Clinical Decision Support System for Detection of Dengue: A Case Comparison Using AHP and Fuzzy AHP

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ABSTRACT

Dengue fever is caused due to the mosquito (*Aedes aegypti*) bite. The symptoms of this fever are similar to other fevers such as Malaria, Chikungunya, and Zika. A common sign of Dengue fever is the sharp fall of blood platelet count, amongst a host of other confusing symptoms, which makes Dengue difficult to diagnose, especially by an inexperienced physician. The purpose of this study is to outline a decision support system (DSS) which would come to the aid of detection of Dengue fever by carrying out an analysis of AHP and fuzzy AHP (FAHP) methodology. The data of confirmed Dengue as diagnosed by a physician is picked up, examined independently using AHP and FAHP approach, and the results obtained are then compared with the diagnosis report of an expert doctor. The outcome is encouraging and indicates that expert systems can be leveraged for the diagnosis of Dengue and can be a useful tool for non-expert physicians.

KEYWORDS

Analytical Hierarchy Process, Decision Support System, Dengue, Medical Diagnosis

1. INTRODUCTION

The most important thing in the medical field is proper and accurate diagnosis as it is challenging even for a well-qualified doctor having ample experience in handling thousands of comparable cases. In many cases, the existing symptom of an infectious disease is an indicator for other problems as well. Moreover, tracing the root cause becomes strenuous due to the co-occurrence of other complex syndromes. For example, even the diagnosis of a patient suffering from a common fever, requires significant scrutiny, as most of the patients have a history of diabetes, hypertension and other related co-morbidity. In light of this, diagnosis involves exploring a whole gamut of links in the chain. Consequently, the possible state space of diagnosis landscape becomes significantly large, which makes it extremely difficult to deal with, especially when resource availability is scarce. On the other hand, to lessen this possibility, the concerned specialist sticks to a particular decision sequence for a given illness trajectory of the patient. However, it increases the risk of loss of life due to unidentified illness and also non-correctable errors in a timely manner.

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Complexity of the diagnostic process is increased due to the imprecision and vagueness involved with the underlying data as patients are not able to express properly their health conditions, thus not allowing healthcare practitioners to interpret the information correctly. This leads to the high levels of imprecision involved in the measuring instruments, ambiguous nature of the symptoms, disease prognosis due to environmental hazards, which is true in case of dengue fever. Early diagnosis and immediate medical attention assist in controlling the epidemic and also restraining the mortality and morbidity rate. Rather than restricting the process of diagnosis to the medical practitioners' judgement only, intelligent decision support system assisting doctors in strengthening their decision-making ability (Musen, Shahar, & Shortliffe, 2001), building confidence in less experienced professionals above the human judgement error, can be explored as specialist doctors hard to avail around the clock. In addition to assisting doctors, the system must handle the complex and diverse symptoms associated with the tropic disease. Hence soft computing techniques are quite suitable for these kind of problems (Oguntimilehin, Adetunmbi, & Abiola, 2013; Samuel & Omisore, 2013; Gambhir, Malika, & Kumar, 2016). Several research employ multiple soft computing intelligent techniques for investigating tropical diseases like malaria (Djam et al., 2011) and dengue (Adawiyah, 2017; Afan, Yen, & Christian, 2014; Gambhir, Malika, & Kumar, 2017).

1.1 Motivation for the Study

Dengue fever is the most common mosquito-borne viral illness in the world, endemic in more than 100 countries, with 2.5 billion people at risk for transmission. Most prevalent in tropical and subtropical areas where there is limited public health infrastructure for mosquito control in areas such as: Africa, Asia, Mexico, and central and south America. The widespread outbreak of dengue, usually in under-developed countries, mainly in monsoon season, poses a challenge for the administration, in terms of treatment with available resources as it is not feasible to scale-up the required healthcare resources in a short notice. Consultation with a physician or a specialist if required is not available in a timely manner in remote areas or even in urban places due to high numbers of patients waiting for consultation. In addition to this, general hospital having proper nursing care, laboratory, and intensive care unit (ICU) facility cannot be multiplied overnight. Besides laboratory tests, dengue serology testing by Elisa kits, is found to be too expensive. In the case of dengue, most importantly the fluid level in the body is maintained, platelet level is constantly monitored and clinical care is provided since no major medication, and surgery is performed in treatment except administering general intravenous antibiotics. In the case of scarcity of doctors, suitable laboratory tests, nurses and other paramedical staff come forward to take the responsibility in the shoulder. In this case, a clinical diagnosis by artificial intelligence techniques comes to the rescue of nursing staff and even less-experienced physicians and house surgeon staff during making an initial assessment about the severity of occurrence of disease.

1.2 Objectives

- To help doctors and patients in diagnosing Dengue disease.
- To develop a decision support system (DSS) for clinically investigating Dengue disease.
- To model the clinical diagnosis and severity assessment process mathematically.
- To compare the efficacy of AHP and Fuzzy AHP while employed in development of DSS.

1.3 Current Research

Few of the current works pertaining to designing of DSS for diagnosis of dengue have been published. Tandra et al. (2019) developed a CDSS by employing adaptive neuro-fuzzy inference system (ANFIS) for diagnosis of multiple diseases like malaria, typhoid, and dengue. However, this study does not focus on analysis of a large number of parameters of dengue, this framework does not explain detailed

step-by-step development. Tan et al. (2020) has designed a tool for predicting dengue haemorrhage fever in patients who have currently discharged from hospitals after being treated for dengue fever. This research does not discuss the diagnostic and assessment process of dengue severity. Aysha et al. (2019) designed a knowledge-based system for dengue diagnosis by using SL5 object language. Nonetheless, the article doesn't mull over the uncertain and multi-pronged judgement process of decision makers. With respect to above concerns, the proposed approach of designing a CDSS intends to address the following issues: (i) diagnosis of dengue infection (ii) severity assessment of disease (iii) single framework based on AHP vs FAHP based simulation (iv) integration of physician's judgement in the decision making process.

1.4 Proposed Solution

In this study, we propose a CDSS in order to meet the above objectives. The current study of conceptualising a clinical DSS for diagnosis of dengue has few significant contributions. They are listed below:

- We proposed a clinical DSS for detection of dengue.
- The proposed DSS employing either AHP or FAHP delivers good performance.
- The proposed DSS achieved better accuracy on a dataset of confirmed dengue infection.

In section 2, we unfold the growth and state- of-the- art of decision support systems designed for assisting clinicians. Section 3 discusses experimental design for simulating AHP and fuzzy AHP methodology utilizing dengue dataset. In section 4, we have compared the diagnostic outcome of AHP and FAHP methodology, further the results obtained in both the cases are matched with the diagnostic result of the specialist doctor. The article is concluded in section 5 highlighting the future scope of improvement.

2. CLINICAL DECISION SUPPORT SYSTEM

Disease diagnosis and clinical decision support tools are attributed back to the year 1960 when statistical methods slowly became employed for inferencing source of a disease (Kulikowski, 1987). During that era, mathematical reasoning and theory of probability were mostly used for analysing the medical data. Further, probabilistic approach paired with Bayesian inference rule, logical reasoning with Boolean logic, symbolic reasoning with semantic net and frames, mathematical reasoning with predicate logic and utility theory, Dempster's evidence theory, regarded as competitive and efficient techniques, were extensively used for the process of reasoning and inferencing. Boolean logic also known as propositional logic considers a proposition as either true or false. This form of reasoning is unable to partitions complex health issues since the case under investigation cannot be put under only two criteria, i.e. black or white. Hence it is realized that Boolean logic which partitions the sample into yes or no, cannot address the complexity involved in medical data.

Clinical decisions are made by a physician based on his experience of dealing similar cases. Decisions are thus the result of automatic processing of historical data of similar kind (Parthiban & Subramanian, 2008). However, general doctors and specialists have a way of identification, hence treatment is not uniform for a patient having interrelated symptoms and conflicting indicators. Furthermore, proper diagnosis is quite challenging at an early stage due to simultaneous presence of multiple factors (Yan et al., 2003). In order to enhance healthcare service quality, Clinical Decision Support System (CDSS), a tool, which comes to the rescue of clinicians, nurses, staff and patients with knowledge and patient- specific information at an appropriate time can be proved worthy and indispensable. CDSS strives to educate healthcare professionals practically and intelligently to cope

with the need of the time. Making the most of CDSS generally lies in screening aptly at a correct time, diagnosing accurately, averting adverse drug effects, etc (Garg et al., 2005).

Statistical tools and Boolean logic can be quite successfully applied to various problems. However, it is realized that they cannot handle uncertainty and vagueness involved in the data which is abundant in healthcare data. Come 1970, other tools based on the principle of artificial intelligence were discovered and exploited by utilizing medical data. At first expert knowledge was encoded in the form of rules. A rule is of the form of 'IF..., THEN' statements and a series of rules are chained to reach at a conclusion. Conversely, the rule-based system seems to be a straight-forward inference mechanism, they can only be utilized for a single domain and the problem having clear deduction. However, it is not practicable for large and complex systems involving conflicting symptoms and unclear and contradicting test reports (Szolovits et al, 1988). On the other hand, a large set of rules become quite hard for interpretation as they have contradictions and at the same time simultaneous inferences out of a given system, laborious to maintain when adding a new rule.

A DSS, capable of handling uncertainty and imprecision, which is prevalent in medical data has always been sought (Uzoka & Barker, 2010). We discuss few of the DSS and underlying techniques used in implementing this. Anooj (2012) presented a DSS for the risk level prediction of heart disease based on the technique of Fuzzy logic. The proposed DSS select attributes and their weightage in first phase whereas the Fuzzy system is developed using those attributes in the second phase. A DSS for tuberculosis diagnosis is studied by Djam & Kimbi (2011). A clinical DSS for diagnosis of Malaria on comparing the effectiveness of AHP and Fuzzy methodology is developed (Uzoka et al., 2011). Results were compared with the diagnostic conclusion of a medical expert, and it was deemed that Fuzzy logic proved to be slightly better than AHP. Further, a CDSS for typhoid fever diagnosis utilising Naïve Bayes, k-nearest neighbour and support vector machine is being developed by Andrianto et al. (2019).

A DSS for Malaria and Dengue diagnosis using Fuzzy logic was designed by Sharma et al. (2013); Further, Afan et al. (2014) developed an expert system based on computational intelligence method, which used a Fuzzy inference system (FIS) to diagnose Dengue haemorrhage fever. Another study employed extreme learning machine to detect the presence of Dengue (Suhaeri et al., 2018). Expert systems for various disease diagnoses have been designed. Few of them are MYCIN for diagnosing bacterial infection, NEOMYCIN for meningitis, MEDI for chest pain and HEME for haematological disease (Ahmed et al., 2017). Recently an expert system for Bowel disease diagnosis hybridising case based reasoning and nearest neighbourhood algorithm is developed by Vedayoko et al. (2017). It has been identified that most of the DSS and expert systems use fuzzy logic or fuzzy logic combining with other techniques, for assessment and evaluation (Muslihudin et al., 2018; Nefeslioglu et al., 2013; Radenovic & Veselinovic, 2017; Siddiqui & Tyagi, 2016).

However, a little work is being published for designing a CDSS for dengue disease detection. Those handfuls of works mostly used the binary classification techniques to discover whether dengue is present or not. Moreover, our research employs AHP and fuzzy version of AHP (FAHP) for simulation to assess the severity of dengue infection. In our knowledge, these three combinations- AHP, FAHP and a confirmed dengue dataset have not been explored yet.

3. RESEARCH DESIGN

We have designed the experimental framework for coining a DSS which is exhibited in Figure 1. Clinical diagnostic dengue dataset is collected, next the parameters are analysed to identify criteria's and sub-criteria's. Correspondingly, a hierarchical structure is created by grouping all the attributes of dengue data. Then, it is subjected to implementing using AHP and FAHP. Additionally, we have devised an algorithm for assessing severity of disease. By utilising the algorithm, severity assessments of patients are performed, then the results of AHP and FAHP are validated by matching with the available diagnostic record as provided by an expert doctor. Hence the efficiencies of the individual techniques in terms of accuracy are computed and further they are evaluated in order to have more insights.

Figure 1. Block diagram of proposed system

3.1 AHP Methodology for Dengue Diagnosis

Analytic Hierarchy Process (AHP) developed by T. Saaty, decomposes a decision making problem into sub-levels, thus creating a hierarchical model (Saaty, 1977). The goal is at the top of the hierarchy; the decision parameters are at the lower level (Tung & Tang, 1998). The hierarchal structure of AHP methodology makes it fit for synthesizing a variety of factors of a complex decision- making process in a hierarchic manner, making it simple to combine the parts in a whole and has the potential to model the unstructured information associated with data like a human centric approach. Hence in later points of time, it is being used in the medical decision support system for various disease diagnoses (Saaty & Vargas, 1998; Vaidya & Kumar, 2006).

In a decision making event, the parameters considered and their values, the criteria and sub-criteria to analyse the alternatives, the weightage of the priorities, aggregating all the criteria to secure the comprehensive ranks of the alternatives is a gruelling exercise (Saaty, 2008). Keeping this in mind, AHP is equipped with a provision of assigning relative importance of each variable when compared to rest of the variables in pairwise fashion (Russoa & Camanho, 2015). The criteria and calculation of their weights are paramount to estimate the alternatives in this method. The user forms an impression about the proportionate weightage of various criteria (Franeka & Krestaa, 2014), and this requires the users' expertise and domain knowledge, given the judgement involves multimodal knowledge. As per the decision maker's pairwise comparisons of the measure (criteria), AHP generates a weight for each measure and it signifies dominance of the measure which has a high value of the weight.

AHP comes under the MCDA techniques. Other MCDA methods include (Velasquez & Hester, 2013): Simple additive weighting [SAW] (Hwang & Yoon, 1981), weighted product method [WPM], techniques for order preference by similarity to identical solution [TOPSIS] (Chen, Cheng, & Lan, 2016), data envelopment analysis [DEA] (Charnels, Cooper, & Rhodes, 1978), case-based

reasoning [CBR], elimination and choice translating reality [ELECTRE] (Roux & Elloy, 1985). AHP methodology consists of three main functions; structuring complexity, measurement, and synthesis (Forman & Gass, 2001).

The advantage of AHP over other MCDM techniques is its flexibility and competency to address underlying inconsistencies in the data, explicit significance of each criterion as it decomposes the data and builds a hierarchical structure of data, ability to capture both subjective and objective evaluation measure coupled with their consistency with alternatives. In addition to this, AHP does not require a training phase. It is based on an expert perception regarding the parameters.

3.2. Empirical Study

First, the symptoms of dengue which need to be considered for diagnosis are identified and it is represented in Table 1. Secondly, the general criteria are structured in hierarchy 1, next level specific criteria in hierarchy 2 and so on. Subsequently, pairwise comparison matrices (PCM) by level are established. Further, consistency index (CI) and consistency ratio (CR) are computed; if the value of CR is less than 0.1, priorities of variables are confirmed, otherwise PCM is updated by changing the assumed priority of symptoms. The detailed process of AHP implementation is represented in a flow diagram and is shown in Figure 3. Moreover, the complete process is divided into three steps as decomposition, prioritization and weight determination, which are elaborated in following sub-sections.

3.2.1. Decomposition

This phase constitutes building a hierarchical structure; the peak of the hierarchy is the goal which is the diagnosis of dengue virus. The decompositions of dengue diagnosis symptoms are presented in a hierarchy in Figure 2.

The analysis for splitting up was carried out with the help of a physician from a national capital region hospital. However, we are not permitted to disclose the name of the hospital. The primary goal; diagnosis is at level 1, followed by general symptoms in level 2, further being decomposed for detailed symptoms in level 3 which symptoms are characterized individually.

3.2.2. Prioritization

This phase involves pairwise comparison of all the possible pairs of criteria, being performed to determine the relative priority of the criteria by using a scale from 1 to 9 for the symptoms. Assigning priority values to selected criteria involves determining weights of those criteria depending on their importance in the problem context and it is performed by consulting with domain experts. The relative importance of those criteria, involves allocation of weights to individual criteria's. The numerical value of weight signifies the importance of the criteria over others. All the possible pairs of criteria in a particular level are being modelled as a pairwise comparison matrix (PCM). Similarly, a series of PCM, one for each level, is constructed. Pairwise comparison is purely on the perception of importance of a symptom over another, measured in an absolute scale. Judgement can be verbal, numeric or graphical. However, AHP uses ratio scale from 1 to 9 as shown in the Table 2. Value in the ratio scale 2 implies symptom, say; A is two times more influential than symptom B. Clearly B is $\frac{1}{2}$ as significant as A. However, few authors have considered their objective judgement scales. Hecker & Varges (1987) assumed a scale of power series; $s=x^2$ where $x=\{1, 2...9\}$. Further geometric series ($s=2^{x-1}$) has been employed (Lootsma, 1989) and even logarithmic functions are used ($s=\log_2(x+1)$) in their judgement (Ishizaka, Balkenbarg & Kaplan, 2010). Among all the proposed scale, linear scale has been used in most of the applications. To check the judgemental error if any caused by the experts' intuition, PCM presents a consistency check by calculating a factor called principal eigen value ($\lambda_{\max}$) or highest eigen value using different judgemental scales:

Table 1. Notation Representation Table

Level	Metrics	Abbreviation / Notation
1	Overall Diagnosis	ODS
2	Fever	FVR
	Pain	PN
	General malaise	GML
	Gastro intestinal Tract	GIT
	Liver profile	LP
	Haematology	HMT
	Respiratory System	RS
	Urology	URO
3	Fever	FVR
	Duration of fever	DF
	Joint pain	JP
	Headache	HD
	Rashes	RSH
	Itching	ICH
	Generalized weakness	GW
	Bleeding sites	BS
	Vomiting	VMT
	Abdominal pain	AP
	SGOT	SGT
	SGPT	SPT
	USG Finding	USG
	Haemoglobin	HMG
	Platelet count	PLC
	Leucocyte count	LC
	Serology	SRL
	Cough	CH
	Shortness of breath	SB
	Oliguria	OLG

Figure 2. Hierarchy of Dengue diagnosis symptoms

Figure 3. AHP detailed process

Table 2. Scales for the Pairwise Comparison (Saaty, 1980)

Absolute scale	Importance definition	Explanation
1	Equally important	Two criteria contribute equally to the objective
3	Moderately important	Perception favour one criterion over another narrowly
5	Strongly important	Judgment strongly favour one criterion over another
7	Very strongly important	Judgment very strongly favour one criterion over another
9	Extremely important	The evidence favouring one criterion over another is of highest possible validity
2, 4, 6, 8	Intermediate values	In case of balance, halfway
Reciprocals	Values for inverse comparison	If criterion C_1 had one of the above numbers assigned to it when compared with criterion C_2 , then C_2 has the reciprocal value when compared with C_1 .

$$\lambda_{max} = \sum_{i=1}^m \frac{(S \cdot V)_i}{m \cdot v_i}$$

m is number of independent rows. S represents pairwise comparison matrix and V is matrix eigen vector.

$$\text{Consistency Index CI} = \frac{\lambda_{max} - m}{m - 1}$$

$$\lambda_{max} = m$$

if PWC is perfectly consistent. Any inconsistency in expert judgement of symptoms is indicated by the value of $(\lambda_{max} - m)$, higher the difference implies inconsistency is higher. Random index (RI) is the consistency index of a randomly generated PWC (Saaty, 1990) also known as average random CI; it is a standard depends on number of criteria (Saaty, 1980). RI is 1.12 when number of criteria is 5, whereas value of RI is 1.49 when number of criteria is 10 and it is 1.59 for 15 criteria. Consistency ratio (CR) is the ratio between CI and RI.

It is evident from Figure 2 that in our data, the attributes FVR, PN, HMT, GML, URO, GIT, LP and RS are laid out hierarchically in level 2. The pairwise comparison matrices were obtained with the help of medical doctors. The PCM for the level 2 criteria of the AHP is represented in Table 3. Similarly, PCM for attributes present in level 3 (From Figure 2) is shown in Table 4.

3.2.3. Weight Determination

This phase discusses the computation of the weights of the symptoms by fusion of level 2 and level 3 variables. This step is accomplished through three main operations (Saaty, 1990):

- The summation of the values in each column of the pairwise comparison matrix.

Table 3. Level 2 Pairwise Comparison Matrix

	FVR	PN	HMT	GML	URO	GIT	LP	RS
FVR	1	5	1	2	6	6	6	6
PN	0.2	1	0.14	3	7	7	7	7
HMT	1	7	1	3	5	5	5	5
GML	0.5	0.33	0.33	1	1	1	1	1
URO	0.17	0.14	0.2	1	1	1	1	1
GIT	0.17	0.14	0.2	1	1	1	1	2
LP	0.17	0.14	0.2	1	1	1	1	2
RS	0.17	0.14	0.2	1	1	0.5	0.5	1

Table 4. Level 3 Pairwise Comparison Matrix

	DF	FVR	VMT	AP	OLG	JP	HD	HMG	PLC	LC	SGT	SPT	USG	SRL	GW	RSH	ICH	BS	SB	CH
DF	1	1	3	3	3	1	3	3	3	3	3	3	4	4	6	4	4	4	4	4
FVR	1	1	4	4	4	1	1	2	2	2	2	2	2	4	4	4	4	4	4	4
VMT	0.33	0.25	1	3	2	1	1	0.5	0.33	4	4	4	4	1	3	3	3	3	3	3
AP	0.33	0.25	0.33	1	0.5	0.3	0.2	0.2	0.25	0.25	0.33	0.3	0.33	0.5	2	2	3	3	3	3
OLG	0.33	0.25	0.5	2	1	0.3	0.5	1	0.25	1	3	3	3	1	5	5	5	5	5	5
JP	1	1	1	4	4	1	1	1	1	0.5	2	2	2	1	5	5	5	5	5	5
HD	0.33	1	1	4	2	1	1	0.33	0.33	0.33	3	3	2	0.3	5	5	5	5	6	6
HMG	0.33	0.5	2	4	1	1	3	1	1	2	3	3	3	5	5	5	5	5	5	5
PLC	0.33	0.5	3	4	4	1	3	1	1	3	3	3	3	3	3	5	5	5	3	3
LC	0.33	0.5	0.25	4	1	2	3	0.5	0.33	1	2	2	2	2	2	2	3	4	4	5
SGT	0.33	0.5	0.25	3	0.33	0.5	0.33	0.33	0.33	0.5	1	1	1	0.5	4	4	4	4	4	5
SPT	0.33	0.5	0.25	3	0.33	0.5	0.33	0.33	0.33	0.5	1	1	2	0.5	2	2	7	6	6	6
USG	0.25	0.5	0.25	3	0.33	0.5	0.5	0.33	0.33	0.5	1	0.5	1	1	5	5	5	5	5	5
SRL	0.25	0.25	1	2	1	1	3	0.2	0.33	0.5	2	2	1	1	4	4	4	4	5	4
GW	0.17	0.25	0.33	0.5	0.2	0.2	0.2	0.2	0.33	0.5	0.25	0.5	0.2	0.3	1	1	2	5	5	4
RSH	0.25	0.25	0.33	0.5	0.2	0.2	0.2	0.2	0.2	0.5	0.25	0.5	0.2	0.3	1	1	4	4	4	3
ICH	0.25	0.25	0.33	0.3	0.2	0.2	0.2	0.2	0.2	0.33	0.25	0.1	0.2	0.3	0.5	0.25	1	3	3	3
BS	0.25	0.25	0.33	0.3	0.2	0.2	0.2	0.2	0.2	0.25	0.25	0.2	0.2	0.3	0.2	0.25	0.3	1	3	3
SB	0.25	0.25	0.33	0.3	0.2	0.2	0.17	0.2	0.33	0.25	0.25	0.2	0.2	0.2	0.2	0.25	0.3	0.3	1	2
CH	0.25	0.25	0.33	0.3	0.2	0.2	0.17	0.2	0.33	0.2	0.2	0.2	0.2	0.3	0.25	0.33	0.3	0.3	1	1

Figure 4. Priorities of level 2 parameters

Figure 5. Priorities of level 3 parameters

- The division of each element in the pairwise comparison matrix by its column total.
- The calculation of the average of the elements in each row of the pairwise comparison matrix (normalising inputs).

Having performed the above calculations for our dengue data, the relative weights of attributes in level 2 (FVR... RS) are computed and is represented in Figure 4. Furthermore, relative priorities for attributes in level 3(FVR, DF... CH) are computed and exhibited in Figure 5. The eigen values and eigen vector for level 2 and 3 have been calculated. the level 2 diagnostic criteria evaluation gives

Table 5. Rating of patients on Dengue diagnosis parameters

	DF	FVR	VMT	AP	OLG	JP	HD	HMG	PLC	LC	SRL	SGT	SPT	USG	GW	RSH	ICH	BS	SB	CH
P1	4	4	2	1	2	2	1	1	4	4	3	4	4	4	1	2	1	1	1	1
P2	4	3	3	2	1	2	2	3	4	4	3	4	4	4	1	1	1	1	2	2
P3	2	3	2	1	1	2	2	1	4	4	2	4	4	2	2	1	1	2	1	1
P4	4	3	2	1	1	1	1	1	4	4	3	3	3	2	2	1	1	1	1	1
P5	4	4	2	2	1	1	1	4	4	2	3	3	2	2	1	2	1	1	2	1
P6	4	3	1	1	1	1	1	1	3	2	2	2	2	2	2	1	1	1	1	1
P7	2	3	2	2	2	1	2	2	1	1	1	1	2	2	2	1	1	1	1	1
P8	4	3	1	1	1	1	1	3	4	4	3	2	2	1	1	1	1	1	1	1
P9	4	3	2	1	1	1	1	3	4	2	3	3	2	2	2	2	1	1	1	1
P10	4	3	1	1	1	1	2	2	4	2	4	4	4	2	1	1	1	2	2	1
P11	2	3	2	2	1	1	1	2	4	2	2	4	4	2	2	1	1	1	1	1
P12	3	3	1	1	1	1	1	2	4	2	3	4	4	2	1	1	1	2	1	1
P13	3	3	2	1	1	1	1	4	4	4	3	4	4	2	4	2	1	1	1	1
P14	2	3	1	1	1	1	2	1	1	2	3	3	3	2	2	1	1	1	1	1
P15	4	3	3	2	2	1	2	1	3	2	3	3	4	2	2	1	1	1	1	1
P16	2	2	2	1	1	1	2	1	2	3	3	2	2	2	2	1	1	1	1	1
P17	4	4	1	1	2	1	2	2	2	3	2	4	4	2	2	1	1	2	1	1
P18	3	2	2	1	1	1	2	1	3	3	3	3	3	2	1	1	1	1	1	1
P19	5	5	4	3	1	3	3	4	5	3	4	3	3	3	3	3	3	1	1	1
P20	4	4	3	3	1	3	3	3	3	3	3	3	2	2	2	2	2	1	2	2
P21	5	5	4	4	1	4	4	5	5	4	4	3	3	3	3	3	3	1	2	3
P22	4	4	2	2	1	2	3	3	3	3	3	2	2	2	2	2	2	1	1	2
P23	4	3	2	1	1	1	2	3	3	3	3	2	3	2	2	1	1	1	1	2
P24	3	3	2	1	1	1	2	2	2	2	2	3	3	2	2	1	1	1	1	2
P25	4	3	3	4	1	2	2	2	2	2	2	2	2	2	2	1	1	1	1	2

an eigenvector, k_1 , while the level 3 variables produce the eigenvector, k_2 , give the prognostic factor index (PFI), for level2 criteria, while k_2 combines with the column vector of the level 3 variables to give the net prognostic factor index (NPFI) for level 3 variables:

$$(PFI)_2 = 0.28FVR + 0.17PN + 0.31HMT + 0.05GML + 0.04URO + 0.044LP + 0.044GIT + 0.035RS$$

$$NPFI = 0.115DF + 0.097FVR + 0.068VMT + 0.023AP + 0.056OLG + 0.074JP + 0.063HD + 0.088HMG + 0.092PLC + 0.059LC + 0.038SGT + 0.041SPT + 0.042USG + 0.052SRL + 0.021GW + 0.021RSH + 0.015ICH + 0.013BS + 0.012SB + 0.011CH \quad (1)$$

From the NPFI, it is learned that the probability of dengue attack is influenced by the parameters those having high values of eigen vector, such as duration of fever (0.28), fever (0.097) and platelet count (0.092).

3.2.4. Assessment

Having various symptoms of dengue infection, the patient is now being assessed for the magnitude and severity of infection. In order to straightforward this process, a numerical scale is formulated in the backdrop knowledge of the prospect values of the dengue symptoms considering low, borderline high, very high and extremely high occurrence. This is formally outlined in Algorithm 1.

Algorithm 1. Severity assessment

```

Input: NPFI numerical value
Output: Dengue intensity level
1. Begin
2. Read NPFI
3. If < NPFI lies between 1.0000 and 1.9999>,
4. then intensity of Dengue is Low;
5. else if < NPFI lies between 2.0000 and 2.4999>,
6. then intensity of Dengue is High;
7. else if < NPFI lies between 2.5000 and 2.9999>,
8. then intensity of Dengue is Very High;
9. else if < NPFI lies between 3.0000 and 3.9999>,
10. then intensity of Dengue Extremely High;
11. End

```

In this case study, we have considered 25 patients data for evaluation of the proposed technique. The original dengue data is transformed into quantitative scale and it is shown in Table 5. All the symptoms of patients P1, P2....P25 are represented in numerical scale. For an example, if fever (FVR) is more than 103F, we consider it as extremely high and assign numerical value 5 for it, similarly we scale as 4 for 102-103F, 3 for 100-102F and so on. Likewise, other parameters are quantified and the transformed data for all 25 patients are represented in Table 5.

In order to calculate NPFI score for patient P1, the values of all the parameters for P1 from Table 5 are put in the Eq(1), thus NPFI value of P1 is computed. Similarly, NPFI value for all the 25 patients are determined. Having the NPFI score, Algorithm1 is executed for assessing the severity and the result is represented in Table 6.

Table 6. Overall diagnosis using AHP

Patient#	NPFI	Assessment	Patient#	NPFI	Assessment
P1	2.431	High	P14	1.9	Low
P2	2.954	Very high	P15	2.42	High
P3	2.332	High	P16	1.8	Low
P4	2.386	High	P17	2.4	High
P5	2.623	Very high	P18	2.065	High
P6	1.977	Low	P19	3.635	Extreme
P7	1.712	Low	P20	2.914	Very high
P8	2.352	High	P21	3.976	Extreme
P9	2.424	High	P22	2.72	Very high
P10	2.412	High	P23	2.462	High
P11	2.176	High	P24	2.078	High
P12	2.24	High	P25	2.326	High
P13	2.616	Very high			

3.3 Fuzzy AHP Methodology for Dengue Diagnosis

Notwithstanding the fact that AHP's simplicity in dealing with both quantitative and qualitative data, it often fails in handling the vague and uncertainty involved in the decision makers' interpretation of knowledge. In crisp AHP, the perception of comparison of a symptom with another symptom is represented by a numeric value (1, 2, 3...). Presumably the priority of fever is higher than headache, while determining the possibility of occurrence of dengue, hence we assign 3 or 5 for fever in the priority matrix. By doing so, we are just transforming the linguistic assessment of the perception to a crisp number. However, human feelings and assessment are vague in most of the cases. Hence it is being criticised as how a qualitative judgement can be transformed to a single exact value. To address this issue, the theory developed by Zadeh (1965) known as fuzzy set theory (FST) is found to be appropriate one mulling it can model the data in the backdrop of uncertainty and impreciseness of human cognition. This theory enables the decision-makers to handle decision making problems quite efficiently (Mardani, Jusoh, & Zavadskas, 2015). It exploits and examines the problem extensively, represents and models the problem mathematically, interprets the intrinsic decision criteria and opts for alternate criteria, model the wide spectrum of qualitative judgement softly. Hence prioritisation task of AHP could be accomplished by employing the notion of FST (Büyüközkan, Çifçi, & Güleriyüz, 2011); consequently the weight determination of disease symptoms would be prejudiced. This hybridisation of AHP and FST known as Fuzzy AHP, a fuzzy extension of AHP is applied in a wide spectrum of decision making problems (Kahraman, Cebeci, & Ruan, 2004; Celik, Er, & Ozok, 2009; Chamodrakas, Batis, & Martakos, 2010; Chan & Kumar, 2007; Fu et al., 2006; Kang & Lee, 2007, Dura'n & Aguilo, 2008; Huang et al., 2008).

The essence of fuzzy logic lies in introduction of a membership function in crisp set that can be modelled to handle the vagueness in qualitative data (Büyüközkan & Çifçi, 2012). A fuzzy set is represented by a pair $\{x, \mu(x)\}$, x is a real number and membership function, $\mu(x)$ has a value lying between $[0, 1]$. However, membership function can be of triangular, trapezoidal and other shapes as well. We use triangular fuzzy number while weighing up the symptoms. A triangular fuzzy number is represented as $\langle l, m, u \rangle$ where $l \leq m \leq u$. The corresponding membership function is represented in Equation (2):

$$\mu_A(x) = \begin{cases} 0, (x < l) \vee (x > u) \\ \frac{x-l}{m-l}, l \leq x \leq m \\ \frac{u-x}{u-m}, m \leq x \leq u \end{cases} \quad (2)$$

3.4. Empirical Study

The experimental details of employing Fuzzy AHP in our case study is presented in following steps:

Step 1: Selecting criteria and sub-criteria.

As discussed in the previous section and represented in Figure 1, hierarchy of criteria and sub-criteria is framed with the prevalent symptoms of dengue fever by consultation with a specialist, working in a general hospital in the national capital region. Prioritisation of eight criteria is accomplished by comparing with fellow criteria; the linguistic terms are used for accessing relative strength of theirs. This is represented in Table 7.

Table 7. Fuzzy scale for pairwise comparison

Assessment	Fuzzy number	Definition	Membership function (l,m,u)
9	9	Extremely more importance (EMI)	(8, 9,10)
7	7	Very strong importance (VSI)	(6, 7, 8)
5	5	Strong importance (SI)	(4, 5, 6)
3	3	Moderate importance (MI)	(2, 3, 4)
1	1	Equal importance (EI)	(1, 1, 2)
1	1	Just equal	(1,1,1)

Step 2: Structure the fuzzy comparison matrix.

Fuzzy pairwise comparison matrix is formed using triangular fuzzy number and it is exhibited in Table 8. The matrix:

$$A = \begin{bmatrix} a_{11} & a_{12} \dots & a_{1n} \\ a_{21} & a_{22} \dots & a_{2n} \\ \dots & \dots & \dots \\ a_{n1} & a_{n2} \dots & a_{nn} \end{bmatrix}$$

where $a_{ij} = 1$ if $i = j$ or a_{ij} takes any value from (1, 3, 5, 7, 9) or $(\frac{1}{1}, \frac{1}{3}, \frac{1}{5}, \frac{1}{7}, \frac{1}{9})$ if $i \neq j$.

Step 3: Weighting criteria and sub-criteria.

Subsequent to framing of comparison matrix, each of the criteria; FVR, PN, GML, GIT, LP, HMT, RS and URO, are weighted relative to each other. Subsequently, every sub-criteria are weighted hierarchy wise (Nazari et al., 2018). For an example, sub-criteria joint pain (JP) and headache (HD)

Table 8. Fuzzy pairwise comparison matrix

	FVR	PN	GML	GIT	LP	HMT	RS	URO
FVR	(1,1,1)	(4, 5,6)	(2, 3,4)	(6, 7,8)	(6, 7,8)	(1, 1,2)	(6, 7,8)	(6, 7,8)
PN	(1/6,1/5,1/4)	(1,1,1)	(2, 3,4)	(6, 7,8)	(6, 7,8)	(1/8,1/7,1/6)	(6, 7,8)	(6, 7,8)
GML	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1,1,1)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)
GIT	(1/8,1/7,1/6)	1/8,1/7,1/6)	(1/2,1,1)	(1,1,1)	(1,1,2)	(1/6,1/5,1/4)	(2,3,4)	(1,1,2)
LP	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/2,1,1)	(1/2,1,1)	(1,1,1)	(1/6,1/5,1/4)	(2,3,4)	(1,1,2)
HMT	(1/2,1,1)	(6, 7,8)	(1/2,1,1)	(4,5,6)	(4,5,6)	(1,1,1)	(4,5,6)	(4,5,6)
RS	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/2,1,1)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/6,1/5,1/4)	(1,1,1)	(1,1,2)
URO	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/2,1,1)	(1/2,1,1)	(1/2,1,1)	(1/6,1/5,1/4)	(1/2,1,1)	(1,1,1)

is associated with criteria pain (PN). JP and HD are weighted and it is represented in Table 10. The priority of JP and HD is computed, whereas the final priority of JP and HD, which depends on priority of their parent criteria, is computed subsequently in Table 16. The detailed step-by-step computational method of calculating priorities of dengue symptoms, on processing over Table 8, is explained in following lines.

Evaluate sum of every criterion (in each row):

$$\sum_{j=1}^m M_{k_i}^j = \left(\sum_{j=1}^m a_{ij} \sum_{j=1}^m b_{ij} \sum_{j=1}^m c_{ij} \right)$$

$i = 1, 2, 3, \dots, n$, where i and j are criteria indices.

This gives rise to the following result:

$$\sum_{j=1}^8 M_{k_1}^j = (32, 38, 45) \text{ for criteria FVR}$$

similarly:

$$\sum_{j=1}^8 M_{k_2}^j = (27.2916, 32.6428, 37.4166) \text{ for criteria PN}$$

$$\sum_{j=1}^8 M_{k_3}^j = (6.5, 6.6666, 12) \text{ for criteria GML}$$

$$\sum_{j=1}^8 M_{k_4}^j = (5.9166, 7.4857, 10.5833) \text{ for criteria GIT}$$

$$\sum_{j=1}^8 M_{k_5}^j = (5.4166, 7.4857, 9.5833) \text{ for criteria LP}$$

$$\sum_{j=1}^8 M_{k_6}^j = (24, 30, 35) \text{ for criteria HMT}$$

$$\sum_{j=1}^8 M_{k_7}^j = (3.4166, 4.1522, 5.5833) \text{ for criteria RS}$$

and:

$$\sum_{j=1}^8 M_{k_8}^j = (3.4166, 5.4857, 5.5833) \text{ for criteria URO}$$

2. Calculate the sum of the fuzzy numbers over all rows and columns (over all criteria):

$$\sum_{i=1}^n \sum_{j=1}^m M_{k_i}^j = (\sum_{i=1}^n \sum_{j=1}^m a_{ij} \sum_{i=1}^n \sum_{j=1}^m b_{ij} \sum_{i=1}^n \sum_{j=1}^m c_{ij})$$

This results:

$$\sum_{i=1}^8 \sum_{j=1}^8 M_{k_i}^j = (107.9624, 131.9188, 160.7498)$$

3. Evaluate the inverse of the previous step where the fuzzy numbers are rearranged.

It is expressed as:

$$\left[\sum_{i=1}^n \sum_{j=1}^m M_{k_i}^j \right]^{-1}$$

applying it over data in Table 8, we have:

$$\sum_{i=1}^8 \sum_{j=1}^8 M_{k_i}^j = \left(\frac{1}{160.7498}, \frac{1}{131.9188}, \frac{1}{107.9624} \right)$$

4. Then multiply the value obtained in Step 1 by that of Step 3, we have:

$$S_i = \sum_{j=1}^m M_{k_i}^j \otimes \left[\sum_{i=1}^n \sum_{j=1}^m M_{k_i}^j \right]^{-1}$$

This results:

$$S_1 = \left(\frac{32}{160.7498}, \frac{38}{131.9188}, \frac{45}{107.9624} \right) = (0.199, 0.288, 0.4168)$$

Similarly, we have:

$$S_2 = (0.1697, 0.2474, 0.3465)$$

$$S_3 = (0.0404, 0.0505, 0.1111)$$

$$S_4 = (0.0368, 0.0567, 0.0980)$$

$$S_5 = (0.0336, 0.0567, 0.0887)$$

$$S_6 = (0.1493, 0.2274, 0.3241)$$

$$S_7 = (0.0212, 0.0314, 0.0517)$$

and:

$$S_8 = (0.0212, 0.0415, 0.0517)$$

Finally, two fuzzy numbers must be compared:

$$V(M_2 \geq M_1) = \text{Supremum} [\min (\mu_{M_1}(x), \mu_{M_2}(y))]]$$

and can be equivalently expressed as follows: Given fuzzy number $M_1(l_1, m_1, u_1)$ and $M_2(l_2, m_2, u_2)$:

$$V(M_2 \geq M_1) = 1$$

$$\text{if } m_2 \geq m_1 \text{ else it is } \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}.$$

By applying above formula we will get:

$$\begin{aligned} V(S_1 \geq S_2) &= 1 \\ V(S_1 \geq S_3) &= 1 \\ V(S_1 \geq S_4) &= 1 \\ V(S_1 \geq S_5) &= 1 \\ V(S_1 \geq S_6) &= 1 \\ V(S_1 \geq S_7) &= 1 \\ V(S_1 \geq S_8) &= 1 \\ V(S_2 \geq S_1) &= 0.7841 \\ V(S_2 \geq S_3) &= 1 \\ V(S_2 \geq S_4) &= 1 \\ V(S_2 \geq S_5) &= 1 \\ V(S_2 \geq S_6) &= 1 \\ V(S_2 \geq S_7) &= 1 \\ V(S_2 \geq S_8) &= 1 \end{aligned}$$

Similarly after calculating for all criteria and the minimum degree of possibility of superiority of each criterion over another is obtained. This further decides the weight vectors of the criteria. The weight vector is given as:

$$W = \{1, 0.7841, 0.2754, 0.4296, 0.5504, 0.6736, 0.3706, 0.4950\}$$

Now we need to normalize the weights, because the outcomes of the previous step are non-normalized weights. The normalized weights can be obtained by dividing the weights (of the previous step) by total weights (summation of all non-normalized weights). This results in:

$$W = \{0.2184, 0.1712, 0.0601, 0.0938, 0.1202, 0.1471, 0.0809, 0.1081\}$$

This is represented graphically in Figure 6.

Figure 6. Priority of criteria

Table 9. Fuzzy comparison matrix of the sub-criteria with respect to FVR

	FVR	DF	Priority
FVR	(1,1,1)	(1,1,2)	0.5
DF	(1/2,1,1)	(1,1,1)	0.5

Table 10. Fuzzy comparison matrix of the sub-criteria with respect to PN

	JP	HD	Priority
JP	(1,1,1)	(1,1,2)	0.5
HD	(1/2,1,1)	(1,1,1)	0.5

Table 11. Fuzzy comparison matrix of the sub-criteria with respect to GML

	RSH	ICH	GW	BS	Priority
RSH	(1,1,1)	(4,5,6)	(1,1,1)	(4,5,6)	0.4137
ICH	(1/6,1/5,1/4)	(1,1,1)	(1/4,1/3,1/2)	(2,3,4)	0.0856
GW	(1,1,2)	(2,3,4)	(1,1,1)	(6,7,8)	0.4137
BS	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1/8,1/7,1/6)	(1,1,1)	0.0867

Table 12. Fuzzy comparison matrix of the sub-criteria with respect to GIT

	VMT	AP	Priority
VMT	(1,1,1)	(2,3,4)	0.7832
AP	(1/4,1/3,1/2)	(1,1,1)	0.2167

Table 13. Fuzzy comparison matrix of the sub-criteria with respect to LP

	SGT	SPT	USG	Priority
SGT	(1,1,1)	(1,1,2)	(1,1,2)	0.3591
SPT	(1/2,1,1)	(1,1,1)	(2,3,4)	0.5596
USG	(1/2,1,1)	(1/4,1/3,1/2)	(1,1,1)	0.0811

Table 14. Fuzzy comparison matrix of the sub-criteria with respect to RS

	CH	SB	Priority
CH	(1,1,1)	(1/4,1/3,1/2)	0.2170
SB	(2,3,4)	(1,1,1)	0.7826

Likewise, the above methods are being executed for the criteria's FVR, PN, GML, GIT, LP, RS and HMT to calculate their weightage and the results are shown in Tables 9–15 respectively. Since the criteria, URO has single sub-criteria (OLG), the priority of OLG is equal with URO. From Table 9. Criteria FVR is decomposed into sub-criteria's FVR and DF, consequently the weightages of sub-criteria's FVR and DF are 0.5 each. Similarly, priorities of other sub-criteria are computed in Tables 10-15.

Table 15. Fuzzy comparison matrix of the sub-criteria with respect to HMT

	HMG	PLC	LC	SRL	Priority
HMG	(1,1,1)	(1,1,2)	(4,5,6)	(6,7,8)	0.4731
PLC	(1/2,1,1)	(1,1,1)	(4,5,6)	(4,5,6)	0.3681
LC	(1/6,1/5,1/4)	(1/6,1/5,1/4)	(1,1,1)	(2,3,4)	0.0645
SRL	(1/8,1/7,1/6)	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1,1,1)	0.0941

- The overall priority of sub- criteria can be obtained by multiplying its computed priority with weightage of parent criteria. The details are exhibited in Table 16.

From the Table 16, we have comparative priorities of all the sub-criteria's and it is exhibited graphically in Figure 7.

Step 4: Evaluating patient's condition.

Having weightage value of all the twenty sub-criteria as represented in Table 16, we calculate net prognostic factor index (NPFI) as below:

$$\text{NPFI} = 0.1092\text{FVR} + 0.1092\text{DF} + 0.0856\text{JP} + 0.0856\text{HD} + 0.0248\text{RSH} + 0.0051\text{ICH} + 0.0248\text{GW} + 0.0052\text{BS} + 0.0336\text{SGT} + 0.0524\text{SPT} + 0.0076\text{USG} + 0.0941\text{VMT} + 0.0260\text{AP} + 0.0695\text{HMG} + 0.0541\text{PLC} + 0.0094\text{LC} + 0.0138\text{SRL} + 0.0175\text{CH} + 0.0633\text{SB} + 0.1081\text{OLG}$$

Table 16. Priority for criteria and sub-criteria for the diagnosis of dengue disease

Criteria	Priority of criteria	Sub-criteria	Priority of sub-criteria	Overall priority of sub-criteria
C1(FVR)	0.2184	FVR	0.5	0.1092
		DF	0.5	0.1092
C2(PN)	0.1712	JP	0.5	0.0856
		HD	0.5	0.0856
C3(GML)	0.0601	RSH	0.4137	0.0248
		ICH	0.0856	0.0051
		GW	0.4137	0.0248
		BS	0.0867	0.0052
C4(LP)	0.0938	SGT	0.3591	0.0336
		SPT	0.5596	0.0524
		USG	0.0811	0.0076
C5(GIT)	0.1202	VMT	0.7832	0.0941
		A P	0.2167	0.0260
C6(HMT)	0.1471	HMG	0.4731	0.0695
		PLC	0.3681	0.0541
		LC	0.0645	0.0094
		SRL	0.0941	0.0138
C7(RS)	0.0809	CH	0.2170	0.0175
		SB	0.7826	0.0633
C8(URO)	0.1081	OLG	1	0.1081

Figure 7. Priority of sub- criteria

Next, the value of symptoms of patient P1 as collected from the hospital is substituted in above equation, it computes NPFI for patient P1. Similarly, numeric NPFI values for twenty-five patients P1, P2, P25 are computed and it is exhibited in Table 17. Next, we apply Algorithm 1, as defined in Section 3.1, in order to measure the severity qualitatively and finally the assessment of patients are presented in Table 17.

Table 17. Overall diagnosis using FAHP

Sl. No	Patient#	NPFI	Assessment
1	P1	2.445	High
2	P2	2.649	Very High
3	P3	2.044	High
4	P4	2.035	High
5	P5	2.416	High
6	P6	1.794	Low
7	P7	1.775	Low
8	P8	2.007	High
9	P9	2.830	Very High
10	P10	2.133	High
11	P11	1.940	Low
12	P12	1.923	Low
13	P13	2.246	High
14	P14	1.735	Low
15	P15	2.283	High
16	P16	1.615	Low
17	P17	2.247	High
18	P18	2.060	High
19	P19	3.314	Extreme
20	P20	2.900	Very High
21	P21	3.704	Extreme
22	P22	2.515	Very High
23	P23	2.270	High
24	P24	1.957	Low
25	P25	2.264	High

4. RESULTS AND DISCUSSION

In this study, we performed an assessment of severity of dengue using AHP and FAHP separately for twenty five patients followed by a comparison of each case with the diagnostic evaluation of a medical expert. The summary of the diagnosis outcome, generated by AHP and FAHP, along with expert diagnosis are presented in Table 18. Having the diagnosis report of all the patients by an expert doctor, each of the patients are evaluated first by AHP, next by FAHP, followed by a comparison

Table 18. Overall Diagnostic Results

Sl. No	Patient#	AHP		FAHP		Expert Diagnosis	Matching
		NPFI	Severity	NPFI	Severity		
1	P1	2.431	High	2.445	High	High	EAF
2	P2	2.954	Very high	2.649	Very high	Very high	EAF
3	P3	2.332	High	2.044	High	High	EAF
4	P4	2.386	High	2.035	High	High	EAF
5	P5	2.623	Very high	2.416	High	High	EF
6	P6	1.977	Low	1.794	Low	Low	EAF
7	P7	1.712	Low	1.775	Low	Low	EAF
8	P8	2.352	High	2.007	High	High	EAF
9	P9	2.424	High	2.83	Very high	Very high	EF
10	P10	2.412	High	2.133	High	High	EAF
11	P11	2.176	High	1.94	Low	Low	EF
12	P12	2.24	High	1.923	Low	High	EA
13	P13	2.616	Very high	2.246	High	High	EF
14	P14	1.941	Low	1.735	Low	Low	EAF
15	P15	2.427	High	2.283	High	High	EAF
16	P16	1.8	Low	1.615	Low	Low	EAF
17	P17	2.419	High	2.247	High	High	EAF
18	P18	2.065	High	2.06	High	High	EAF
19	P19	3.635	Extreme	3.314	Extreme	Extreme	EAF
20	P20	2.914	Very high	2.9	Very high	Very high	EAF
21	P21	3.976	Extreme	3.704	Extreme	Extreme	EAF
22	P22	2.72	Very high	2.515	Very High	Very High	EAF
23	P23	2.462	High	2.27	High	High	EAF
24	P24	2.078	High	1.957	Low	Low	EF
25	P25	2.326	High	2.264	High	High	EAF

between these three results. It can be seen from the Table 18, the last column matching indicates exactness of the result of these three methods; EAF conveys, all the three diagnosis; expert (E), AHP (A) and FAHP (F) corresponds, while EA implies perfect matching between expert and AHP diagnosis, but FAHP diagnostic result does not match with either of them. Similarly EF signifies diagnosis provided by expert doctor matches with that of FAHP with a variation of AHP. From the table, clearly there is a matching of 80% between AHP's outcome and experts' investigation, whereas twenty four out of twenty five patients are diagnosed exactly both by doctor and FAHP, giving rise to a 96% match. Hence accuracies of AHP and FAHP are 80% and 96% respectively. Overall, 76% of diagnosis result of AHP and FAHP coincides. The Pearson Correlation signifies, a very high correlation among FAHP and doctors' diagnosis (0.974) while a correlation of 0.864 among doctor and AHP methodology. Further, the correlation of AHP/FAHP is very high (0.850). Additionally it indicates that all the false diagnosis of AHP and FAHP, which matched each other, had a deviation

of one linguistic value from the expert' diagnosis. Moreover, the result shows that, FAHP is slightly better than AHP in terms of matching with expert diagnosis.

The statistical analyses of the result of these three methods are outlined in Table 19. AHP diagnostic evaluation has a mean of 2.200 with standard deviation of 0.8165 (N=25). A simple t-test reveals that the t- value for AHP is 13.472 (df=24) for lower and upper extreme at 1.863 and 2.537 respectively. A simple χ^2 test for testing the hypothesis reveal that the null hypothesis as the categories of AHP occurs with equal probability is rejected at significant level 0.05 (p=0.004). Similarly, p-value for FAHP diagnosis is 0.028.

A graph showing the comparison result of AHP, FAHP and doctor's evaluation for all the 25 cases are represented in Figure 8.

Table 19. System Performance

	Mean	Std. Deviation	N	t	df	p	Pearson Correlation	
AHP	2.200	0.8165	25	13.472	24	0.004	F- 0.850	E- 0.864
FAHP	2.040	0.8888	25	11.476	24	0.028	A-0.850	E-0.974
Expert	2.120	0.8813	25	12.028	24	0.038	A- 0.864	F- 0.974

Figure 8. Case wise comparison of results

5. CONCLUSION AND FUTURE SCOPE

Decision support systems, is an attempt to solve decision making problems artificially, which requires human-like intelligence, follow a series of steps. Beginning with acquiring expert knowledge by questionnaire or interaction, and representing it by a rule base (Malek & Sadeghian, 2009), generating probable diagnosis, examining closely for exact matching of hypothesis and quantifying it with additional historical cases. DSS provides the physicians in time clinical information and assessment for the diagnosis and treatment of Dengue.

In medical diagnosis, quite a large number of features are being analysed for an exhaustive and sound decision making. Rather than analysing individually all the parameters, which involve complexity, a hierarchy of a group of the parameters is evaluated for the best result. Since the inception of AHP by Satty, several investigations have been carried out for the use of AHP and FAHP for decision making in medical diagnosis. However, comparisons of AHP and FAHP, in the case of tropical disease like malaria, dengue have not been reported, especially the application of those two techniques for a single case while dealing with a clinical diagnosis case. AHP and Fuzzy based reasoning simulate the thinking and reasoning process on account of their flexibility in modelling the reasoning process. In our study, no significant difference is observed when analysing dengue data either by using AHP or FAHP. However, FAHP yielded a slightly better result in terms of accuracy than AHP. Hence a DSS built on executing either of two techniques, can be equally supportive for a less-experienced physician.

We have validated the model by using few patients' record; however, the model can be tested for a large pool of similar data. The clinical assessment criteria may be further developed by incorporating co-morbidity conditions, which exist in the original dataset; they are diabetes, hypertension, COPD, dengue with malaria, dengue with chikungunya. In the future other approximation methods such as rough set, soft set integrating with decision making techniques such as TOPSIS, DEA can be explored. Additionally, hybrid techniques such as ANFIS can also be employed in the current data, and the result can be compared with the existing one.

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