International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:10, No:2, 2016

A Framework for Early Differential Diagnosis of Tropical Confusable Diseases Using the Fuzzy Cognitive Map Engine

Faith-Michael E. Uzoka, Boluwaji A. Akinnuwesi, Taiwo Amoo, Flora Aladi, Stephen Fashoto, Moses Olaniyan, Joseph Osuji

***Abstract*—**The overarching aim of this study is to develop a soft-computing system for the differential diagnosis of tropical diseases. These conditions are of concern to health bodies, physicians, and the community at large because of their mortality rates, and difficulties in early diagnosis due to the fact that they present with symptoms that overlap, and thus become 'confusable'. We report on the first phase of our study, which focuses on the development of a fuzzy cognitive map model for early differential diagnosis of tropical diseases. We used malaria as a case disease to show the effectiveness of the FCM technology as an aid to the medical practitioner in the diagnosis of tropical diseases. Our model takes cognizance of manifested symptoms and other non-clinical factors that could contribute to symptoms manifestations. Our model showed 85% accuracy in diagnosis, as against the physicians' initial hypothesis, which stood at 55% accuracy. It is expected that the next stage of our study will provide a multi-disease, multi-symptom model that also improves efficiency by utilizing a decision support filter that works on an algorithm, which mimics the physician's diagnosis process.

***Keywords*—**Medical diagnosis, tropical diseases, fuzzy cognitive map, decision support filters, malaria differential diagnosis.

I. Introduction

A number of tropical diseases present with symptoms that overlap, and thus become 'confusable'. These diseases are of concern to health bodies, physicians, and the community at large because of difficulties in early diagnosis and their mortality rates. According to the World Health Organization [1] malaria, diarrhoeal diseases and tuberculosis are on the list of top ten killers in low and middle income countries. The need for accurate and timely diagnosis of these diseases is fast becoming a global issue. A number of tourists visit tropical regions of Africa, Asia and South America, and return home with some of these tropical (sometimes infectious) diseases.

The task of making an effective and efficient early differential diagnosis of tropical diseases is pivotal in ensuring that the illness does not take a dangerous trajectory [2]. It has been recognized in [3] that quick and accurate diagnosis and timely initiation of treatment is a sine-qua-non to the reduction of complications, costs and human suffering. One key component of patient care and hospital efficiency is the optimization of the diagnostic process in terms of the number and duration of patient examinations, with corresponding accuracy, sensitivity, and specificity, as this is known to reduce morbidity and mortality rates, control costs and improve both doctor-patient and community-facility relationships [4]. Medical diagnosis, like other diagnostic processes, is made more complex because of the level of imprecision involved. Patients may not be able to describe exactly what has happened to them or how they feel; doctors and other health care practitioners may not understand or interpret exactly what they hear or observe; laboratory reports are not instantaneous and may come with some degree of error [5]. This conundrum is compounded when a particular pathological process presents with ambiguous symptoms that are similar to those of other conditions, as in the case of a number of tropical diseases, or in situations when expert medical practitioners are inexperienced or in short supply and pressured [6].

A number of physicians (especially in non-tropical regions) may not have adequate experiential knowledge to effectively carry out an early diagnosis and therapy of tropical diseases. *We believe that a decision support system (DSS) would significantly improve the efficiency and effectiveness of physicians in early differential diagnosis of tropical confusable diseases*. Clinical decision support systems help in reducing cost and bring about improvement in practitioner performance and consultative outcomes by utilizing patient's data and some inference procedures to generate case specific advice and suggestions to the physician [7], [8]. A number of medical decision support models have attempted to address the subjects of knowledge acquisition, representation, and utilization in medical diagnosis. However, most of these models have only addressed some individual and in most cases, non-tropical diseases. There is also the exclusion of non-clinical (especially environmental and personal factors) in the construction of most decision support systems. These factors have the potentials of exerting subliminal effects on symptom manifestations.

There is the need to develop a decision support model for

Faith-Michael E. Uzoka is with the Dept. of Math and Computing, Mount Royal Univ. Calgary, Canada (e-mail: fuzoka@mtroyal.ca).
Boluwaji A. Akinnuwesi is with the Dept. of Computer Science, Lagos State University, Lagos, Nigeria.
Taiwo Amoo, is with the Dept. of Computer Science, Covenant University, Ota, Nigeria.
Flora Aladi is with the Health Watch Medical Clinic, Calgary, Canada.
Stephen Fashoto is with the School of Computing, Kampala International University, Uganda.
Moses Olaniyan is with the Dept. of Computer Engineering, Federal University, Oye, Nigeria.
Joseph Osuji is with the School of Nursing, Mount Royal University, Calgary, Canada.

diagnosing tropical diseases, with consideration given to the complex semantic and multi-dimensional causal relationships that exist among diseases, symptoms and other non-clinical (mostly environmental and socio-economic) concomitants. Our study intends to address this need by developing a decision support model, based on the experiential knowledge of medical experts. An effective decision support model for diagnosis of tropical diseases can only be developed though the engineering of experiential knowledge of physicians who are experts in the management of such conditions. This knowledge resides mainly in the tropics, where the physicians constantly deal with these conditions. In this paper, we present the framework of our study, which attempts to model the physician's diagnosis process, using the fuzzy cognitive map inference structure.

II. Tropical Diseases

Tropical diseases are those diseases that are prevalent in, or unique to tropical and subtropical regions. They are of concern to communities, health organizations and individuals because of: 1) difficulty in early diagnosis, and 2) high mortality rates. The World Health Organization recognizes some tropical diseases as *neglected* because of the lack of adequate attention to these diseases, which are not so rampant, but still exist. Fig. 1 shows some examples of tropical diseases that are either confusable, neglected or infectious. We argue that while there is a huge amount of attention on the prevention and cure of some of the tropical diseases (e.g. malaria), a number of the tropical diseases are neglected.

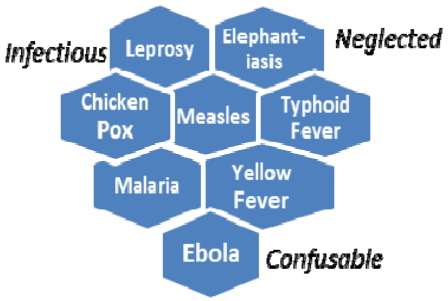

Fig. 1 Examples of Tropical Diseases

Malaria is one of the tropical diseases that has drawn the attention of the international health community. World Health Organization in 2015 reported that about 3.2 billion people were at risk of malaria infection globally, while 480,000 died of malaria attack in 2015. Sub-Saharan Africa accounted for 91% of the deaths. Though data on a number of tropical infections remain unavailable in some parts of the world, it is noted that these conditions are not limited to tropics. There is the spread of this conditions to other parts of the world through tourism [9]. The World Health Organization data in [1] on tropical diseases (Table I) is concerning.

TABLE I
Tropical Disease Infections in 2013 [1]

WHO Region	Malaria	Measles	Yellow Fever	Tuberculosis	Cholera
Africa	44,737,004	171,178	277	1,337,696	49465
Americas	427,014	490	26	220510	61152
South East Asia	1,613,722	30101	No Data	2,098,170	6049
Europe	No Data	26385	0	297,545	No Data
Eastern Mediterranean	1,060,999	20844	No Data	434,473	12147
Western pacific	398,530	31706	No Data	1,342,404	246
Global	48,237,390	280,744	No Data	5,730,798	No Data

While it is recognized that the tropical diseases are not localized to tropical developing regions, it is important to note that these regions (Africa, South East Asia, and Eastern Mediterranean) are highly affected. Disease management involves prevention, diagnosis, and treatment. Global health organizations have invested huge amounts of money on prevention and treatment. The diagnosis of these tropical diseases still poses a challenge in terms of: 1). *Process* - a number of tropical diseases present with confusable symptoms, and risk factors are confused for symptoms; 2). *Access* - low access to medical personnel and facilities, especially in developing countries; and 3). *Affordability* - most people are unable to afford health care, and in most cases, resort to self-diagnosis and self-medication. The uncomfortable reality presented by [1] is that a number of less developing countries have serious health care access issues (Table II).

TABLE II
Health Care Assess Parameters

		Per 10,000 Population			
WHO Region	Per Capita health expenditure ($)	Physicians	Nurses & Midwives	Pharmaceutical Personnel	Hospitals
Africa	105	2.7	12.4	0.8	0.8
Americas	3,599	21.5	44.9	7.2	No Data
South East Asia	68	5.9	15.3	3.8	No Data
Europe	2270	32.1	80.2	6.8	No Data
Eastern Mediterranean	245	12.7	18.0	6.5	0.9
Western pacific	730	15.5	26.2	4.6	No Data

Considering the very low health care budget in developing regions (especially Africa), there is the need to find alternate low cost, and efficient means of ensuring access to health care. The use of information technology has severally been advocated for the management of diseases, especially in situations, where traditional access is a challenge. Diffusion of technology (especially cell phones and tablets) has increased considerably in developing countries (especially in Africa and Asia) in the last decade [10]. Therefore, solutions that would utilize information technology in ensuring better health care access would be of high utility in the developing world.

III. Medical Decision Support Systems

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 [11]. By early 1970's, it became evident that statistical tools were unable to deal with very complex clinical problems [12], paving the way for the exploration of artificial intelligence (AI) principles in medical diagnosis. This era 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 explains the physicians thinking processes and reasoning in medical diagnosis [11]. Pattern recognition methods were the focus of AI applications in medical diagnosis until 1974, when Shortliffe published the first rule based approach for therapy advice in infectious diseases [13]. Rule based programs used the "if-then-rules" in chains of deductions to reach a conclusion. However, it was later observed that purely rule-based systems were only good for narrow domains of medicine, because most serious diagnostic problems were so broad and complex that straightforward attempts to chain together larger sets of rules encountered major difficulties, hence such systems lacked the model of the disease or clinical reasoning [5].

As research in the application of DSS in medical diagnosis deepened, emphasis shifted to the representation and utilization of unstructured, imprecise, and dynamic knowledge. It is noted in [14], [15] that uncertainty and imprecision characterize the sources of information available to medical DSSs. These sources include the patient, physician, laboratory and other technical methods of evaluation, including the mathematical models that simulate the diagnostic process. Medical DSS researchers have resorted to soft-computing techniques for the management of issues of uncertainty and imprecision in medical diagnosis [16].

Over time, it become a popular trend to develop medical decision support systems that tend to harness the synergy between two or more soft-computing technologies in order to increase efficiency and effectiveness in the management of imprecision (e.g. [17]-[20]. One of the highly effective and efficient hybrid technologies is the fuzzy-cognitive map [FCM] [21], which is a hybridization of the fuzzy logic [22] and the cognitive map [CM] concept [23]. The use of FCM in medical diagnosis was not very popular until the early 2000s when a number of medical decision support system researchers found that a synergistic combination of the fuzzy logic and cognitive map modeling techniques is known to be very effective in dealing with vagueness, uncertainty, and multi-factor causal associations in medical diagnosis (e.g. [24]). In [25], it was established that the FCM is a viable knowledge extraction method which provides the opportunity of dynamically combining information obtained during patient interrogation with physicians' experiential knowledge engineered into the knowledge base. In [26] FCM method was employed in medical DSS modelling that showed the effects of symptom ordering, temporal uncertainty and symptom strengths on the diagnosis efficiency.

The recognition of the existence of multi-causal relationships between the disease(s) and symptoms on one hand and among symptoms on the other hand, makes the use of FCM very appropriate in medical diagnosis decision modeling. This is because of the ability of the FCM to simplify the multivariate relationships that are at play in medical diagnosis. The physician is challenged with the need to piece through a reasonable amount of multi-dimensional input information, which could become explosive [27], especially considering the fact that the human mind can only handle a limited amount (7±2 pieces) of combinatorial information at the same time before the decision process begins to experience decay in quality [28]. A number of recent medical DSS models have taken advantage of the strengths of the FCM in uncertainty and imprecision management (e.g. [29]-[32]). However, these models are not scalable to multi-disease (especially tropical disease) analysis. There is the need to develop a decision support model that addresses a broad spectrum of 'confusable' tropical conditions.

IV. System Architecture

Our model, which is based on the FCM procedure attempts to do the following: 1). utilize some brute-force algorithmic procedure to mimic the mental algorithm employed by physicians in the diagnosis process; 2) minimize the number of steps in the initial investigation process in order to arrive at a hypothesis; 3) Increase the efficiency and effectiveness of diagnosis by considering a broader spectrum of symptoms and affecters, and implementing meta-hypothesis that increases physician's confidence in the diagnosis process. FCM has been chosen for this study for the following reasons:

a. It is a dynamic modeling tool that helps in representing knowledge in an environment of uncertainty and imprecision. In [26], the authors considered the etiology of diseases and demonstrated that FCMs can encode fuzzy causal structures in order to support symptom information elicitation and diagnostic reasoning.
b. FCMs can exhibit enhanced usefulness through their ability to evolve dynamically through recurrent feedback and the facility to combine knowledge bases through the union of a number of FCMs [33], [34], [25]
c. FCM is one of the few decision support systems that are characterized by fast computation, which provides real-time results, and provides fast and crisp modeling methodology for creating and simulating qualitative

dynamic systems with feedback [35], [36].

The architecture of our proposed system (Fig. 2) is adapted from the hybridization model in [37] and the FCM model with learning and feedback mechanism presented by [29]. It consists of the knowledge base, inference module; diagnostic system; and user Interface.

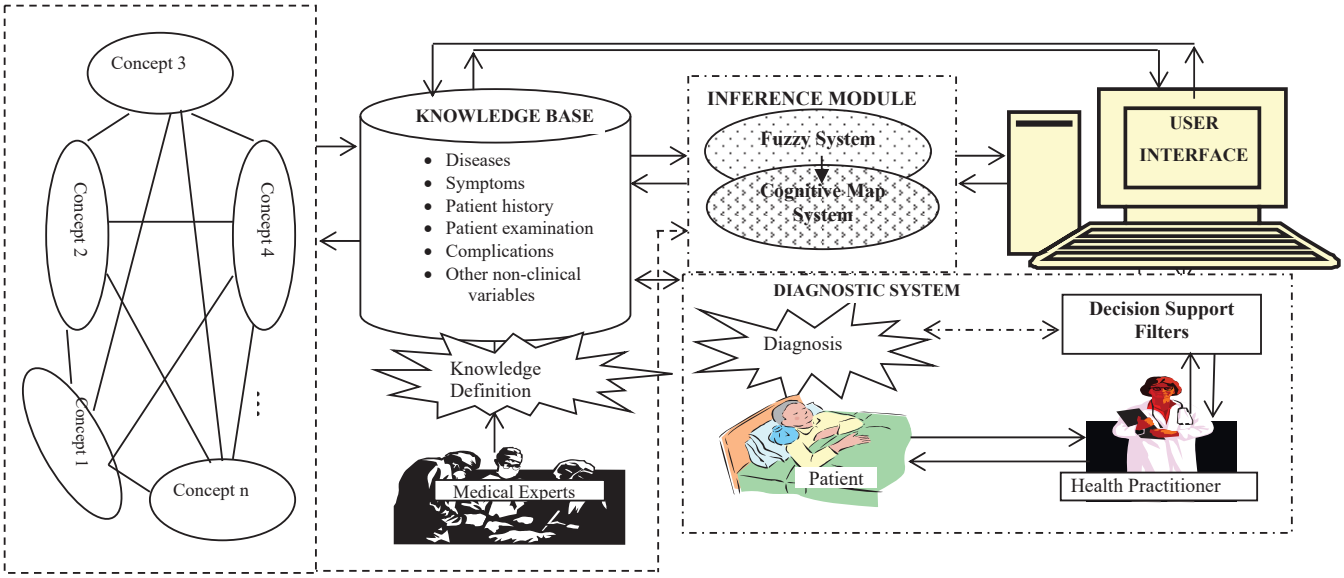

Fig. 2 The Architecture of the Fuzzy-Cognitive Map Medical Diagnosis System

Knowledge is a key factor in the performance of intelligent systems. The *knowledge base* is composed of quantitative (structured) and qualitative (unstructured) knowledge of medical diagnosis. The structured knowledge is concerned with facts, rules and events, which are commonly agreed upon by experts in the field of medicine. The unstructured knowledge is heuristic knowledge, which is acquired by domain (medical) experts through experience, good practice, guesses and judgment [38], [39].

The *inference module* is concerned with the adoption of an appropriate line of diagnostic reasoning, leading to the formulation of a body of consultative advice on a given medical phenomenon. Information generated from patient's interrogation is converted into fuzzy scales before utilization in the diagnostic analysis. The system then sets up a multi-dimensional relation of diseases, symptoms, non-clinical factors, weighting factors and intensities, leading to the identification of the suspected disease(s). The inference module interfaces with the cognitive map analytical model (CMAM), which provides it with a dynamic input for learning and adaptation.

The Decision Support Filter

The decision support filter attempts to provide an ability for the system to mimic the mental model of diagnosis by physicians.

From medical literature, there seems to be no laid down number of major symptoms (N_s) to be obtained from a patient before a physician could start arriving at some hypothesis relating to some diseases ($J_{D;\ D}$ = disease hypothesized). A quicker arrival at hypotheses facilitates a more directed further investigation. This increases the efficiency and effectiveness of diagnosis. A stronger hypothesis (JD. <JD..<JD…) increases the then confidence of the physician in focusing on a given disease D.

From experiential information obtained from practicing physicians, averagely, elicitation of two or three symptoms should be adequate in hypothesizing on the disease(s) (i.e. J_D). Sometimes, a combinatorial analysis of previous hypothesis with additional symptom elicitation results in a stronger meta-hypothesis (J_D..or J_D…)

From our disease symptom matrix, it is evident that fever is common to all of the tropical diseases under consideration. Therefore, the presence fever points to the possible existence of any of the following conditions: Malaria (M), Typhoid Fever (T), Chicken Pox (C), Measles (S), Hepatities B(H), Yellow Fever(Y) and Urinary Track Infection (U) in elderly and children]. This implies that the first point of entry into the symptom elicitation could be the determination of the presence or absence of fever.

The goals of our model are:

a. To utilize some brute-force algorithmic procedure to mimic the mental algorithm employed by physicians in the diagnosis process.
b. To minimize the number of steps in the initial investigation process in order to arrive at a hypothesis leading to further investigation.
c. Increase the efficiency and effectiveness of diagnosis by attending to a broader spectrum of symptoms and implementing meta-hypothesis that increases the confidence of the physician in the diagnosis process. This

is especially important for physicians who are experienced in the diagnosis of tropical diseases.

From the disease symptom matrix, an elimination matrix is extracted, which indicates the presence or absence of a symptom relating to a disease. The last column of the matrix shows the spread of the symptom (S_{ND}) in terms of the number of diseases associated with the symptom. This number is utilized in deciding on the sequence of the interrogation algorithm, which is implemented by the system as a physician guide.

TABLE III
DECISION ELICITATION MATRIX

Symptoms	DISEASES							
	M	T	C	S	H	Y	U	S_{ND}
Fever	Y	Y	Y	Y	Y	Y	Y	7
Headache	Y	Y	Y	Y	N	Y	N	5
Abdominal Pain	N	Y	N	N	Y	N	Y	3
Jaundice	Y	Y	N	N	Y	Y	Y	4
Nausea	Y	Y	Y	N	Y	Y	Y	6
Vomiting	Y	Y	N	N	Y	Y	Y	6
Fatigue	Y	Y	N	N	N	N	N	2
Chills	Y	Y	N	N	N	N	Y	3
Diarrhoea	N	Y	N	N	N	N	N	1
Constipation	N	Y	N	N	N	Y	N	2
Running Nose	N	N	Y	Y	N	N	N	2
Rashes	N	N	Y	Y	N	N	N	2

The lower the value of S_{ND}, the higher the chances of effective and efficient diagnosis. The levels of interrogation ($_{Ik:k\ =\ 1min\ldots NDmax}$) are dependent on the hierarchy of disease/symptom spread (ND) and intensity of symptom manifestation (as shown by the disease-symptom matrix (Table III) i.e. $\theta(I_\alpha) > \theta(I_{\alpha+1})$ and $\phi(I_\alpha) > \phi(I_{\alpha+1})$ where θ and ϕ are manifestation spread (among diseases) and intensity weight (on a scale of 1 – 5 obtained from the disease-symptom matrix) respectively.

The symptom to be considered in the next I level of interrogation is the one with the highest (best) association with any of the previous I_s with I_α having a higher priority over $I_{\alpha+1}$.

The following constitutes the interrogation algorithm which is a quasi-declarative brute-force algorithm.

I_1: $Fever_T \Rightarrow I_2$

I_2:
- $I_{2.1}$: $Nausea_T \Rightarrow J_S'$
- $I_{2.2}$: $Diarrhoea \Rightarrow J_T., I_5$

I_3: $Headache_T \Rightarrow J_S., J_T., I_4, I_5$

I_4: $Running\ Nose_T \wedge \vee Rashes_T \Rightarrow J_C, J_S (J_M', J_T', J_H', J_Y', J_U')$

I_5:
- $I_{5.1}$: $Constipation_T \wedge Vomiting_T \wedge Fatigue_T \wedge I_{2.2} \vee I_3 \Rightarrow J_T..$
- $I_{5.2}$: $Constipation_T \wedge \vee Vomiting_T \wedge Fatigue_T \wedge I_3 \Rightarrow J_M$
- $I_{5.3}$: $Constipation_T \wedge Vomiting_T \wedge \vee Fatigue_T \wedge I_3 \Rightarrow J_T..$

I_6:
- $I_{6.1}$: $AbdominalPain_T \wedge Jaudice_T \wedge Chills_T \Rightarrow J_T.$
- $I_{6.2}$: $I_{6.1} \wedge (I_{2.2} \vee I_3) \Rightarrow J_T..$
- $I_{6.3}$: $I_{6.1} \wedge I_{5.1} \Rightarrow J_{T\ldots}$
- $I_{6.4}$: $(Jaudice_T \wedge \vee Chills_T) \wedge (AbdominalPain_F) \Rightarrow J_M$
- $I_{6.5}$: $I_{6.4} \wedge I_{5.5} \Rightarrow J_{M\ldots}$
- $I_{6.6}$: $(AbdominalPain_T \wedge Jaudice_T) \wedge Chills_F \Rightarrow J_H.$
- $I_{6.7}$: $I_{6.6} \wedge I_{2.1} \Rightarrow J_{H..}$
- $I_{6.8}$: $Vomiting_T \wedge Chills_T \wedge I_{2.1} \Rightarrow J_U..$
- $I_{6.9}$: $Vomiting_T \wedge Chills_F) \wedge AbdominalPain_F \Rightarrow J_Y.$
- $I_{6.10}$: $I_{6.9} \wedge I_{5.2} \vee I_{2.1} \Rightarrow J_Y..$

Algorithm Explanation

I_1: The first interrogation involves fever, which is common to the diseases under consideration. If fever is present ($Fever_T$), then move to the next interrogation. Note that the level of presence of fever or any other symptom is evaluated via a triangular fuzzy function that is generally defined as: $P_s = \alpha(\beta, \lambda, \mu)$ where: P_s is the presence of symptom; α is a confidence factor; β is the lower bound of the triangular fuzzy number; λ is the mid-point of the fuzzy number, μ is the upper bound of the fuzzy number

I_2: This has two alternate decision points (I_2 and $I_{2,2}$) because Nausea and Diarrhoea present the same chances of disease elimination at opposing sides of the coin. If Nausea is present ($Nausea_T$) then Measles would not be suspected. Also, if diarrhoea is present, then typhoid fever is suspected and interrogation I_5 is triggered.

I_3: Constipation relates to typhoid with intensity weight of 3, while headache relates to measles with intensity of 4. Therefore, I_3 focuses on headache.

Next, the focus on other symptoms that have ND of 2 or 5 with intensity weight ($w_i \geq 3$) and with some proximity (relationship) with already utilized symptoms – nausea, diarrhoea, headache. Symptoms in the category that have not yet been considered are shown in Table IV:

TABLE IV
SYMPTOMS WITH ND OF 2 OR 5 WITH $w_i \geq 3$

Symptom	ND	Disease (wi)
Vomiting	5	
Fatigue	2	Malaria (4)
Constipation	2	Yellow fever (4)
Running Nose	2	Chicken Pox (4), Measles (4)
Rashes	2	Chicken Pox (5), Measles (5)

I_4: It is easier to eliminate or carryout further investigation on Chicken Pox or Measles since both have identical intensity combination for running nose and rashes, therefore, I_4 deals with running nose and/or rashes (Running Nose$\wedge\vee$Rashes). Note that: $\wedge$ stands for logical AND; $\vee$ stands for logical OR; $\wedge\vee$ stands for AND/OR.

The presence of either or both symptoms could signal and inclination towards the chicken pox/measles hypothesis.

I_5: Next, we deal with constipation, fatigue, vomiting. Constipation, vomiting and fatigue are all associated with typhoid, while constipation and vomiting are associated with yellow fever; fatigue and vomiting are associated with malaria, therefore, I_5 considers three sublevels dealing with typhoid, yellow fever, and malaria. Because $I_{2.2}$ and I_3 had already considered typhoid, if $I_{2.2}$ and I_3 are true and the combination of constipation, fatigue and vomiting are present, then the confidence level of typhoid hypothesis increases. This equally applies in the case of measles ($I_{5.3}$).

I_6: The next consideration is for symptoms with a diseases spread of 3 or 4. Starting with either those relating to previously considered diseases or those with high intensity weight (w_i). The three symptoms under consideration here are: Abdominal pain, Jaundice and Chills.

If the three of the symptoms are present, then the typhoid fever would be suspected; if there is jaundice and/or chills and no abdominal pain, we suspect malaria; if there is abdominal pain and jaundice with no chills plus $I_{2.1}$ is true, then suspect hepatitis B; if vomiting and chills plus $I_{2.1}$, then strongly suspect UTI; if vomiting, no chills, no abdominal pain and $I_{2.1}$, then strongly suspect yellow fever.

V. Preliminary Results and Discussion

Our study follows a two-stage model application and evaluation. The first stage deals with static structure of the fuzzy cognitive map methodology that aggregates symptoms/risk factors with respect to malaria, and applies the semantic cause-effect relationships to case diagnosis. This is encoded in the knowledge base and inference mechanism. The second stage involves the application of the interrogation algorithm in the diagnosis process to optimize efficiency of the diagnosis process. This phase is actualized in the application of the decision support filters. This paper presents initial results of the first stage model application and evaluation using malaria as a case. Twenty patients' data were subjected to the FCM model in the diagnosis of malaria. Table V shows the comparative summary of the doctors' initial hypotheses, final diagnoses, and the system's diagnoses.

TABLE V
Diagnosis Comparative Summary

Patient No.	Patient Age (Years)	Doctor-Exp. (Years)	Initial Hypothesis	Further Investigation	Final Doctor Diagnosis	FCM Diagnosis	AD (Doc.)	AD (FCM)
1	41-60	<5	Malaria (Mild)	Blood film ++	Moderate	Moderate	0	1
2	41-60	<5	Malaria (Mild)	Blood film ++	Moderate	Moderate	0	1
3	21-40	$5 \le y \le 10$	Malaria (Severe)	Blood film +++	Severe	Moderate	1	0
4	11-20	$5 \le y \le 10$	Malaria (Moderate)	Blood film ++	Moderate	Moderate	1	1
5	21-40	$5 \le y \le 10$	Malaria (Mild)	Blood film ++	Moderate	Moderate	0	1
6	<10	$5 \le y \le 10$	Malaria (Moderate)	Blood film +	Mild	Mild	0	1
7	>60	$5 \le y \le 10$	Malaria (Moderate)	Blood film ++	Moderate	Moderate	1	1
8	<10	$5 \le y \le 10$	Malaria (Severe)	Blood film +++	Severe	Moderate	0	0
9	41-60	$5 \le y \le 10$	Malaria (Severe)	Blood film ++	Moderate	Mild	0	0
10	21-40	$10 < y \le 15$	Malaria (Mild)	Blood film ++	Moderate	Moderate	0	1
11	41-60	$10 < y \le 15$	Malaria (Mild)	Blood film +	Mild	Mild	1	1
12	41-60	>15	Malaria (Mild)	Blood film +	Moderate	Moderate	0	1
13	21-40	>15	Malaria (Severe)	Blood film +++	Severe	Severe	1	1
14	<10	<5	Malaria (Mild)	Blood film +	Mild	Mild	1	1
15	41-60	$5 \le y \le 10$	Malaria (Mild)	Blood film +	Mild	Mild	1	1
16	41-60	$10 < y \le 15$	Malaria (Severe)	Blood film +++	Severe	Severe	1	1
17	21-40	$10 < y \le 15$	Malaria (Moderate)	Blood film ++	Moderate	Moderate	1	1
18	<10	$10 < y \le 15$	Malaria (Moderate)	Blood film ++	Moderate	Moderate	1	1
19	>60	<5	Malaria (Severe)	Blood film +++	Severe	Severe	1	1
20	21-40	$5 \le y \le 10$	Malaria (Severe)	Blood film +++	Moderate	Moderate	0	1

Majority of the patients (45%) involved in the study were above 40 years of age, while 20% were less than 10 years old, and 35% were between 11 and 40 years. Majority (80%) of the physicians had a considerable levels of experience (5 years and above) in the diagnosis of tropical diseases. The accuracy of the doctor's initial hypothesis vs that of the FCM model are shown in the last two columns, where 1 indicates a perfect match with the final (confirmatory) diagnosis, while 0 indicates a misclassification of the malaria intensity. The initial hypotheses by the physicians correctly matched the final diagnosis in 55% of the cases, whereas that of the FCM was 85%. This result is interesting because one would expect the accuracy of classification to be more for the doctors than for the FCM system. It is also important to note that the physician's level of experience had insignificant correlation (0.14) with the accuracy of the initial hypothesis. This

suggests that irrespective of the experience of the doctor, there is a good chance of misclassification in the absence of lab tests; thus underscoring the utility of the FCM decision support system in the diagnosis of tropical diseases.

The overall weight matrix revealed that all the concepts show some form of positive relationship with malaria except age, which has negative relationship. This implies that the predisposition to malaria reduces as age increases. This is in consonance with the findings reported in [40], [41]. However, one should be cautious is generalizing the age-malaria relationship as the subjects of this study were mainly adults. A contrary finding by [42], suggested that persons above 40 are more likely to be prone to malaria attack. Fever showed the highest causal relationship with malaria. This is true for most tropical diseases [43], and informed the starting point of the diagnosis algorithm (I_1) in the decision support filter. The confusability of fever-related presentations could be better mitigated through further tests or with the use of decision support systems, with knowledge structures that have the capability to conduct an efficient symptom/risk factor combinatorial analysis. Endemicity is also shown to be a very important risk factor in diagnosis of tropical diseases, necessitating additional support for people in these areas for prevention, diagnosis and control of these tropical diseases.

VI. Conclusion

With increased level of acceptance and diffusion of health information systems (HIS), there is a systematic push toward integrated diagnostic decision support systems. According to [44], health information systems have the potentials of improving medical diagnosis, eliminating needless medical testing, reducing diagnosis errors, improving health care quality, and decreasing paper work – including legibility concerns. In this study, we have developed a framework for the use of fuzzy cognitive maps in the diagnosis of tropical diseases. Our model takes cognizance of the inter symptom causative interactions, and integrates risk factors in the decision process. We also recognize the possibility of interactions between risk factors and the disease. For example, poor sanitation and endemicity recorded a fairly strong positive relationship with malaria.

The physicians' final diagnosis (after further investigation) points to the superiority of the FCM diagnosis over the physicians' initial hypothesis, irrespective of the years of experience of the physicians. This study points to the effectiveness of the Fuzzy Cognitive map as the classification technology and the utility of decision support systems in medical diagnosis. In [45], it was determined that medical predictions by mechanical systems outperformed the clinical ones by 10%. However, the evidence of outperformance of physicians by decision support systems needs to be further studied as indicated in [46]. The generalizability of this study is limited by the small amount of test data used. Furthermore, it is important to recognize that isolation of malaria diagnosis does not present a realistic view of the entire diagnosis process. It is expected that the next stage of our study, which utilizes over 2000 patients' data with multi-disease, multi-symptom/risk factor relationships, will provide a better model, and make a significant contribution in the physician- DSS effectiveness and efficiency discourse.

References

[1] WHO [World health organization] (2015); World Health Organization, World Health Statistics 2015, World Health Organization, Geneva, Switzerland.

[2] Orimadegun, A., Amodu, O., Olumese, P., and Omotade, O. (2008). Early home treatment of childhood fevers with ineffective antimalarials is deleterious in the outcome of severe malaria. Malaria journal, 7(1), 143.

[3] Thierfelder, C., Schill, C., Hatz, C. and Nuesch, R. (2008). Trends in imported malaria to Besel, Switzerland. Journal of Travel Medicine, 15(6), 432-436.

[4] Podgorelec V. and Kokol P. (2001); Towards more optimal medical diagnosing with evolutionary algorithms. Journal of Medical Systems, 25 (3), 195-219

[5] Szolovits, P; Patil, R.S; and Schwartz W.B (1988); "Artificial Intelligence in Medical Diagnosis", Annals of Internal Medicine, 108(1):80-87

[6] Driver, C. (2009). Malaria and its avoidance. Practice Nurse, 37(8), 19-24.

[7] Wyatt, J and Spiegelhalter, D. (1991), "Field trials of medical decision-aids: potential problems and solutions", in Clayton, P. (Eds), Proceedings of the Fifteenth Annual Symposium on Computer Applications in Medical Care, American Medical Informatics Association, Washington, DC, pp.3-7.

[8] Seising, R. (2006). From vagueness in medical thought to the foundations of fuzzy reasoning in medical diagnosis. Artificial Intelligence in Medicine, 38, 237-257.

[9] Schlagenhauf, P., Weld, L., Goorhuis, A., Gautret, P., Weber, R., von Sonnenburg, F., ... & Grobusch, M. P. (2015). Travel-associated infection presenting in Europe (2008–12): an analysis of EuroTravNet longitudinal, surveillance data, and evaluation of the effect of the pre-travel consultation. The Lancet Infectious Diseases, 15(1), 55-64

[10] Rotberg, R. I., & Aker, J. C. (2013). Mobile phones: uplifting weak and failed states. The Washington Quarterly, 36(1), 111-125.

[11] Kulikowski, C.A (1987); "Artificial Intelligence in Medicine: A Personal Retrospective on its Emergence and Early Evolution", ACM (0-89791-248-9/87/0011/0199), pp199-206

[12] Gorry, G.A (1973); "Computer Assisted Clinical Decision Making Methods", Journal of Medicine, 12: 45-51

[13] Shortliffe, E. H. (1974); "MYCIN: A rule-based computer program for advising physicians regarding antimicrobial therapy selection", Proceedings of the ACM National Congress (SIGBIO Session), p. 739.

[14] Szolovits, P (1995); "Uncertainty and Decisions in Medical Informatics"; Methods of Information in Medicine, 34:111-121

[15] Kaeding, A.K and Flor T. (1995); "Processing Unexact Information in a Medical Used Multiparadigm System", Proceedings of the 1995 ACM symposium on Applied computing 1995, Nashville, Tennessee, United States February 26 - 28, 1995, pp590-592

[16] Song, Q., Kasabov, N (2003)., "A Novel Generic Higher-order TSK Fuzzy Model for Prediction and Applications for Medical Decision Support", Proc. of The Eighth Australian and New Zealand Intelligence Information Systems Conference (ANZIIS2003), Sydney, Australia, 10 – 12, December, 2003, pp. 241 – 245.

[17] Lisboa, P. J., and Taktak, A. F. (2006). The use of artificial neural networks in decision support in cancer: a systematic review. Neural networks, 19(4), 408-415.

[18] Polat, K., and Güneş, S. (2007). A hybrid approach to medical decision support systems: Combining feature selection, fuzzy weighted pre-processing and AIRS. computer methods and programs in biomedicine, 88(2), 164-174.

[19] Obot O. and Uzoka F.M.E (2009); A Framework for Application of Neuro-Case-Rule base Hybridization in Medical Diagnosis Applied Soft Computing Journal, 9: 245-253

[20] Barca, C. C., Rodríguez, J. M., Puddu, P. E., Luštrek, M., Cvetković, B., Bordone, M., ... and Tamburini, E. (2014, January). Advanced Medical Expert Support Tool (A-MEST): EHR-Based Integration of Multiple Risk Assessment Solutions for Congestive Heart Failure Patients. In XIII Mediterranean Conference on Medical and Biological Engineering and Computing 2013 (pp. 1334-1337). Springer International Publishing.

[21] Kosko B. (1986); Fuzzy Cognitive Maps. International Journal of Man-Machine Studies 24, 65–75
[22] Zadeh, L. A (1965).: "Fuzzy Sets and Systems"; In: Fox, J. (ed.): Proceedings Symposium on System Theory, Polytechnic Institute of Brooklyn, April 1965, pp. 29-37.
[23] Tolman E.C. (1948); Cognitive maps in rats and men. Psychological Review, 55 (4): 189–208.
[24] Georgopoulos, V. C., Malandraki, G. A., and Stylios, C. D. (2003). A fuzzy cognitive map approach to differential diagnosis of specific language impairment. Artificial intelligence in Medicine, 29(3), 261-278.
[25] Papageorgiou, E. I., Papandrianos, N. I., Karagianni, G., Kyriazopoulos, G. C., and Sfyras, D. (2009, August). A fuzzy cognitive map based tool for prediction of infectious diseases. In Fuzzy Systems, 2009. FUZZ-IEEE 2009. IEEE International Conference on (pp. 2094-2099). IEEE.
[26] John, R. I., and Innocent, P. R. (2005). Modeling uncertainty in clinical diagnosis using fuzzy logic. Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 35(6), 1340-1350.
[27] Reggia, J. A., Nau, D. S., and Wang, P. Y. (1983). Diagnostic expert systems based on a set covering model. International Journal of Man-Machine Studies, 19(5), 437-460.
[28] 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
[29] Papageorgiou, E. I., Papandrianos, N. I., Apostolopoulos, D. J., and Vassilakos, P. J. (2008, June). Fuzzy cognitive map based decision support system for thyroid diagnosis management. In Fuzzy Systems, 2008. FUZZ-IEEE 2008. (IEEE World Congress on Computational Intelligence). IEEE International Conference on (pp. 1204-1211). IEEE.
[30] Lopes, M. H. B. D. M., Ortega, N. R. S., Silveira, P. S. P., Massad, E., Higa, R., and Marin, H. D. F. (2013). Fuzzy cognitive map in differential diagnosis of alterations in urinary elimination: A nursing approach. International journal of medical informatics, 82(3), 201-208.
[31] Mago, V. K., Papageorgiou, E. I., and Mago, A. (2014). Employing Fuzzy Cognitive Map for Periodontal Disease Assessment. In Fuzzy Cognitive Maps for Applied Sciences and Engineering (pp. 375-389). Springer Berlin Heidelberg.
[32] Marateb, H. R., Mansourian, M., Faghihimani, E., Amini, M., and Farina, D. (2014). A hybrid intelligent system for diagnosing microalbuminuria in type 2 diabetes patients without having to measure urinary albumin. Computers in Biology and Medicine, 45, 34-42.
[33] Khan, M. S., Chong, A., and Quaddus, M. (1987). Fuzzy cognitive maps and intelligent decision support–a review. School of Information Technology, Murdoch University, Graduate School of Business, Curtin University of Technology, GPO Box U. Downloaded on December 10, 2013 from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.127.7815&rep=rep1&type=pdf
[34] Khan, M. S., and Quaddus, M. (2004). Group decision support using fuzzy cognitive maps for causal reasoning. Group Decision and Negotiation, 13(5), 463-480.p
[35] Taber, R. (1991). Knowledge processing with fuzzy cognitive maps. Expert Systems with Applications, 2(1), 83-87.
[36] Carvalho J.P. and Tomé J.A. (1999); Rule Based Fuzzy Cognitive Maps and Fuzzy Cognitive Maps - A Comparative Study, Proceedings of the 18th International Conference of the North American Fuzzy Information Processing Society, NAFIPS99, New York. Accessed on July 5, 2012 from http://www.inesc-id.pt/pt/indicadores/Ficheiros/1037.pdf
[37] Uzoka, F.M.E., and Barker, K. (2010). Expert Systems and Uncertainty in Medical Diagnosis: A Proposal for Fuzzy-ANP Hybridization. International Journal of Medical Engineering and Informatics, 2(2), 329-342.
[38] Ermine, J.L (1995); Expert System: Theory and Practice, New Dehli, Prentice Hall of India Private Limited.
[39] Obot, O. U., Uzoka, F. M., Akinyokun, O. C., and Andy, J. J. (2013). Conventional and neuro-fuzzy framework for diagnosis and therapy of cardiovascular disease. Bio-Algorithms and Med-Systems, 9(3), 115-133.
[40] Reibnegger, G., Fuchs, D., Hausen, A., Schmutzhard, E., Werner, E. R., & Wachter, H. (1987). The dependence of cell-mediated immune activation in malaria on age and endemicity. Transactions of the Royal Society of Tropical Medicine and Hygiene, 81(5), 729-729.
[41] Dondorp, A. M., Lee, S. J., Faiz, M. A., Mishra, S., Price, R., Tjitra, E., ... & White, N. J. (2008). The relationship between age and the manifestations of and mortality associated with severe malaria. Clinical Infectious Diseases, 47(2), 151-157.
[42] Schwartz E, Sedetzki S, Murad H, and Raveh D (2001); Age as a risk factor for severe plasmodium falciparum malaria in non-immune patients. Clinical Infectious Diseases, 33(10): 1774-1777
[43] Doherty, J. F., Grant, A. D., & Bryceson, A. D. M. (1995). Fever as the presenting complaint of travellers returning from the tropics. Qjm, 88(4), 277-281.
[44] Cantrill, M. D., (2010). Computers in patient care: the promise and the challenge. Communications of the ACM, 53(9): 42-47.
[45] Grove, W. M., Zald, D. H., Lebow, B. S., Snitz, B. E., & Nelson, C. (2000). Clinical versus mechanical prediction: a meta-analysis. Psychological assessment, 12(1), 19-30.
[46] Bright, T. J., Wong, A., Dhurjati, R., Bristow, E., Bastian, L., Coeytaux, R. R., ... & Lobach, D. (2012). Effect of clinical decision-support systemsa systematic review. Annals of internal medicine, 157(1), 29-43.