141LA+0.0015 FI+0.0117CT +0.0069LOA+0.0387LE+0.0159ST + 0.0035FI + 0.0037BM + 0.0223DP + 0.0030SP + 0.0058BG + 0.0028CF + 0.0055GV$

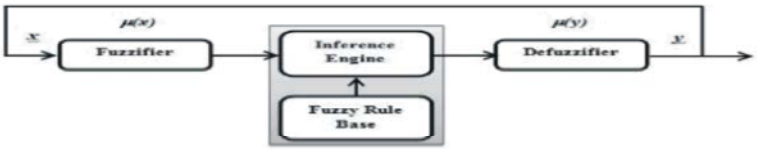

Fig. 2: Basic Architecture of a fuzzy system

Table 3: Tuberculosis Intensity Scale

Rating	ADFI Range	Tuberculosis Intensity
1	0.0000-2.4042	Very low
2	2.4043-4.8084	Low
3	4.8085-7.2126	Moderate
4	7.2127-9.6168	Severe
5	9.6169-12.021	Very severe

Table 4: Case study of patients Diagnosed

Patients number	ADFI	Tuberculosis Intensity
001	8.2140	Severe
002	1.2045	Very Low
003	9.7 110	Very severe
004	7.1243	Moderate
005	5.4673	Moderate
006	10.2354	v. severe
007	6.3214	Moderate
008	7.1201	Moderate
009	7.1475	Moderate
010	2.3568	Very low

The finalstep is the diagnosis of the patient's state of health with respect to tuberculosis based on the rating on the factors or variables. The sum of the ratings on the factors is derived as a basis for determining the intensity of tuberculosis. The final diagnosis is given as: $W_i = \Sigma R_{ij} \lambda_j$, where W_i is the weighted diagnosis of patients i, $R_{ij}$is the rating of the patient on variable j, λ_j is the eigenvector of variable j.

The tables of eigenvalues and eigenvectors for level 2 criteria and level 3 alternatives respectively were computed. The level 2 diagnostic criteria evaluation gives an eigenvector, λ_1, while the level 3 alternatives produce the eigenvector, λ_2. $\lambda_1$combines with the column vector of level 2 factors to give the diagnostic factor index for level 2 criteria (DFI_1), while $\lambda_2$combines with the column vector of the level 3 variables (DFI_2). The ADFI forms the basis of diagnosing patients and determining the intensity of tuberculosis. In order to determine the intensity of tuberculosis, a scale of intensity is formed, based on the "standard criteria" for tuberculosis whereby each of the variables is considered to have uniform values drawing froma likert scale, to determine the intensity of tuberculosis. This is shown in the Table 3.

It is observed that the likelihood of tuberculosis attack is influenced more by the variables that have high values on the eigenvector; such as Cough (0.4119), Weight loss (0.3699), Blood in urine (0.3598) and Anxieties (0.0288).These variables also belong to the level2 criteria that have high ratings on the level 2 eigen vector; namely, physical symptoms and cognitive, which are very common symptoms of tuberculosis. Evidence from the results also shows that uncomplicated tuberculosis has reasonably low impact on the respiratory and gastrointestinal systems. In Table 4, the case study of the 10 patients used for the system evaluation is presented.

The Fuzzy Methodology for Tuberculosis Diagnosis: The knowledge base for tuberculosis contains both static and dynamic information. There are qualitative and quantitative variables, which are analysed in order to arrive at a diagnostic conclusion. The fuzzy logic of the diagnosis of tuberculosis involves fuzzification, inference, knowledge base and defuzzification (Figure 2).

A fuzzy set (A) of the diagnosis attributes and its element denoted by X, is then defined from the input variables using Eq. (5). This is done before the fuzzification process.

$$V = [(X,\mu_v(X))|X \square V, \mu_v(X) \square [0,1]\} \quad (5)$$

where:
$\mu_v(X)$ is the membership function of X in V and μ_v is the degree of X in V in the interval of [0,1]. This research intend to employs Triangular Membership Function (TMF) defined in eq. 5.

Layer 1;Fuzzification layer: This layer calculates Membership value for premise parameter. Every node in the layer 1 is an adaptive node. The input layer (Layer 0) has 5 nodes, each corresponding to a category of tuberculosis symptoms; which pass external crisp value to layer1. Layer 1 consists of 15 fuzzification nodes; the outputs of this layer are the fuzzy membership grade defined by:

$$O_{1,i} = \mu_{Ai}(x_1), \text{ for I=1,2,3;} \quad (6)$$

$O_{1,i}= \mu_{Bi-3}(x_2)$, for I=4,5,6; (7)

$O_{1,i}= \mu_{Ci-3}(x_3)$, for I=7,8,9; (8)

$O_{1,i}= \mu_{Di-3}(x_4)$, for I=10,11,12; (9)

$O_{1,i}= \mu_{Ei-3}(x_5)$, for I=13,14,15; (10)

Where X_1, X_2, X_3, X_4 and X_5 is the input to the node i; A_i to E_i are linguistic fuzzy set associated with this node. $O_{1,i}$ is the membership functions (MFs) grade of a fuzzy set and it specifies the degree to which the given input X_1 through X_5 satisfies the quantifier. The triangular membership function in Equation (5) such that $a \leq x < b$ is adopted.

The fuzzifier carries out fuzzification, which comprises the process of transforming crisp values into grades of membership for linguistic terms of fuzzy sets. It begins with the transformation of the raw data using the functions that are expressed in Eq.(5). During the process, linguistic labels are attached to the symptoms and the diagnostic steps are accompanied by associated degrees of intensity. After the patient has provided the medical doctor with the symptoms, the medical doctor assigns subjective values to the symptoms and supplies them to the system. The system fuzzifies the values according to the function defined as:

This defines the linguistic label: mild, moderate, severe and very severe for the symptoms provided by the patient. Furthermore, these linguistic labels are assigned some degrees of membership μ(x) based on the triangular fuzzy number. The triangular fuzzy number represents a three valued judgment. It is still vague and ambiguous to say a patient has low or moderate fever, cough, weight loss, etc. The equations which translate to the table below define the degree to which one can say that the symptom is very low, low, moderate, intense, or very intense. For example, a patient complains that he coughs regularly, so a medical doctor assigns 3.5 (out of 5) value to his cough and supplies it to the system. The system will in turn recognize this as severe coughing and evaluates the degree of severity as (3.5-1)/4 = 0.625, that is 62.5% intensity. Also, if the medical doctor had assigned a value of 4 to cough, it would have still been labelled as severe cough but the degree would have been (4-1)/4 = 0.75 (75%).

Layer 2; Rule Layer: It is fixed nodes labelled M which multiples the incoming signals and sends the product out. Each node output represents the firing strength of the rule with "and" operator as the T-norm. The outputs of this layer can be represented as:

$$O_{2,i}= w_i = \mu_{Ai}(x_1)\times \mu_{Bi}(x_2)\times \mu_{Ci}(x_3)\times \mu_{Di}(x_4)\times \mu_{Ei}(x_5), \quad I=1,2,3,4,5 \tag{12}$$

$$w_i = Min\{\mu_{Ai}(x_1)\times \mu_{Bi}(x_2)\times \mu_{Ci}(x_3)\times \mu_{Di}(x_4)\times \mu_{Ei}(x_5)\} \tag{13}$$

Layer 3 Normalize Firing Strength: Every node in this layer is a circle labelled N. The ith node calculates the ratio of the its rule's firing strength to the sum of all rule's firing strengths. Output of this layer is called normalized firing strengths and is given as:

$$\varpi_i = \frac{\omega_i}{\omega_i + \omega_2 + \omega_3 + \omega_4 + \omega_5}, \quad i = 1,2,3,4,5 \tag{14}$$

Layer 4: Consequent Layer: In this layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model), where the output of layer 3 and {pi,qi, ri} is the parameter set. Thus, the outputs of this layer are given by:

$$O_i^4 = \underline{\omega}_i f_i = \underline{\omega}_i(P_i X + q_i y + r_i), \quad where\ i = 1,2,3,....243 \tag{15}$$

That i is the normalized weighting factor of the iw[th] rule, f, is the output of the i[th] rule and pi, qi, ri is consequent parameter set.

The Root Sum Square (RSS) method of drawing inference was introduced in order to further optimize the performance of the inference engine. The RSS technique is known to combine the effects of the fired rules by scaling their functions at their respective magnitude. This is achieved through equation (14)

$$Rss = \sum_{i=1}^{n}(R^2) \tag{16}$$

where R_k represent a firing rule in the rule base and n represent the number of fired rules for a particular diagnosis case.

Layer 5: Overall Output: The CoG method is adopted in this study because it is more accurate in representing fuzzy sets of any shape. The centre of gravity (CoG) is an averaging technique. The difference is that the (point)

Table 5: Assignment of weight to tuberculosis Diagnosis Variables

ID	WL	FG	FR	CH	BP	CP	NS	BU	IN	SL	WH	AX	VC	WM	LP	LA	FI	CT	LA	LE	ST	BM	OP	SP	BG	CF	GV
1	3.5	4	3	4	2	3.5	2	4	2	1	2.5	4	4	2	1	4	1	1	4	2.5	1	4	1	2	4	1	1
2	2	3	2	3	1	5	1	3	2	3	3	1	2	3	1	2	3	1	3.5	3	1	2	5	1	2	3	1
3	3	1	4	2	3	2.5	3	2.5	3	2	1	3	2	2.5	4	2	2	4	2.5	2	4	2	2	4	5	2	4
4	4	5	2	2	3.5	3	2.5	3	3.5	3	2	1	4	2	2	4	2	2	4	2	5	4	2	2	4	2	2
5	3	2	3.5	2	2	2	3	3	2	3	2	3	2	2	3.5	2	5	1	2	2	1	2	2	1	2	2	1
6	1	2	1	4	3	5	3	2	3	1	2	3	1	1	2	2	1	2	1	1	2	1	1	2	1	1	2
7	3.5	4	2	5	2	2.5	1	2	4	5	1	2	3	3	3.5	2	3	3	5	3	3	4	3	4	3	3	3
8	2	3	3	2	3.5	3	2	4	3	2	4	2	2	3	2	2	3	2	2	3	2	2.5	3	5	2	3	2
9	1	2	2	2	3	3	3.5	1	1	5	1	2	3	2	2.5	3	2	2	3	2	2	3	2	2	3	2	2
10	3	2	1	5	1	1	2	2	2	1	1	1	2	4	1	2	4	1	2	4	1	2	4	1	2	4	1

Table 6: Fuzzy Numbers of diagnosis variables presented in table 5

ID	WL	FG	FR	CH	BP	CP	NS	BU	IN	SL	WH	AX	VC	WM	LP	LA	FI	CT	LA	LE	ST	BM	OP	SP	BG	CF	GV
1	0.63	0.75	0.5	0.75	0.25	0.63	0.25	0.75	0.25	0	0.38	0.75	0.75	0.25	0	0.75	0	0	0.75	0.38	0	0.75	0	0.25	0.75	0	0
2	0.50	0.83	0.50	0.83	0.17	0.83	0.17	0.83	0.50	0.83	0.83	0.17	0.50	0.83	0.17	0.83	0.17	0.83	0.50	0.83	0.83	0.17	0.50	0.83	0.50	0.83	0.17
3	0.50	0.17	0.83	0.50	0.83	0.50	0.83	0.50	0.83	0.50	0.17	0.83	0.50	0.50	0.83	0.50	0.83	0.50	0.83	0.50	0.17	0.83	0.50	0.17	0.83	0.50	0.83
4	0.83	0.50	0.50	0.50	0.83	0.83	0.50	0.83	0.83	0.83	0.50	0.17	0.83	0.50	0.50	0.83	0.50	0.83	0.83	0.83	0.50	0.17	0.83	0.50	0.50	0.50	0.83
5	0.83	0.50	0.83	0.50	0.50	0.50	0.83	0.83	0.50	0.83	0.50	0.83	0.50	0.50	0.17	0.50	0.83	0.83	0.50	0.83	0.50	0.83	0.83	0.50	0.83	0.50	0.50
6	0.17	0.50	0.17	0.83	0.83	0.83	0.83	0.50	0.83	0.17	0.50	0.83	0.17	0.17	0.50	0.83	0.83	0.50	0.83	0.17	0.50	0.83	0.17	0.50	0.17	0.83	0.83
7	0.83	0.83	0.50	0.50	0.50	0.17	0.17	0.50	0.83	0.50	0.17	0.50	0.83	0.83	0.83	0.17	0.17	0.50	0.83	0.50	0.17	0.50	0.83	0.83	0.50	0.50	0.50
8	0.50	0.83	0.83	0.50	0.83	0.83	0.50	0.83	0.83	0.50	0.83	0.50	0.50	0.83	0.50	0.83	0.50	0.83	0.83	0.50	0.83	0.50	0.50	0.83	0.83	0.50	0.83
9	0.17	0.50	0.50	0.50	0.83	0.83	0.83	0.17	0.17	0.50	0.17	0.50	0.83	0.50	0.50	0.83	0.83	0.17	0.17	0.50	0.17	0.50	0.17	0.50	0.50	0.50	0.83
10	0.83	0.50	0.17	0.83	0.17	0.17	0.50	0.50	0.50	0.17	0.17	0.17	0.50	0.83	0.17	0.17	0.50	0.50	0.50	0.17	0.17	0.17	0.83	0.50	0.17	0.83	0.17

masses are replaced by the membership values. The single node in this layer is circle node labelled Σ that computes overall output as the summation of all incoming signals, i.e.,

$$O_i^5 = overall\ output = \sum_i \omega_i f = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i}$$

In the design of the diagnosis process, we simulate a set of rules which serve as the algorithm of the proposed system. The symptoms have been trained in such a way that a particular combination yields a particular result. Table 5 shows the weight assigned to the diagnosis variables of the patients observed during the case study. The degree of signs, symptoms and investigation to show weather the disease is mild, moderate, severe or very severe for the patients are defined by the table.

System Algorithm: For example, patients "001" complained of having constant weight loss. The doctor assigned a value of 3.5 (out of 4) to his weight loss (WL) diagnosis variable and supplies it to the system. The system in turn recognizes this as moderate and evaluates the degree of severity as: (3.5 - 1)/4 = 0.625 using the triangular fuzzifier. The equivalent of the values presented in Table 5 is shown in Table 6.

Using the RSS inference procedure presented above, we have the following diagnostic computations:

$$\text{Mild} = \sqrt{R4^2 + R13^2 + R20^2} = \sqrt{0.40^2 + 0.60^2 + 20^2} = 0.75$$

$$\text{Moderate} = \sqrt{R3^2 + R19^2} = \sqrt{0.20^2 + 0.80^2} = 0.80$$

$$\text{Severe} = \sqrt{R15^2} = \sqrt{20^2} = 0.20$$

$$\text{Very severe} = \sqrt{R2^2 + R4^2} = \sqrt{0.10^2 + 0.74^2} = 0.55$$

The output of the inference engine is transformed into an exact numeric value for easy analysis using COG technique as presented in equation (15).

$$\text{Crisp value} = \frac{(0.75 * 0.4) + (0.80 * 0.6) + (0.20 * 0.9) + (0.55 * 1)}{(0.75) + (0.80) + (0.20) + (0.55)}$$

$$= \frac{(0.3) + (0.48) + (0.55)}{(2.30)} = 0.65652 = 66$$

The crisp value (0.66) shows that the patient with ID "001" has tuberculosis with severe severity at 66%.

Table 7: Crisp output for ten patients

S/N	PATIENT NO.	% POSSIBILITY	DIAGNOSIS
1	001	0.6565	severe
2	002	0.2231	Very low
3	003	0.6722	severe
4	004	0.5642	moderate
5	005	0.5945	moderate
6	006	0.7058	severe
7	007	0.5912	moderate
8	008	0.9227 947	Very severe
9	009	0.5833	moderate
10	010	0.3345	Very low

Table 8: Results summary

		Medical Experts Diagnosis		AHP Result			Fuzzy Results		
S/N	Patient No.		Numeric scale	ADFI	Tuberculosis Intensity	Numeric scale	%possibility	Tuberculosis Intensity	Numeric scale
1	001	severe	4	8.2140	Severe	4*	66	severe	4
2	002	low	2	1.2045	Very Low	1*	22	Very low	1
3	003	Very severe	5	9.7110	Severe	4	67	Very severe	5
4	004	moderate	3	7.1243	Moderate	3*	56	moderate	3
5	005	Moderate	3	5.4673	Moderate	3*	59	moderate	3
6	006	severe	4	10.2354	Very severe	5	71	severe	4
7	007	moderate	3	6.3214	Moderate	3*	59	moderate	3
8	008	Verysevere	5	7.1201	Moderate	3	92	Very severe	5
9	009	moderate	3	7.1475	Moderate	3*	58	moderate	3
10	010	Very low	1	2.368	Very low	1*	33	Very low	1

Table 9: System performance Summary

	AHP	FUZZY
Per cent of true diagnosis	82	91
MSE	0.2	0.233333
RMSE	0.483046	0.447214
Variance	0.185057	0.165517
Percent matching diagnosis (fuzzy/AHP)		70
Pearson correlation (overall diagnosis		0.835477
Pearson correlation (false diagnosis		0.118217
T Stat		0.328339
P(T<=t) one tail		0.372507
T Critical one tail		1.699127
P(T<=t) two tail		0.745014

RESULTS AND DISCUSSION

The study evaluated the diagnosis of ten patients using AHP and the fuzzy methodology separately. The essence of the study was to ascertain the degree to which each method represents the true diagnosis of the patient. Table 8 presents summary of the diagnosis from each method, as compared with the diagnosis of medical experts, while the system performance results are display in table 9. The intensity of tuberculosis was rated as very low(1), low (2), moderate (3), severe(4) and very severe (5).

Indicates a Match in Diagnosis Between the Ahp and Fuzzy Methods: Table 9 shows that the AHP had 82% correct diagnosis, while the fuzzy system had 91% correct diagnosis. This shows that the fuzzy system had fair better results. However, the mean square error (MSE) and root mean square errors (RMSE) computations did not indicate a significant variation in performance. The AHP method had RMSE of 49.10% while the fuzzy method had RMSE of 45.71%, which shows an insignificant difference of 3.39%. A high correlation (0.88) existed between the diagnosis modelled using the AHP method and the fuzzy method. Though, the correlation of false diagnosis was low (0.12). This indicates a convergence of true diagnosis and a divergence of false diagnosis between the AHP and fuzzy methodologies.

The study was built on the alternative hypothesis that there is a significant difference between the AHP as an engine for tuberculosis diagnosis system and fuzzy power tuberculosis system. A paired two sample t-test was carried out in order to verify the hypothesis. The result indicates that both at one tail and two tails, the computed t value are less than the critical value. Thus, the alternative hypothesis is upheld, indicating that there is no significant difference in diagnosis results between the AHP and fuzzy methodology.

CONCLUSION

This research has compared the fuzzy methodology with the analytic hierarchy process (AHP) and has experimentally ascertained their levels of effectiveness/utility in the medical diagnosis. The study is an effort towards determining the component that is more effective in analysis, synthesis and evaluation of medical symptoms and diseases in order to choose the entrant technology for the inference engine in a hybrid diagnosis system. The results showed relative significant statistical difference between the AHP and fuzzy logic in terms of reliability in diagnosis of tuberculosis. However, a close observation of the performance summary (Table 9) shows that the fuzzy logic is slightly better than the AHP, with 3.1% difference in true diagnosis and 0.16% differential in mean square error. While this study utilized tuberculosis as a case, it is important to note that this may not present the level of generalization necessary to conclude that fuzzy logic has slight relative superiority in the inference process especially when there is no statistical significance shown by the output variations. It

is postulated that several experimental trails utilizing varying diseases and large number of cases may make the difference in results to be very infinitesimal. We therefore conclude that a fuzzy engine tuned by AHP or AHP inference engine tune by fuzzy logic would produce about the same level of optimality of diagnosis.

REFERENCES

1. Abraham, A. and J. Nath, 2002. Intelligent Systems: Architectures and perspectives, Recent Advances in Intelligent paradigms an application, Springer Verlag Germany, Chapter, 1: 1-35.
2. Akinyokun, O.C. and O.A. Adeniji, 1991. Expserimental study of Intelligent Computer Aided Medical Diagnostics and therapy; AMSE Journal of Modelling, simulation and control; France, 27(3): 1-20.
3. Ali, A. and N. Mehli, 2010. A fuzzy expert system for heart disease diagnosis. Proceedings of the International Multi Conference of Engineers and Computer Scientists, 1: 134-139.
4. Ashish, Kumar Mourya, Pawan,Tyagi, Ashutosh and Bhatnagar, 2016. Genetic Algorithm and their applicability in Medical Diagnostic: A Survey International Journal of Scientific & Engineering Research, Volume 7, Issue 12, December-2016 1143 ISSN 2229-5518.
5. Asogbon, M.G., O.W. Samuel, M.O. Omisore and O. Awonusi, 2016. Enhanced Neuro-Fuzzy System Based on Genetic Algorithm for Medical Diagnosis: Journal of Medical Diagnostic Methods, J. Med. Diagn Meth 2016, 5:1 DOI; 10.4172/2168-9784.1000205 ISSN: 2168-9784.
6. Atul, K.P., P. Prabhat and K.L. Jaiswal, 2014. Classification model for the Heart disease diagnosis.Global Journal of Medical Research Diseases, 14(1): 1-7, online ISSN: 2249-4618 & Print ISSN: 0975-5888.
7. Back, T.D., B. Fogel and Z. Michalewic, 2000. Evolutionary computation 1: Basic Algorithms and Operators vol. 1: CRC Press.
8. Brans, J.P. and P. Vincke, 1985. A preference ranking organization method: The PROMETHEE method for MCDM. Management Science, 31(6): 647-656.
9. Szolovits, P., 1995. Uncertainty and decisions in Medical Informatics: Methods of Information in Medicine, 34: 111-121.
10. Davis, R., 1982. Expert Systems: where are we ? And where do we go from here? AI Magazine, (3): 3-22.
11. Kaeding, A.K. and T. Flor, 1995. Processing Unexact Information in a Medical used Multiparadigm System, Proceeding of the 1995 ACM symposium on Applied computing 1995, Nashville, United States Feb. 26-28,1995, pp: 590-592.
12. Kulikowski, C.A., 1987. Artificial Intelligence in Medicine: A personal Retrospective on its Emergence and early Evolution, pp: 199-206.
13. Yager, R.R., 1988. On ordered weighted averaging aggregation operators in multi criteria decision making. IEEE Transactions on Systems Man and Cybernetics, 18: 183-190.
14. Bevilacqua, M., A. D'Amore and F. Polonara, 2004. A Multi-Criteria Decision Approach to Choosing The Optimal Blanching-Freezing System, Journal of Food Engineering, 63: 253-263.
15. Saaty, T.L., 2005. Analytic Hierarchy Process. Encyclopaedia of Biostatistics, publisher John Wiley & Sons, Ltd, 1: 1-3.
16. Saaty, T.L., 2004. Decision Making -The Analytic Hierarchy and Network processes (AHP). Journal of Systems and Systems Engineering, 13(1): 1-34.
17. Stewart, M., 1993. A partly true story, Scientific American, 268: 110-112.
18. Rao, V.B. and P. Kokol, 2001. Towards more Optimal Medical Diagnosing with Evolutionary Algorithms, Journal of Medical System, 25(3): 195-219.
19. Chin-Teng, L. and C.S.L. George, 1991. Neural-network-based fuzzy logic control and decision system. IEEE Transactions on Computers, 40: 1320-1336.
20. Cheng, Q., H. Li and H. Huangetal, 2017. An enhanced grey wolf optimization based feature selection wrapped kernel extreme learning machine for medical diagnosis, Computational and Mathematical Methods in Medicine, Article ID9512741, 15: 2017.
21. Critto, A., N. Nadal, M. Samiolo and C. Carlon, 2002. DESYRE-Decision Supports system for Rehabilitation of contaminated sites: Objective sand structure. Proceedings of the integrated assessment and decision support conference, Lugano, Switzerland.
22. Dubois, D. and H. Prade, 2013. A class of fuzzy measures based on triangular norms. Int. J. Gen. Syst., 8: 43-61.
23. Durairaj, M. and R. Deepika, 2015. Comparative analysis of classification algorithms for the prediction of Leukemia cancer. International Journal of Advanced Research in Computer Science and Software Engineering, 5(8): 787-791.

24. Evangelos, Triantaphyllou and Staurt Mann, 1995. Using the Analytic Hierarchy Process for Decision Making in Engineering Applications: Some Challenges, International Journal. of Industrial Engineering: Application and Practice, pp: 35-40.
25. García-Cascales, M.S., 2012. Technique for Order Preference by Similarity to Ideal Solution: Journal of Mathematical and Computer Modelling, 56(6): 123-132.
26. Ken, B., U.O. Okure and O. Joseph, 2011. Miller, G. A. (1956). The magical number even, plus or minus two: Some limits on our capacity for processing information. Psychological Review, 63: 81-97.
27. Lee, C.C., 1990. Fuzzy logic in control system-Fuzzy logic controller-Part I & II. IEEE Transaction on Systems-Man, Cybernetics, 20: 404-435.
28. Ledley, P.S. and L.B. Lusted, 1959. Reasoning Foundation of Medical Diagnosis: Symbolic Logic, Probability and value theory Aid our Understanding of how physician Reason, Science, 130: 9-21.
29. Liu, P.H. and C.C. Wei, 2000. A group decision making technique for appraising the performance of organizations. International Journal of the Computer, the Internet and Management, 8(2): 39-49.
30. Rivero Cetal, 2015. Fuzzy logic and RULA method for assessing the risk of working. Procedia Manufacturing, 3: 4816-4822.
31. Safoora, Y., A. Fatemeh, A. Mohamed, D. Coco, E.L. Joshua, S. Congzheng and A.D.C. Lee, 2017. Predicting clinical outcomes from large scale cancer genomic profiles with deep survival models. BioRxiv Journal, doi: http://dx.doi.org/10.1101/131367
32. Ojokoh, B.A., M.O. Omisore, O.W. Samuel and T.O. Ogunniyi, 2012. A Fuzzy logic based personalized recommender system. International Journal of Computer Science, Information Technology & Security (ijcsits), 2: 1008-1015.
33. Salleh, S., 2015. Task Allocation In A Multiprocessor System Using Fuzzy Logic, Journal of Technological Advancement, 25: 69-79.
34. Miller, G.A., 1956. The magical number even, plus or minus two: Some limits on our capacity for processing information. Psychological Review, 63: 81-97.
35. Obot, O.U. and F.M.E. Uzoka, 2009. Fuzzy-rule base framework for the management of tropical diseases. International Journal of Medical Engineering and Informatics 1: 7-17.
36. Shameem, A.F. and D. Manimeglai, 2015. Analysis of significant factors for dengue infection prognosis using the random forest classifier.International Journal of Advanced Computer Science and Applications, 6(2): 12-17.
37. Salomon, V.P. and J.A.B. Montevechi, 2001. A compilation of comparisons on the analytic hierarchy process and other multiple criteria decision making methods: Proceedings of the 6th AHP conference, Berne, Switzerland, August2-4, 2001 (pp: 413-420).
38. Samuel, O.W. and M.O. Omisore, 2013. Hybrid intelligent system for the diagnosis of typhoid fever. Journal of Computer Engineering & Information Technology, 2: 2.
39. Samuel, O.W., M.O. Omisore and B.A. Ojokoh, 2013. A web based decision support system driven by fuzzy logic for the diagnosis of typhoid fever. Expert Systems with Applications, 40: 4164-4171.
40. Sikchi, Rajendra and R. Qamar, 2013. Decision Support System for the Diagnosis of Asthma Severity Using Fuzzy Logic", proceedings of International Multi-conference of Engineers and Computer Scientists 2012, Vol I, IMECS, march 14-16, 2012.
41. Steiguer, J.E., J. Duberstein and V. Lopes, 2003. The analytic hierarchy process as a means for integrated watershed management. Proceedings of 1st interagency conference on research in the Watersheds, USA (pp: 736-740).
42. Uzoka, F.M.E. and J.O. Famuyiwa, 2004. A framework for the application of knowledge technology to the management of diseases. International Journal of Health Care Quality Assurance, 17(4).
43. Wainer, J. and S. Sandri, 1999. Fuzzy temporal/categorical information in diagnosis. Journal of Intelligent Information Systems, 1: 9-29.
44. Yuchen, Z., 2016. Distributed Machine Learning with Communication Constraints (A published Doctoral thesis). California, Berkeley.
45. Zadeh, L., M. Nikravesh and V. Loia, 2004. Fuzzy logic and the Internet. Studies in fuzziness and soft-computing, vol. 137. Berlin, Springer.
46. Zadeh, L.A., 1965. Information and Control, 8: 338-353, 2014.