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Intelligent means of using Fuzzy Logic to determine the severity of Listeriosis disease.

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***Abstract*— *Listeriosis is an uncommon bacterial infection that is potentially fatal in the foetus, in newborns and immune compromised adults. Although the number of reported cases may be small but the high death rate associated with this infection is a significant public health concern and the reported cases as presented in is worrisome. The objective of this study is to design an intelligent means of using Fuzzy Logic for determining the severity of Listeriosis disease; this will assist the medical practitioners in the process of early discovery of the disease and proffer necessary medications. Ladoke Akintola University Teaching Hospital (LAUTECH), Osogbo, Nigeria was used for the research. To ensure the confidentiality of the information collected and the anonymity, international ethical standards were followed. We used 8 clinical symptoms and 2 types of listeriosis diseases as our dataset. The system is developed in an environment characterized by Microsoft XP Professional operating system, Microsoft Access Database Management System, Visual BASIC Application Language and Microsoft Excel. We also performed training, testing and validation. The correct classified records are stored in the knowledge base. Rule extraction with the correct classified data was also performed.*

***Keywords*— listeriosis, fuzzy logic, intelligent, severity, diagnosis.**

I. INTRODUCTION

Listeriosis is a rare but potentially serious infection caused by Listeria monocytogenes. This organism can be found throughout the environment in soil, vegetation and animals. The main route of transmission is believed to be through consumption of contaminated food. However, infection can also be transmitted, although very rare, directly from infected animals to humans, as well as between humans [1]. In neonatal infections, L. monocytogenes can be transmitted from mother to child in uterus or during passage through the infected birth canal. There are also rare reports of nosocomial transmission attributed to contaminated material or patient-to-patient transmission via healthcare workers [1]. The bacterium is particularly successful in causing food borne disease, because it survives food-processing technologies that rely on acidic or salty conditions [2], and, unlike many pathogens, can continue to multiply slowly at low temperatures, allowing for growth even in properly refrigerated foods. Only food products that will allow growth of *L. monocytogenes* after contamination are likely to cause human cases or outbreaks. In addition, only certain subpopulations (the elderly, pregnant women, and the immune compromised) are likely to contract listeriosis.

Listeriosis outbreaks are so deadly, because while *L. monocytogenes* infections can lead to mild flu-like symptoms and, in rare cases, gastrointestinal disease symptoms, typical listeriosis cases present as an invasive disease with symptoms including septicemia, meningitis, and spontaneous abortions in pregnant women. While invasive listeriosis represents a rare food borne disease (with 3–5 cases of listeriosis per year per million population being a typical rate for most developed countries), a large proportion of the cases (approximately 20%) have a lethal outcome. lead to deaths of the infected individual. From a mechanistic point of view, *L. monocytogenes* infections are characterized by this pathogen's ability not to only invade and survive in host cells, but also to spread from host cell to host cell without exiting in the extracellular space, which facilitates avoidance of the host's hormonal immune system. In addition, *L. monocytogenes* has the ability to penetrate the intestinal placental, and blood-brain barriers.

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L. monocytogenes causes two forms of listeriosis: non-invasive gastrointestinal listeriosis and invasive listeriosis. In immune competent individuals, non-invasive listeriosis develops as a typical febrile gastroenteritis. In Immunocompromised adults, such as the elderly and patients receiving immunosuppressive agents, listeriosis can manifest as septicemia or meningoencephalitis. Invasive listeriosis can also be acquired by the fetus from its infected mother via the placenta [3].

Listeriosis is an uncommon bacterial infection that is potentially fatal in the foetus, in newborns and immunocompromised adults. [1,2] opined that Listeria monocytogenes (Lm) cause invasive listeriosis with central nervous system involvement (meningitis, meningoencephalitis) and bactaeremia with a high case fatality rate (20% to 30%). Lm also causes non-invasive disease such as gastroenteritis [4]. Lm is widely distributed in the environment and can contaminate a wide variety of foods [5, 6]. Listeriosis is relatively rare disease with 0.1 to 10 cases per million people per year depending on the countries and region of the world. Although the number of reported cases may be small but the high death rate associated with this infection is a significant public health concern [7] and the reported cases as presented in [8] is worrisome. The objective of this study is to design an intelligent means of using Fuzzy Logic for diagnosing Listeriosis disease that will assist the medical practitioners in the process of early discovery of the disease and proffer necessary medications before it snowball into a severe stage.

II. REVIEW OF LITERATURE

A sample case of listeriosis in Austria between 1997 and 2007 was presented in [9]. It was confirmed that; the average incidence of listeriosis in Austria in the period studied was 0.168 cases per 100,000 population. The majority of the cases (90.0%) were caused by systemic infection [10], [11], and [12] only 9.3% of the cases were local infection. They also affirmed that "among non-pregnancy associated cases, the fatality rate was 28.7% (39/136) and among the pregnancy associated cases, 35.7% (5/14 miscarriage x3, stillbirth x1, and one death in a new birth within 15 days of birth)".

Severity cases of listeriosis were emphasized in [13], [14], [15], and through early detection it will reduce the consequence of the disease. Majorly, when such cases are not treated at the early it causes high rate of fatality [16], [17], [18].

The outbreak of listeriosis and it's accompany risks was outlined by [19], [20]. Also reporting of listeriosis was dominated by people over the age of 60 and women of child-bearing age (ages 20 – 29), the latter being cases associated with pregnancy [21]. Food is considered the major source of *L. monocytogenes* infections in New Zealand with an estimated 84.9% of reported listeriosis cases likely to be food borne. Listeriosis is typically associated with the consumption of chilled, long shelf-life, ready-to-eat (RTE) foods that do not undergo a listericidal processing step or where there is a risk of post-processing contamination. Typical foods include smoked fish, pâté, cooked meats, small goods, unpasteurized milk and dairy products. Therefore, the joint Australia and New Zealand Food Standards Code has established microbiological limits for certain high risk foods that have been associated with past outbreaks and food incidents [22]. The various presentations above does not include any scientific method of determining the severity of listeriosis, hence the need for our study.

III. RESEARCH METHODS

Ladoke Akintola University Teaching Hospital (LAUTECH), Osogbo, Nigeria was used for the research. To ensure the confidentiality of the information collected and the anonymity, International ethical standards were followed. We used 8 clinical symptoms and 2 types of listeriosis diseases for our dataset. The expert system is developed in an environment characterized by Microsoft XP Professional operating system, Microsoft Access Database Management System, Visual BASIC Application Language and Microsoft Excel. We also performed training, testing and validation. The correct classified records are stored in the knowledge base. Rule extraction with the correct classified data was also performed.

a. Fuzzy C-Means Clustering (FCM)

One of the most widely used fuzzy clustering algorithms is Fuzzy C-Means Clustering (FCM) algorithm. The algorithm attempts to partition a finite collection of elements X={X1, X2... Xn} into a collection of c fuzzy clusters with respect to some given criterion. Given a finite set of data, the algorithm returns a list of c cluster centers V, such that; V =Vi, i=1, 2,..., c and a partition matrix U such that U = Uij ,i =1,..., c , j =1,..., n.. Where Uij is a numerical value in [0, 1] that indicates the degree to which the element Xj belongs to i-th cluster.

The fuzzy logic linguistic description of the typical FCM algorithm is presented below:

Start

Step 1: Select the number of clusters c ($2 \le c \le n$), exponential weight μ

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(1<μ<∞), initial partition matrix U0, and the termination criterion ε.
Also, set the iteration index i to 0.

Step 2: Calculate the fuzzy cluster centers {Vi 1| i=1, 2... c} by using U1.

Step 3: Calculate the new partition matrix U1+1 by using {Vi 1| i=1, 2, c}.

Step 4: Calculate the new partition matrix = ‖ U1+1 - U1‖ = | Uij 1+1 – Uij 1 |. If >ε, then set l = l+ 1 and go to step 2. If ≤ε, then stop.

Stop

b. Model of Fuzzy C-Means Clustering for Listeriosis diseases

In this study, a model of the fuzzy C-means expert system for the diagnosis of listeriosis diseases is shown in Fig. 1. It consists of a Knowledge base system, Fuzzy C-means inference engine and decision support module. The knowledge base is made of the details of the patients, the observed clinical symptoms and data. The values of the clinical symptoms are vague and imprecise hence the adoption of fuzzy logic as a means of analyzing these information. These values therefore constitute the fuzzy parameters of the knowledge base. The fuzzy set of the clinical symptoms characteristics is represented by 'P' which is defined as: P = {p1, p2… pN} where pi represents the jth parameter and n is the total number of parameters (in this study, n= 8). Neural network provides the structured intelligent learning for all forms of the symptoms of obstetrics fistula diseases, which serves as a platform for the inference engine.

The inference engine consists of reasoning algorithms, driven by production rules. These production rules are evaluated by using the forward chaining approach of reasoning. The fuzzy logic and Fuzzy C-means algorithm provides the rules for the partitioning of patients into a number of identifiable clusters with respect to a suitable similarity measure. The patients were classified according to the 2 types of listeriosis.

Fuzzy logic is a superset of the conventional Boolean logic with capability for handling imprecise (vague) and incomplete data that are commonly found in medical records. It resembles human decision making with its ability to work from approximate reasoning and ultimately find a precise solution to a given problem. The process of diagnosing listeriosis by the fuzzy logic involves the following stages:

a. Fuzzification of input variables (values of signs, symptoms, and laboratory test results).
b. Establishment of the fuzzy rule base.
c. Building the decision making logic of the fuzzy logic component (inference engine).
d. Defuzzification of the output of the inference engine into crisp values.

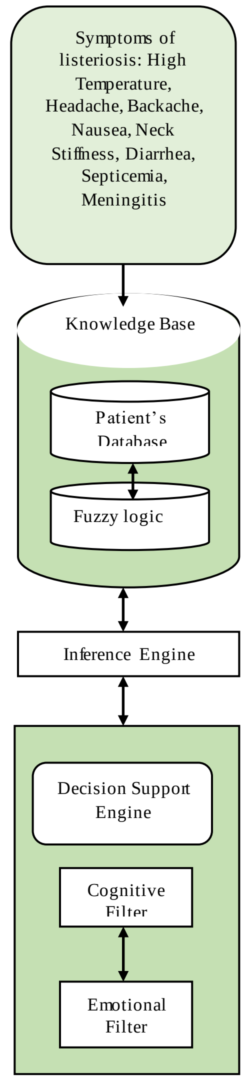

Fig.1: A Model of Fuzzy Logic for Determination of the Severity of Listeriosis Disease

A fuzzy set of mild and more severe forms of the disease serves as the input variables (signs, symptoms, and laboratory test results) are defined. The input variables are fuzzified and the membership functions defined for them are applied to their actual values to determine the degree of the truth preceding each rule.

IV. RESULTS AND DISCUSSIONS

In designing the FCM Knowledge Base System for determining the severity of Listeriosis, the needed sets of parameters or symptoms are presented in Table 1, while types of Listeriosis are in Table 2.

Table 1: Symptoms of Listeriosis

P	Input Field	Code
1	High Temperature	HT
2	Headache	HA
3	Backache	BA
4	Nausea	NS
5	Neck Stiffness	NS
6	Diarrhea	DR
7	Septicemia	SM
8	Meningitis	MG

We presented the architecture/model of the FCM system for determining the severity of Listeriosis of Listeriosis in Figure 1. It comprises of knowledge base system, fuzzy c-means inference engine and decision support system. The knowledge base system holds the symptoms for listeriosis. The values of the parameters are vague and imprecise hence the adoption of fuzzy logic as a means of analyzing these information. Those parameters therefore constitute the fuzzy parameter of the knowledge base.

The fuzzy set of parameters is represented by 'P' which is defined as P= P1, P2,…, Pn Where Pi represents the jth parameter and n is the total number of parameter (in this case n = 8). The set of linguistic values which is modeled as a linker scale denoted by 'L' is given as L = (Mild or Severe).

Table 2: Types of Listeriosis

No	Types of Listeriosis	Description	Cluster code
1	Non invasive	Mild form	NI
2	Invasive	More Severe form	IS

The clustering of the data is achieved using the typical FCM algorithm presented in Figure 2. Neural networks provide the structure for the parameters which serves as a platform for the inference engine. The inference engine consists of reasoning algorithms driven by production rules. These production rules are evaluated by using the forward chaining approach of reasoning. The inference mechanism is fuzzy logic driven. The cognitive filter of the decision support engine takes as input the output report of the inference engine and applies the objective rules to rank the individual on the presence or absence of listeriosis disease. Using the emotional filter as input the output report of the cognitive filter and applies the subjective rules in the study of listeriosis disease for ranking individuals on the availability of the disease.

Table 3: FCM membership grade of all patients in all clusters

PNO	**C1** (NI)	**C2** (IS)
P1	0.76	0.75
P2	0.75	0.61
P3	0.64	0.71
P4	0.31	0.25
P5	0.55	0.67
P6	0.35	0.36
P7	0.18	0.85
P8	0.15	0.95

A typical FCM membership grade table (Table 3) using 8 parameters and 2 clusters which shows the degree of membership of each parameter of listeriosis is represented in Figure 3. From Table3, it could be observed that from the various degrees of membership there are no unitary (crisp) coefficients, indicating that each data point belongs to more than one cluster. For example P3 = (0.10/c1 +0.03/c2+0.30/c3+0.52/c4+0.05/c5) where c1, c2, c5 are clusters, and in this study represents Noninvasive form (NI), and Invasive form (IS). Each of the symptoms highlighted in Table1 is represented with P (starting from 1 – 8, i.e., P1-P8).

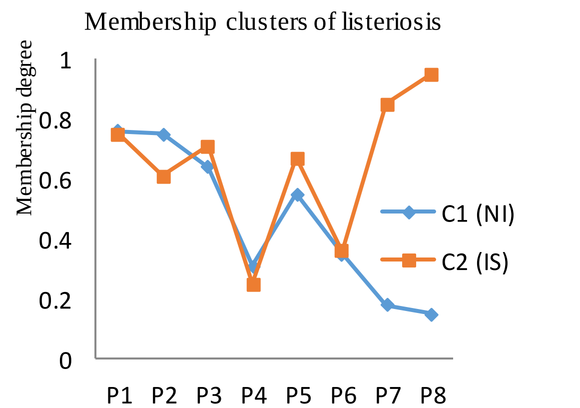

Fig 2: Membership Clusters of Listeriosis

The membership grades of parameters in all clusters are presented in table 3and the degree of membership of the clusters is presented in Figure 2. Cluster 2 has the highest

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degree (0.95) for symptom P8; also Cluster 2 has the degree (0.85) for symptom P7, which are indications of severe cases of listeriosis. Cluster 1 has the highest degree (0.76) for symptom P1, and the degree (0.75) for symptom P2, these are indicative of mild forms of the disease. The presentations of degrees for P3, P4, P5 and P6 for both clusters are interwoven.

V. CONCLUSIONS

The study presents a diagnostic fuzzy cluster platform to help in the diagnosis of listeriosis diseases using a set of symptoms and demonstrates the practical application of soft computing in the domain of diagnostic pattern appraised by determining the extent of membership of individual symptoms. The classification, verification and matching of symptoms to the clusters was necessary especially in some complex scenarios. The study is to assist users in determining the type and severity of listeriosis disease on patient(s). It will also assist the medical practitioners in making necessary prescriptions for the early treatment of the disease whether mild or severe.

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