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Comparison of Fuzzy Logic and Analytic Hierarchy Process (AHP) Effectiveness as Engines for The Development of Intelligent Medical Diagnostic Systems

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ABSTRACT

Medical diagnosis involves a complex decision process that involves a lot of vagueness and uncertainty management, especially when the disease has multiple symptoms. A number of researchers have utilized the fuzzy-analytical hierarchy process (fuzzy-AHP) methodology in handling imprecise data in medical diagnosis and therapy. This is because fuzzy-AHP system is capable of accommodating inherent uncertainty and vagueness in multi-criteria decision making with hierarchical structuring. This study attempts to do a case comparison of the effectiveness of the fuzzy verses the AHP methodology in medical diagnosis in order to provide a framework for determining the appropriate backbone in a fuzzy-AHP hybrid system. The results of the study indicate a non-significant relative superiority of the fuzzy technology over the AHP technology.

Keywords: Fuzzy Logic, Analytic Hierarchy Process (AHP), Engines, Medical Diagnostic & System

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1. BACKGROUND OF THE STUDY

The task of carrying out an effective and efficient differential 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 (Akinyokun and Adeniyi, 1991). 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. 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 (Szolovis, 1988). 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 (Kulikowski, 1987). 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 (Ledley and lusted, 1959). 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 alternatives and criteria. The scores for each alternative are combined with measures of each criterion's importance (ie 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.

By the early 1970s, it became evident that statistical tools were unable to deal with most complex clinical problems (Gorry, 1973). 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 (Kulikowski, 1987). Pattern recognition methods were the focus of AI application in medical diagnosis until 1974 when shortliffe published the first rule based approach for therapy advice in infectious diseases (Shortliffe, 1974). Rule based programs use the "if –then –rule" in chains of deductions to reach a conclusion. Szolovits observed (Szolovits et al , 1988) 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 (Davis, 1982). 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 (Swartout, 1996).

As research in medical diagnosis deepened, emphasis shifted to the representation and utilization of unstructured, imprecise, and dynamic knowledge. Szolovits recognized (Szolovits, 1995) that uncertainty is the central and critical fact about medical reasoning. Uncertainty and imprecision characterizes 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 (Kaeding and Flor, 1995). Researchers in medical diagnostic systems in the past decade have attempted to find ways to manage uncertainty in medical diagnosis using soft computing methods (Szolovits, 1995). 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 (pople, 1982). Evolutionary algorithm (podgorelec and kokol, 2001) , case-based reasoning (Ochi-okorie, 1998), and hypertext-based systems and knowledge base technology (Uzoka and Famuyiwa, 2004) have been applied in the management of imprecise and unstructured medical knowledge. Obot and Uzoka (2009) 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 (Bonissone and Goebel, 2001) and the ability of AHP to mathematically model unstructured information (Saaty, 1977).

The AHP has been proposed for the building of the kernel of medical decision support system in (Rabelo et al. 1996), while a framework for utilizing AHP in the diagnosis of fever has been reported as well (Saaty and Vargas, 1998). Fuzzy models are discussed elsewhere (Wainer and Sandri, 1999). 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 (Hartwich and Jaanssen, 2000). The AHP is based on four axioms: reciprocal judgements, homogeneous elements, hierarchic or feedback dependent structure and rank order expectations (Saaty, 2004). Fuzzy logic (Zadeh, 1965) is a generalization of the conventional set theory as a mathematical way to represent vagueness of parameters. 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 (Abraham and Nath, 2000).

This research seeks to compare the fuzzy methodology with the analytic hierarchy process (AHP) methodology in order to experimentally ascertain their levels of effectiveness/utility in the medical diagnosis. This would assist medical decision system builders in deciding on which of the tools should form the backbone in a fuzzy-AHP (or AHP-fuzzy) system. Depression will be utilized as an experimental case study. Data for thirty patients are to be collect with the help of six medical doctors from four hospitals for the purposed of conducting the experiment. Each doctor will be requested to obtain diagnosis for five depression patients. With the consent of the patients the doctor utilized a 'diagnosis sheet' with which he rate each patients based on the twenty five identified depression symptoms. At the end of the all necessary investigation, the doctor provides a diagnosis, indicating the intensity of depression. This data constituted the true diagnosis. The symptoms evaluations on the diagnosis sheet for each patient were then processed using AHP and fuzzy methodologies independently to obtain diagnosis which were then compared with the final diagnosis by the medical doctors in order to evaluate the quality of the diagnoses by fuzzy and AHP methodologies.

2. AIM AND OBJECTIVES OF THE STUDY

The research is aimed at performance comparison of fuzzy logic and analytic hierarchy process (AHP) as engines for the development of intelligent medical systems. The specific objectives are to;

1. provide a framework for determining the appropriate backbone in a fuzzy-AHP hybrid system
2. To provide performance comparison of fuzzy logic and analytic hierarchy process (AHP) as engine in medical intelligent system
3. Design an intelligent system that utilizes fuzzy logic and analytic hierarchy process (AHP) in medical diagnosis.

4. Generate from reports from the system and prescribe cure for depression disease.
5. Provide an updatable knowledge base where medical experts can supply data on diagnostic information they have gathered

3. RESEARCH METHODOLOGY

1) The analytic hierarchy process (AHP) for depression 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 (Saaty, 1977). The variables involved in depression 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 (Miller 1956). 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 depression diagnostic variable into hierarchy is presented in figure1.

LEVEL 1 (GOAL)	LEVEL 2 (CRITERIA)	LEVEL 3 (VARIABLES)
DEPRESSION DIAGNOSIS	Physical symptoms (ps)	Weight loss (WL), loss of energy (LE), Tiredness (TR), Decline in speech (DS).
	Cognitive symptom (cs)	Idecision (IN), self dislike (SL), Worthlessness(WH), Failure(FL)
	Emotional symptom (es)	Loss of pleasure(LP), loss of concentration (LC), Feel irritated (FI).
	Motivational symptoms (ms)	Loss of appetite (LA), Loss of energy (LE), Suicidal thought (ST)
	Physiological symptom (pys)	Body mass index(BM), Diastolic blood pressure(DBP), systolic blood pressure(SBP)

Figure 1 Hierarchy of Basic Depression Diagnosis Criteria

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 (factors) (Sarkis and Sundarra, 2001). This can be represented mathematically in the following (Uzoka and Ijatuyi, 2004):

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$\{a_{ij}\}$, 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: $\lambda_k = \frac{\sum_{j=1}^{n} E_{kj}}{n}$ (2)

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

The next step is the evaluation of the patient's state of health with respect to depression 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 depression. The final evaluation (diagnosis) is given as: $W_i = \sum R_{ij} \lambda_j$, 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 variables respectively were computed. The level 2 diagnostic criteria evaluation gives an eigenvector, λ_1, while the level 3 variables produce the eigenvector, λ_2. λ_1 combines with the column vector of level 2 factors to give the diagnostic factor index for level 2 criteria (DFI_1), while λ_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 depression. In order to determine the intensity of depression, a scale of intensity is formed, based on state of 'perfect information' whereby each of the variables is considered to have uniform values drawing from a likert scale, to determine the intensity of depression.

Table 1-Depression Intensity Scale

Uniform Rating	ADFI Range	Depression Intensity
1	0.0000-0.16524	Very low
2	0.16525-0.33047	low
3	0.33048-0.49571	moderate
4	0.49572-0.66095	High
5	0.66096-0.82618	Very high

In table 2, the case study of the ten patients used for the system evaluation is presented. This is based on the diagnosis of the rating of patients on depression diagnosis variable.

Table 2- Case study of patients Diagnosed

Patients number	ADFI	Depression Intensity
195	0.610783	High
087	0.361289	Moderate
421	0.49842	High
182	0.60113	High
008	0.461251	Moderate
694	0.479785	Moderate
387	0.456735	Moderate
021	0.364672	Moderate
201	0.606026	High
756	0.431987	Moderate

2) The fuzzy methodology for depression diagnosis

The knowledge base for depression contains both static and dynamic information. There are qualitative and quantitative variables, which are analyzed in order to arrive at a diagnostic conclusion. The fuzzy logic of the diagnosis of depression of depression involves fuzzification, inference and defuzzification. A fuzzy set (A) of the diagnosis attributes and its element denoted by X, is then defined from the input variables using Eq. (3). This is done before the fuzzification process.

$$V = [(X, \mu_v(X)) \mid X \in V, \mu_v(X) \in [0,1]\} \quad (3)$$

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. 3.

$$\mu(x) = \begin{cases} 1, & if \quad x = b \\ \frac{x-a}{b-a} & if\ a \le x < b \\ \frac{c-x}{c-b} & if\ b \le x < c \\ 0, & if\ c \le x \end{cases} \quad (4)$$

Where a, b and c are the parameters of the membership function governing the triangular membership functions; b represents the value for which $\mu(x) = 1$ and is defined as $b = (a + c)/2$. The actual membership functions of each element in the fuzzy set are derived as described in (Jang et al., 2004; Akinyokun, et al 2009). Each of these attribute was described by the linguistic terms: *Mild, moderate, severe.*

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 depression 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:

$O_{1,i} = \mu_{Ai}(x_1)$, for i=1,2,3; (5)
$O_{1,i} = \mu_{Bi-3}(x_2)$, for i=4,5,6 ; (6)
$O_{1,i} = \mu_{Ci-3}(x_3)$, for i=7,8,9; (7)
$O_{1,i} = \mu_{Di-3}(x_4)$, for i=10,11,12; (8)
$O_{1,i} = \mu_{Ei-3}(x_5)$, for i=13,14,15; (9)

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 (4) such that $a \le x < b$ is adopted.

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:

$$O_{2,i} = w_i = \mu_{Ai}(x_1) \times \mu_{Bi}(x_2) \times \mu_{Ci}(x_3) \times \mu_{Di}(x_4) \times \mu_{Ei}(x_5)\ , i=1,2,3,4,5 \qquad (10)$$
$$w_i = Min\{\ \mu_{Ai}(x_1) \times \mu_{Bi}(x_2) \times \mu_{Ci}(x_3) \times \mu_{Di}(x_4) \times \mu_{Ei}(x_5)\} \qquad (11)$$

Layer 3 Normalize firing strength : Every node in this layer is a circle labeled N. The ith node calculates the ratio of the ith 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 :

$$\varpi_i = \frac{\omega_i}{\omega_i + \omega_2 + \omega_3 + \omega_4 + \omega_5}\ ,\ i=1,2,3,4,5 \qquad (12)$$

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:

$$O_i^4 = \overline{\omega}_i f_i = \overline{\omega}_i(P_i X + q_i y + r_i), \quad \text{where } i = 1,2,3,\ldots,243 \qquad (13)$$

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)

$$RSS = \sum_{i=1}^{n} (R^2) \qquad (14)$$

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

$$O_i^5 = overall\ output = \sum_i \overline{\omega} f_i = \frac{\Sigma_i\ \omega_i f_i}{\Sigma_i\ \omega_i} \qquad (15)$$

4. 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 1 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 2. The intensity of depression was rated as low (1), moderate (2), intense (3), and very high (4)

Table 3: Results summary

S/N	Patient No.	Medical Diagnosis	Experts	AHP Result			Fuzzy Results		
			Numeric scale	ADFI	Depression Intensity	Numeric scale	%possibility	Depression Intensity	Numeric scale
1	192	Intense	3	0.610783	High	3*	59	Int	3*
2	087	Moderate	2	0.361289	Moderate	2*	42	Mod	2*
3	421	High	3	0.49842	High	3	48	Mod	2
4	182	High	3	0.60113	High	3*	56	Int	3*
5	008	Moderate	2	0.461251	Moderate	2*	44	Mod	2*
6	694	Moderate	2	0.479785	Moderate	2*	48	Mod	2*
7	387	High	3	0.456735	Moderate	2*	54	Mod	2*
8	021	Moderate	2	0.364672	Moderate	2*	41	Mod	2*
9	201	High	3	0.606026	Moderate	2	62	Int	3
10	756	moderate	2	0.431987	Moderate	2*	49	Mod	2*

- Indicates a match in diagnosis between the AHP and fuzzy methods

Table 2 shows that the AHP had 77% correct diagnosis, while the fuzzy system had 82% 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 48.30% while the fuzzy method had RMSE of 44.72%, which shows an insignificant difference of 3.58%. a high correlation (0.84) existed between the diagnosis modelled using the AHP method and the fuzzy method. However ,the correlation of false diagnosis was low (0.11). This indicates a convergence of true diagnosis, and a divergence of false diagnosis between the AHP and fuzzy methodologies.

Table 4 : System performance Summary

	AHP	FUZZY
Per cent of true diagnosis	76	80
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 (falsel diagnosis		0.118217
tStat		0.328339
P(T<=t) one tail		0.372507
T Critical one tail		1.699127
P(T<=t) two tail		0.745014

The study was built on the hypothesis that there is a significant difference between the AHP power depression diagnosis system and fuzzy power depression system. A paired two sample t-test was carried out in order to verified the hypothesis. The result indicate 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.

5. CONCLUSION

Medical diagnosis is a complex function that requires the combinatorial analysis of decision variable, most of which are qualitative in nature. It is possible to group these variables and arrange them in a hierarchical structure for the purpose of analysis. There is a high level of uncertainty management of medical diagnosis. This is because human reasoning and decision making is fuzzy, involving a high degree of vagueness in evidence, concept utilization and mental model formulation (Wang and Elhag 2006). The introduction of the Analytic Hierarchy process (AHP) by Saaty (1981) enhanced understanding of the hierarchical structuring of decision variables and popularized the methodology of pairwise comparison of such variables to determine their relative importance in the decision matrix.

However, the application of only the AHP to evaluation of alternatives has some limitations (Chou et al. 2006). Its sole use in medical diagnosis would have the following shortcomings: 1) AHP uses crisp values for scoring purposes. The derivation of weights attached to symptom is carried out by medical experts, whose perceptions and feelings about a given weight are vague. 2) The diagnosis of a given patient is subjective and relative by nature. It would be inappropriate to assign crisp value to subjective judgment, especially when the data is imprecise or fuzzy.

The combination of fuzzy preference relations and AHP methodology in multi-criteria decision analysis gained prominence with the work of Van et al. (1983) which compared fuzzy ratios described by triangular membership. FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy or missing input information. FL does not require precise inputs, is inherently robust, and can process any reasonable number of inputs and numerous outputs can be generated, though system complexity increases rapidly with more inputs and outputs.

Simple, plain language rules are used to describe the desired system response in terms of linguistic variables rather than mathematical formulas, which makes FL work closely to the way human reasoning does. Besides, dealing with uncertainty, fuzzy logic models common-sense reasoning, which is difficult in conventional system that model mainly exact reasoning (Giarratana and Riley 2005).

This research seeks to compare the fuzzy methodology with the analytic hierarchy process (AHP) methodology in order to experimentally ascertain their levels of effectiveness/utility in the medical diagnosis. This study presents one of the efforts aimed at utilizing fuzzy logic and analytic hierarchy process (AHP) in medical diagnosis, with the aim of determining the component that is more effective in analysis, synthesis and evaluation of medical symptoms and diseases.

The more effective technology would ultimately be proposed to form the entrant technology of the inference engine in a hybrid diagnosis system. The result from the two engines will show the more effective technology to be used by intelligent system builder in developing medical diagnosis system.

The results shown that there is no statistical difference between the AHP and fuzzy logic in terms of effectiveness of diagnosis of depression. However, a close observation of the performance summary (Table 3) shows that the fuzzy logic is slightly better than the AHP, with 0.05% difference in true diagnosis, and 0.16% differential in mean square error.

While this study utilized depression as a case, it is importance to note that this may not present the level of generalization necessary to conclude the slight relative superiority of fuzzy logic 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.

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