Journal of the Nigerian Association of Mathematical Physics
Volume 30, (*May, 2015*), pp 271 – 280

An Intelligent Clustering Based Methodology for Confusable Diseases Diagnosis and Monitoring

Okure U. Obot and Udoinyang G. Inyang

Department of Computer Science, Faculty of Science, University of Uyo, Nigeria,.

Abstract

The combination of non-specific clinical manifestations that characterize confusable tropical disease and the probable lack of expertise and experience among physicians exponentially increases the potential for misdiagnosis and subsequent increased morbidity and mortality rates resulting from these diseases. In this paper, an intelligent system driven by fuzzy clustering algorithm and Adaptive Neuro-Fuzzy Inference System for the investigation, diagnosis and management of similar and confusing symptoms of confusable diseases was developed. Data on patients diagnosed and confirmed by laboratory tests of viral hepatitis (H), malaria (M), typhoid fever (T) and urinary tract infection (U) were used for training, testing and validation of the system. The system assigns patients with severity levels in all the clusters. Results on clusters validity are satisfactory. Overlapping symptoms analysis shows that symptoms of both H and T have highest degree of overlapping while symptoms common to M and U yielded the least impact. Symptoms common to M, H and T only, have equal impact with that of M, T and U only. The symptoms that are common to all the four diseases under study yielded a 12.8% contribution to the degree of severity of each of the CTD diseases. The system compares favorably with diagnosis arrived at by experienced physicians and also provides patients' level of severity in each confusable disease and the degree of confusability of any two or more confusable diseases.

Key words: Confusable diseases; viral hepatitis; malaria; typhoid fever; urinary tract infection; Clustering, ANFIS

1.0 Introduction

Tropical diseases are associated with high level of mortality rate and also very common in developing countries [1]. However, these diseases are increasingly being encountered at hospital emergency rooms in developed world [2,3]. This, in part, can be attributed to the ease and efficiency of global travel. It is not uncommon in the developed world to observe that specialty medical practitioners in tropical conditions are in short supply, and most major health centers do not have tropical disease management units attached to them [4]. As such medical doctors encounter difficulties in critically analyzing and diagnosing tropical diseases, especially when confronted with non-specific manifestations or clinical symptoms common to other diseases. A confusable disease is a disease which may show similar symptoms and/or signs to other diseases. The combination of non-specific clinical manifestations and probable lack of expertise and experience among primary care and emergency physicians in the developing world exponentially increases the potential for the misdiagnosis and subsequent higher possibility of increased morbidity and mortality rates. In order to ascertain the etiology of the symptoms presented by patients, medical practitioners often depend on guess work, buy time for the symptoms to resolve on their own, or subject clients to unnecessary laboratory investigations with attendant delays leading to disease complications and even death.

In consideration of the fact that these conditions are considered exotic in the west, there is abject lack of specialties among medical practitioners, and most major health centers do not even have tropical disease management units attached to them. As such medical doctors encounter difficulties in analyzing and diagnosing tropical diseases, especially when confronted with conditions that present with non-specific manifestations or share similar clinical symptoms. This increased number of mortalities provides the impetus to investigate the utility of a computer based diagnostic aid to support physicians in diagnosing such conditions. This will be in addition to the recommendation that primary care physicians sharpen their skills to identify and manage tropical disease. Africa also accounts for 91% of world's deaths resulting from malaria. There is also an indication that as at 2006, Nigeria had the 7th highest maternal mortality rate of 156 (per 100000 population), which was

Corresponding author: U.G. Inyang, E-mail: udoiinyang@yahoo.com, Tel.: +2348036688711.

beyond the African average of 104. Nigeria is one of the countries in the world where health records are still manually kept, resulting in delays at the record units and almost non existent national health information.

The rest of the paper is organized as follows. Section 2 gives a review of related works with a list of overlapping symptoms. In Section 3, the FCM algorithm is described while methodology and design of the intelligent clustering based system and results are presented in Section 4. Section 5, deals with the validity of clusters and weights of overlapping symptoms. Some conclusions and findings are reported in Section 6.

2.0 Related Works

In [5] it is opined that there is a scope to many infectious diseases with the same or similar symptoms, and therefore doctors generally diagnose a disease from the relative strength of the symptoms, but what is lacking is the ability to perform a relative ranking or quantification of the relative levels of these symptoms. The use of the neurofuzzy methodology is meant to resolve this ambiguity by assigning some degrees of influence on the manifestations through fuzzification of these symptoms, and subsequent defuzzification. Whereas the hard clustering method requires an object to either belong to group or not, fuzzy clustering allows an object to belong to several groups (clusters) simultaneously with varying degrees of membership. A patient having a myriad of symptoms of tropical diseases could be diagnosed to be suffering from more than one of the tropical diseases at the same time with varying degrees of membership.

Fever, flu-like symptoms, abdominal discomforts and other non-specific symptoms are common complaints when a traveler contracts different forms of tropical diseases. Although malaria is the main cause of fever in those returning from tropics [6], other tropical conditions also present with fever as well as other non-specific symptoms that can at best be confusing to medical doctors not specifically trained to diagnose and manage tropical diseases. Tropical disease symptoms might vary in intensity due to genetic, immunological, and virulence characteristics of the individual and the infecting organism. This varying intensity of symptoms adds another layer of complexity when diagnosing these conditions. Sometimes, for returning travelers, more than one type of infection may co-exist at the same time, which makes disease diagnosis and management more challenging for physicians. Four conditions that are the focus of this research include malaria, typhoid fever, viral hepatitis and urinary tract infections (U). U is prevalent not only in the tropical region but presents symptoms similar to the other three diseases under study. Studies have shown that some symptoms of viral hepatitis (H) include fever, fatigue, nausea, vomiting, abdominal pain, dizziness, anorexia, lethargy, weight loss, itching, dark colored urine and clay coloured stool [7,8]. Symptoms of malaria (M) will vary according to the stage of the disease and may include Viral Hepatitis, fever, headache, nausea, anorexia, delirium, and rapid bounding pulse, malaise, fatigue, myalgia, or muscle pain, abdominal pain, vomiting, diarrhea, fatigue, diaphoresis, chills, [9,10]. Common symptoms of typhoid fever (T) include fever, abdominal pain, diarrhea, anorexia, nausea, vomiting, fatigue, headache, malaise, a characteristic body rash, enlargement of the liver and spleen, bradycardia, lethargy, sweating, chills and muscle pain [10,11]. Common symptoms of U include, fever, cloudy urine, frequent urination, dysuria, lower abdominal pain, nausea, vomiting, nocturia, urinary urgency, low back pain, fatigue, headache, and anorexia[12,13].

From the forgoing, it is evident that these diseases present a good spectrum of overlapping symptoms, and could potentially confuse a clinician trying to differentially diagnose any of these conditions. The application of soft computing technology to medical diagnosis of some diseases are discussed in [14-19]. The clinical manifestations of the conditions under consideration as deduced from [20,21,22] are presented in Table 1. As shown in Table 1, a total of twenty two (22) symptoms account for the CTD of H, M, T, and U. “1” denotes the presence of a symptom in determining the disease while ‘0” implies absence of the symptom in that disease. It is evident that the diseases considered in this work have common symptom hence are confusing during medical diagnosis. In this work, these diseases are called as Confusable Tropical Diseases (CTDs).

Table 1: Symptoms of Confusable Tropical Diseases

S/N	Symptom		Tropical Diseases			
	Symptom Description	**Code**	**Malaria (M)**	**Viral Hepatitis (H)**	**Typhoid (T)**	**Urinary Track Infection (U)**
1	Abnormal Breathing	a1	1	1	1	1
2	Loss of Appetite	*a*2	1	1	1	1
3	Backache	b1	1	0	1	0
4	Chill	c1	1	1	1	1
5	Cough	c2	1	1	1	1
6	Dehydration	d1	1	1	1	1
7	Delirium	d2	1	1	1	1
8	Diarrhea	d3	1	0	1	0
9	Dizziness	d4	1	0	0	0
10	Excessive Sleeping	e1	1	0	1	0
11	Fever	f1	1	1	0	0
12	Headache	h1	1	1	1	1
13	Joint Pain	j1	1	1	1	1
14	Muscle Ache	m1	1	1	1	0
15	Nausea	n1	0	0	1	0
16	Paleness	p1	0	1	1	0
17	Shivering	s1	0	1	1	1
18	Stomach Discomfort	s2	0	0	1	0
19	Sweating	s3	1	0	1	0
20	Tiredness	t1	1	1	1	0
21	Vomiting	v1	0	1	1	0
22	Yellowish Eye	y1	0	1	1	0

3.0 Overview of Fuzzy C-Means Algorithm

The fuzzy c-means (FCM) algorithm is an iterative algorithm that generalizes the hard c-means algorithm to allow any point partially belongs to multiple clusters [23]. The aim of FCM is to find clusters centers that minimize a dissimilarity function and then partition a finite collection of elements, $X=\{x_1, x_2, x_{3,\ldots} x_n\}$, into a collection of fuzzy clusters, $C=\{c_1, c_2, \ldots, c_p\}$ with respect to some given criterion [24]. The algorithm is implemented in the following steps [23,25,26,27].

Set m,c, and ε, such that $m > 1,\ 2 \le c < n$, and $0 < £ < 1$

i. Initialize $U=[u_{ij}]$ Matrix, U(0)

ii. At k-step: calculate the centre vectors $C(k)=[c_{i,j}]$ with U(k)

$$C_j = \frac{\sum_{i=1}^{n} u_{ij}^{m} x_i}{\sum_{i=1}^{n} u_{ij}^{m}} \quad . \quad . \quad . \quad (1)$$

iii. Update U(k) , U(k+1)

$$u_{ij} = \sum_{k=1}^{p} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{-2}{m-1}} \quad . \quad . \quad . \quad (2)$$

with the following constraints :

$$0 \le u_{ij} < 1, \qquad \forall i, j$$

$$\sum_{j=1}^{p} u_{ij} = 1, \qquad \forall i \quad . \quad . \quad . \quad (3)$$

v. if ||U(k+1) - U(k)|| < ε then STOP: otherwise return to step (iii)

where,

U - partition matrix

u_{ij} - degree of membership of x_i in the cluster j
x_i - the *ith* of d-dimensional measured data
c_j - the d-dimension centre of the cluster
ε - termination criterion
k - maximum number of iteration steps
m - the fuzzification parameter
p - the number of clusters
d - the dimension of the dataset

4.0 Methodology

5.0 Dataset Collection, Description and Pre-processing

The datasets for the study were collected from general hospitals in Akwa Ibom State, South -South, Nigeria. Specialist doctors provided information on patients already diagnosed and confirmed as having Malaria (M), Urinary Tract Infection(U) or Viral Hepatitis (H) and Typhoid(T). From the physicians' physical examination of the patients and the patients self reported account of symptoms, the medical doctor assigns linguistic values 'very severe', Severe, 'moderate' and 'mild', depending on the stage or severity of the symptom or disease. These linguistics variables were transformed into crisp values 4,3,2 and 1 respectively. Data on a total of 67 patients were collected by the four physicians based on the set of symptoms presented in Table 1. Symptoms that are not of any of these confusable diseases were discarded. The training dataset consists of 49 records while 18 records were used as the test dataset. The sequence of steps adopted in this work for the development of system for differential diagnosis of confusable tropical diseases is presented in Figure 1.

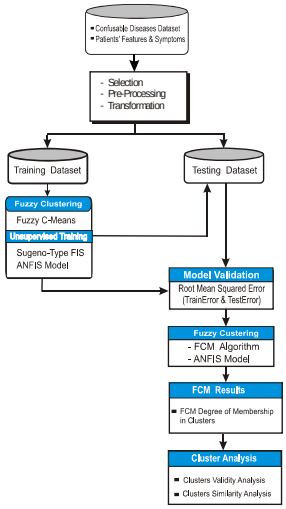

Figure 1: Methodology of Intelligent Clustering Based System for Differential Diagnosis of CTD

6.0 Conceptual Representation of Confusable Tropical Diseases Diagnosis (CTDD)

The classical set representation of the four CTDs, M, T, U and H is presented in Figure 2. As shown in Figure 2.0 there are fifteen (15) labeled sections each representing a subset of any one or more CTDs. The shaded portions represent the overlapping symptoms while the non-shaded portions A,C,D and F are specific symptoms of the respective CTD. The intersecting subsets give the degree or measure of contribution of the overlapping symptoms to each of the CTDs. From set theory, the algebraic sum representation of the each set in CTD {M, T, U, H} is as follows: M={A∪B∪K∪L∪P∪R∪Q∪O} , T={C∪G∪B∪K∪L∪P∪N∪J}, U= {G∪D∪K∪Q∪L∪O∪J∪E } and H={F∪N∪J∪E∪O∪L∪P∪R}

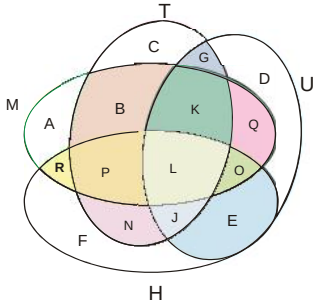

Figure 2: Classical Set Diagram of CTDs

As depicted in Figure 2, the problem of Confusable Tropical Disease Diagnosis (CTDD) can be formalized as a classification problem, where a set of overlapping and non-overlapping symptoms are measured and a set of partial diagnostic values ($«_{d_i}$) are defined for the CTDs set X= $\{d_1,d_2,...,d_c\}$, where $«_{d_i}$ represents the degree (proportion) to which any patient suffers from the *ith* disease or the chances (probability) that a patient is suffering from the *ith* disease, i=1,2,3…, n. Such that $«_{d_i}(x)$: $X \rightarrow [0,1]$ and $\sum_{i=1}^{n} «_{d_i} = 1$. Let $\mu_M(x)$ represents the degree to which any patient suffers from malaria, $\mu_U(x)$ represents the degree to which a patient suffers from U, $\mu_H(x)$ and $\mu_T(x)$ represent the degree to which a patient suffers from H and T respectively.

7.0 FCM and ANFIS based System for Differential Diagnosis and Results

This paper considers a method by which fuzzy membership functions are created for four (4) clusters of CTD. The major components of the system are Knowledge Base (KB) and Inference Engine (IE). The KB contains symptoms, fuzzy linguistics values, fuzzy rules and fuzzy membership values. The IE is driven by FCM clustering algorithms and Adaptive Neuro Fuzzy inference system (ANFIS). Takagi-Sugeno-type Fuzzy inference system was generated using subtractive clustering in determining the number of rules and antecedent membership functions; and linear least squares estimation method for determining each rule's consequent. The initial FCM parameters were set as; m=2, ε=0.01, and k=200. The training dataset consists of 49 records while 18 records were used as the test dataset. The mean of all the data points was the initial cluster center.

The performances of the FCM objective function while partitioning the training data set into four clusters is depicted in Figure 3. As shown in Figure 3, the initial value of the objective function is 418.55, and decreases to 323.89 at the 4th iteration without further change. The properties of the ANFIS model are presented in Table 2 while the graph of the testing error is presented in Figure 4. The Root Mean Square Error (RMSE) for training and testing are 0.2020 and 0.2000 respectively. The patient's severity level in each confusable disease is presented in Table 3 and Figure 5.

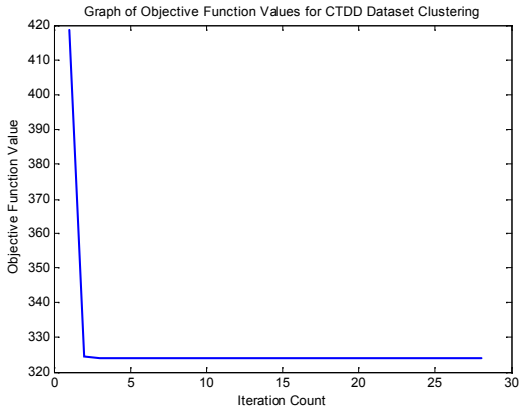

Figure 3: Objective Function of CTDD Dataset Clustering

Table 2: Description of ANFIS Training Parameters for CTDD dataset Clustering

ANFIS Parameter	**Values**
Number of nodes	1681
Number of linear parameters	828
Number of nonlinear parameters	1584
Total number of parameters	2412
Number of training data pairs	49
Number of checking data pairs	18
Number of fuzzy rules	36

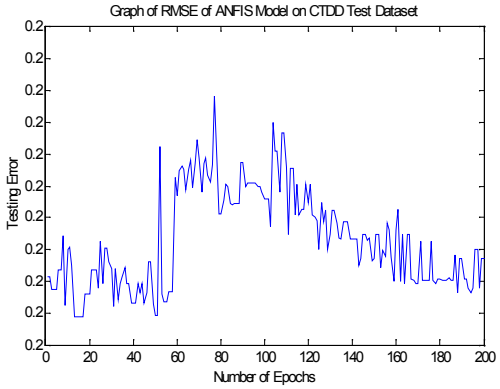

Figure 4: Graph of Testing error

Table 3: Patients' FCM Degree of Membership in CTD

Patient ID	Degree of Membership				Patient ID	Degree of Membership			
	M	H	T	U		M	H	T	U
01	0.18	0.2	0.53	0.09	26	0.25	0.31	0.38	0.06
02	0.68	0.12	0.19	0.01	27	0.16	0.24	0.27	0.33
03	0.28	0.21	0.45	0.06	28	0.64	0.19	0.15	0.02
04	0.03	0.05	0.05	0.87	29	0.25	0.46	0.26	0.03
05	0.46	0.18	0.33	0.03	30	0.43	0.24	0.26	0.07
06	0.19	0.21	0.4	0.2	31	0.21	0.51	0.23	0.05
07	0.42	0.18	0.38	0.02	32	0.72	0.12	0.15	0.01
08	0.56	0.14	0.27	0.03	33	0.28	0.22	0.43	0.07
09	0.83	0.06	0.1	0.01	34	0.14	0.42	0.32	0.12
10	0.17	0.54	0.19	0.1	35	0.15	0.27	0.38	0.2
11	0.03	0.04	0.05	0.88	36	0.68	0.12	0.19	0.01
13	0.16	0.25	0.28	0.31	38	0.87	0.05	0.05	0.03
14	0.6	0.19	0.18	0.03	39	0.39	0.19	0.34	0.08
15	0.25	0.46	0.26	0.03	40	0.15	0.21	0.3	0.34
16	0.48	0.22	0.26	0.04	41	0.34	0.22	0.38	0.06
17	0.26	0.47	0.24	0.03	42	0.18	0.2	0.53	0.09
18	0.55	0.21	0.21	0.03	43	0.06	0.83	0.1	0.01
19	0.27	0.24	0.35	0.14	44	0.17	0.54	0.19	0.1
20	0.14	0.33	0.36	0.17	45	0.03	0.04	0.05	0.88
21	0.43	0.16	0.38	0.03	46	0.18	0.33	0.35	0.14
22	0.57	0.13	0.27	0.03	47	0.17	0.22	0.29	0.32
23	0.06	0.83	0.1	0.01	48	0.64	0.19	0.15	0.02
24	0.17	0.54	0.19	0.1	49	0.25	0.46	0.26	0.03
25	0.07	0.09	0.11	0.73					

The FCM Clustering results presented in Table 4 and Figure 5 show that patients suffer from the four confusable diseases with varying degree of severity. Seventeen (17) patients have highest degree of severity in malaria and Eleven (11) patients in Hepatitis. The degree of severity of Thirteen (13) patients is highest in Typhoid while eight (8) patients depict highest degree of severity in U. Patient P12, P23 and P46 possess competing degree of severity level in Typhoid and Hepatitis, for this category of patients, the physician may treat the patient based on experience or may consider the most life threatening case(s). The results show the CTD with the highest severity level and also provide information on the commencement of diseases. This information will guide the medical experts on which CTD a patient may be treated at a particular instance of time which in turn will ensure an early treatment of any of CTDs.

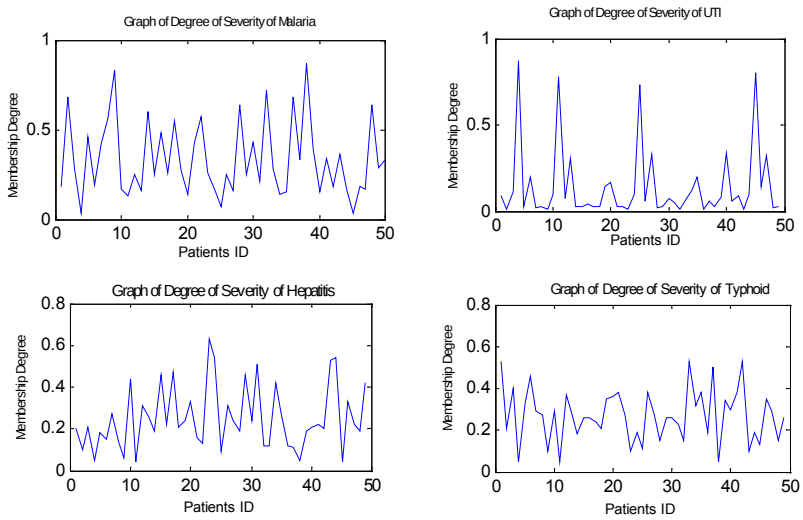

Figure 5: Graphs of Patients Severity levels in each of the CTD

8.0 Cluster Result Analysis

9.0 CTD Cluster Validity Analysis

In most applications, the final partitions of any dataset require some sort of evaluation [28]. Cluster Validity is aimed at assessing the used clustering scheme and also to compare the clustering structure produced by the algorithm. In this paper cluster validity indices suitable for fuzzy clustering were used in assessing the validity of the clustering results of CTDs. Since the number of clusters is pre-defined, Partition Coefficient (PC) given in [29] and Partition Entropy Coefficient (PE) presented in [30], are suitable indices for validating the fuzzy clusters. PC and PE indices are defined in Equations 4 and 5 respectively [29].

$$PC = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{2} \quad . \quad . \quad . \quad (4)$$

where $\frac{1}{c} \le PC \le 1$

$$PE = -\frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N} u_{ij}\log_{2}(u_{ij}) \quad . \quad . \quad . \quad (5)$$

where $0 \le PC \le \log_{a}(c)$

where *N* is the number of cases (patients), *c* is the number of clusters and 'a' is the base of the logarithm.
In this paper, N=49, c=4, a=4. The result yields 0.396 and 0.795 for PC and PE respectively. The PC value is in the range [¼,1] and closer to the lower bound (0.25) depicting the existence of fuzzy partitions. Similarly, the PE value of 0.795 lies within the required range of [0, $\log_4 4$] (0,1). The PE value is closer to the upper bound which explains the existence of fuzzy clusters. The results from both validity indices (PC, PE) validate the clustering results according to [28,31].

10.0 Fuzzy Weights of Overlapping Symptoms

Let X be a finite set of patients, X={P01,P02,P03,P04,P05,P06,P07, . . ., P49} . As shown in Table 3 the 4 fuzzy partitions sets of X, are represented as follows:
M= {0.18/P01, 0.68/P02, 0.28/P03, 0.03/P04, … , 0.29/P49}
H = {0.20/P01, 0.10/P02, 0.21/P03, 0.05/P04, … , 0.42/P49}
T = {0.53/P01, 0.21/P02, 0.40/P03, 0.05/P04, … , 0.26/P49}
U = {0.09/P01, 0.01/P02, 0.11/P03, 0.87/P04, … , 0.03/P49}
The degree of overlap of any two fuzzy sets, say M and T, is determined using Equation 6 as in [32,33].

$$¥_{M,T} = \frac{\sum_{i=1}^{N}[\min(«_{M_i}, «_{T_i})]}{\sum_{i=1}^{N}[\max(«_{M_i}, «_{T_i})]} \quad . \quad . \quad . \quad (6)$$

where $«_{M_i}$ and $«_{T_i}$ are individual membership scores (degree of severity) in the sets M and T and N is the total number of patients. The degree of overlap of the CTD fuzzy sets are as presented in Table 4.

Table 4: Degree of Overlapping Symptoms of CTD

S/N	Overlapping Fuzzy Sets	Degree of Overlapping
1	M,H	0.419
2	M,T	0.486
3	M,U	0.168
4	H,T	0.567
5	H,U	0.233
6	T,U	0.250
7	M,H,T	0.144
8	M,H,U	0.138
9	M,T,U	0.144
10	H,T,U	0.190
11	M,H,T,U	0.128

The result depicted in Table 4 depicts the impact of the overlapping symptoms of CTD. The weight of the overlapping symptoms of M and T explains 41.9% of both diseases while the common symptoms of H and U contributes 23.3% to the severity of both diseases. The results depicts that symptoms of both H and T have highest degree of overlapping while symptoms common to M and U yields the least impact. In the second category, (overlapping symptoms of any three diseases), the symptoms common to M, H and T only, have equal impact with that of M, T and U only (14.44%). The symptoms that are common to all the four diseases under study yielded a 12.8% contribution to the degree of severity of each of the CTD diseases.

11.0 Conclusion

The combination of non-specific clinical manifestations that characterize Confusable Tropical diseases and the probable lack of expertise and experience among primary care and emergency physicians exponentially increases the potential for misdiagnosis and subsequent increased morbidity and mortality rates resulting from these diseases. This paper proposes an intelligent system driven by Adaptive Neuro-Fuzzy Inference System and fuzzy clustering to assist physicians investigate, diagnose and manage similar and confusing symptoms for timely and accurate diagnosis of confusable diseases. Data on patients diagnosed and confirmed by laboratory tests of viral hepatitis, malaria, typhoid fever and urinary tract infection were collected and used for training, testing and validation of the system. The system assigns patients with severity levels in all the clusters, this in turn guides physician on which disease to treat at any given time. The validity of the clusters was confirmed with PC and PE indices producing satisfactory results of 0.396 and 0.795 respectively. Findings on the impact of the overlapping symptoms of CTD show that the weight of the overlapping symptoms of M and T explains 41.9% of both diseases. Symptoms common to H and U contributes 23.3% to the severity of both diseases. The results depicts that symptoms of both H and T have highest degree of overlapping while symptoms common to M and U yields the least impact. Symptoms common to M, H and T only, have equal impact with that of M, T and U only (14.44%). The symptoms that are common to all the four diseases under study yielded a 12.8% contribution to the degree of severity of each of the CTD diseases. The system compares favorably with diagnosis conducted by experienced physicians and also provides patients' level of severity in each confusable disease and the degree of confusability of any two or more diseases. As a further research, the impact of specific symptoms of each confusable disease and a comparative analysis of results with bio-inspired algorithms is necessary.

12.0 References

[1] Olabiyisi, S. S., Omidiora, E.O, Olaniyan, O.M and Derikoma, O. (2011). A Decision Support Model for Tropical Diseases Using Fuzzy Logic. African Journal of Computer & ICT. 4(2),1-6

[2] Keller, A., Frey, M., Schmid, H., Steffen, R., Walker, T. and Schlagenhaut, P. (2008). Imported Tropical Fever in Switzerland 1993-2004. *Journal of Travel medicine,* 15(4), 248-251.

[3] Birnbaumer, D. M. and Rutkowski, A. (2003). Malaria: A Comprehensive Review for the Emergency Physician. *Topics in Emergency Medicine,* 25(1), 2-12.

[4] Suh, K. N., Kain, K. C. and Keystone, J. S. (2004). Malaria. *Canadian Medical Association Journal,* 170(1), 1693-1702.

[5] Konar A. (2000). Artificial Intelligence and Soft Computing; Behavioural and Cognitive Modeling of the Human Brain, CRC press, New York.

[6] Ryan, E. T., Wilson, M. E. and Kain, K. C. (2002). Illness After International Travel. *New England Journal of Medicine*, 347(7), 505-506.

[7] Karkey, A., Aryjal, A., Basnyat, B. and Baker, S. (2008). Kathmandu Nepal: Still and Enteric Fever Capital of the World. *Journal of Infections in Developing Countries*, 2(6), 461-465.

[8] Khuroo, M. S. (2003). Viral hepatitis in international travelers: Risks and prevention. *International Journal of Antimicrobial Agents*, 21(2), 143-152.

[9] Campbell, S. (2008). Malaria Control and Prevention. *Primary Health care*, 18(7), 25-29.

[10] Hunter, A., Denman-Vitale, S., Garzon, L., Allen, P. J. & Schumann, L. (2009). Global Infections: Recognition, Management and Prevention. *Nurse Practitioner*, 32(2), 34-42.

[11] Basnyat, B., markey, A. p., Zimmerman, M. D. & Murdoch, D. R. (2005). Enteric (typhoid) fever in Travelers. *Clinical Infectious Diseases*, 15;41(10), 1467-1472.

[12] Woodford, H. (2009). Diagnosis and Management of Urinary Tract Infections in Hospitalized Older People. *Journal of the American Geriatrics Society*, 57(1), 107-114.

[13] Zeller, V., Didier, B., Dos-Santos, G., Bossi, P. & Caumes, E. (2003). Upper Urinary Tract Infection as a Leading Cause of Fever among Female Travelers Returning from the Tropics. *Journal of Travel Medicine*, 10, 139-146.

[14] Obot O.U and Uzoka F-M.E (2008). Fuzzy-Rule Base Framework for the Management of Tropical Diseases; International Journal of Medical Engineering and Informatics, 1(1), 7-17.

[15] Saritas, I., Allahverdi, N. Sert, U. (2003). A Fuzzy Expert System Design for Diagnosis of Prostrate Cancer', Proceedings of International Conference on Computer Systems and technologies, Kanya, Turkey.

[16] Brause, R. and Friedrich, F. (2000). A Neuro-Fuzzy Approach as Medical Diagnosis Interface', in Proceedings of European Symposium on Artificial Neural Networks (ESANN), (1), 201-206.

[17] Nunes, C.S., Mahfouf, M., Kinkens, D.A. and Peacock, J.E. (2005). Modeling and Multivariable Control in Anesthesia Using Neural-Fuzzy paradigm', Artificial Intelligence in Medicine, Elsvier, (35),195-206.

[18] Akinyokun, O. C., Obot, O. U., Andy, J.J. and Aletor, V.A. (2006). Design of a Neuro-fuzzy expert System for the Diagnosis and Therapy of Cardiovascular Diseases', In Proceedings of the 42nd Annual Conference of Science Association of Nigeria Ijebu-Ode,Nigeria,7.

[19] Uzoka, F. M. E., Osuji, J. C. and Obot, O. (2011). Clinical decision support system (DSS) in the diagnosis of malaria: A Case Comparison of Two Soft Computing Methodologies. *Expert Systems with Applications*, 38(3), 1269-2922

[20] Obot, O. U. (1999). Knowledge-based server for Diagnosis and Therapy of Tropical Diseases', M. Tech Thesis, Federal University of Technology, Akure.

[21] Uzoka, F-M.E and Famuyiwa, F.O (2004). A Framework for the Application of Knowledge Technology to the Management of Diseases, *International Journal of Health Care Quality Assurance*, (17)4, 194-204.

[22] Uzoka, F-M.E. and Baker, K (2004). AHP-based Malaria Diagnosis Decision Support System, *International Conference for Health Telemedicine and Health ICT*, Luxembourg, 6-8.

[23] Kumar, P., Verma, P., & Shrma, R. (2010). Comparative Analysis of Fuzzy C Mean and Hard C Means Algorithm. International Journal of Information Technology and Knowledge Management, 2(2010), 1-5.

[24] Ekong, V. E., Onibere, E. A., and Imianvan, A. A. (2011). Fuzzy Cluster Means System for the Diagnosis of Liver Diseases. International Journal of Computer Science and Technology, 2(3), 205-209.

[25] Inyang, U. G. and Akinyokun, O. C. (2006). Fuzzy Cluster Means System for Matching Human Behavior Patterns to Ethnic groups. Proceedings of the International Conference on New Trends in Mathematics and Computer Science with Applications to Real World Problems (NTMCS2006), Covenant University, Ota, Nigeria (pp. 429-434).

[26] Inyang, U. G. and Joshua, E. E. (2013). Fuzzy Clustering of Students' Data Repository for At-Risks Students Identification and Monitoring. Computer and Information Science. 6(4), 37-50 doi:10.5539/cis.v6n4p37

[27] Zuviria, M. N., and Deepa, M. (2013). A Robust Fuzzy Neighborhood Based C Means Algorithm for Image Clustering. *International Journal of Advanced Research in Computer Science and Software Engineering*, 3(3), 87-94.

[28] Halkidi, M., Gunopulos. D., Vazirgiannis, M., Kumar, N and Domeniconi, C. (2008). A Clustering Framework Based on Subjective and Objective Validity Criteria. ACM Transactions on Knowledge Discovery from Data, 1(4), 1-25

[29] Trauwaert, E., (1988). On the meaning of Dunns Partition Coefficient for Fuzzy Clusters. *Fuzzy Sets Systems* (25), 217–242.

[30] Hung, Wen-Liang, and Yang, Miin-Shen (2008). On Similarity Measures between intuitionist Fuzzy Sets. International Journal of Intelligent Systems, (23) 364–383

[31] Dhar, M. (2013). On Cardinality of Fuzzy Sets. International Journal of Intelligent Systems and Applications. (60), 47-52. doi: 10.5815/ijisa.2013.06.06

[32] Visa, S and Ralescu, A. (2003). Workshop on Learning from Imbalanced Datasets II, ICML, Washinton Dc
[33] Innocent, P. R., John, R. I. and Garibaldi, J. M. (2004). Fuzzy Methods and Medical Diagnosis. Applied Artificial Intelligence 19(2005) pp 60-98.