

A LINGUISTIC FUZZY EXPERT SYSTEM FOR CONTAGIOUS DISEASES DETECTION AND ISOLATION

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ABSTRACT

This paper presents an electronic Expert system platform to detect and diagnose existing and new cases of contagious diseases as they occur with minimal contact with the index patient(s) and healthcare personnel with a confidence level that can be used to initiate or suggest appropriate follow-up action(s). The aim is to use ICT tools for patient-diagnosis, raise a red flag in real-time and thus contain contagious cases which may degenerate into an epidemic by providing a way to analyze vague and ambiguous input data from visible and reported symptoms in patients. A re-useable Expert system which makes use of fuzzy reasoning techniques and design methodology was used in this work. The Expert system is premised on rule-based fuzzy logic which captures the ambiguity, imprecision and nuances involved in disease reporting and detection using the Mamdani model. The software developed for the Fuzzy Expert system, called SOSIC, presents its diagnosis with fuzzy values between 0 to 1 corresponding to its level of confidence for the fuzzy inputs. The current approach to e-diagnosis and detection of contagious diseases using the SOSIC software is not completely contactless, thus ongoing investigations are geared towards improving SOSIC to be contactless. The developed system which runs on a computer system provides a safe procedure with minimum contact between patients and healthcare personnel to address early detection and diagnosis issues that may help forestall chain-infection and epidemics. The fuzzy based Expert system can be further extended to accommodate the detection of a wider array of symptoms as new cases arise; thus this paper fulfils an identified need in safe healthcare practice.

KEYWORDS: Fuzzy Expert Systems, Contagious Diseases Control, SOSIC Diagnosis, Preventing Diseases, Quarantining.

INTRODUCTION

Imagine a scenario of patient trying desperately to see a doctor especially in public hospitals and primary health care without a mechanism to track who comes in and go out. This leaves much to be desired from researchers and scientists especially from West African, a region which have been plagued with contagious diseases such as Ebola virus disease (EVD), Lassa fever, e.t.c. Experiences such as undue waste of time, frustration and delays, exploitation and lackadaisical attitude of some of the healthcare givers also increase the rate of contagion. In a developing country such as Nigeria, where there is consistent trade union and government disagreements over salaries, entitlements, working conditions and health care facilities, life threatening situations and conditions may further be compromised by these healthcare institutions. This is further complicated by the fact that diseases outbreaks usually have debilitating consequences, endangering even the healthcare givers' health and the populace if not detected, isolated and controlled as it emerges in public through an index case. It is therefore a matter of urgency and necessity for a review of the health institution's modus operandi in tandem with recent developments and best practices available in other climes. This work advocates a way for healthcare givers to examine patients in emergencies with a view to minimizing contact with yet to be properly diagnosed patients that may be a host to contagious diseases such as Influenza (flu), Lassa fever and EVD among others. By minimal contact, nurses and other lower cadre healthcare givers who hitherto are the first to receive patients on arrival in the emergency units of hospitals and clinics are allowed to have a general idea of the case they are dealing with. This idea is based on deploying an expert system comparable to MYCIN to help reduce the window period prior to when a patient who may be an index case of a contagious disease finally sees the doctor. This should help with reducing the risk of infecting medical personnel or even other patients that may be exposed in the general patient out-ward unit.

The disease prevention and isolation approach we have chosen for this expert system is to help protect everybody involved either directly or indirectly in the event of a disease outbreak by helping to contain the spread, kick start quarantine procedures where necessary and proffer initial solutions verifiable by trained medical personnel if necessary. Thus it serves as an electronic form of first aid pending final diagnosis by trained personnel and can serve as a referral to Emergency Diseases Hospitals (EDH) if available. This work allows healthcare personnel and even the patients-to-be-diagnosed to respond to basic or simple questions from the software package we have developed. The designed Expert system which runs on the personal

computer can be administered to patients at about one metre to healthcare personnel at the general open ward for out-patients. The structured information related approach adopted by the system will help reduce the severity for spreading of contagious diseases bearing in mind that there is normally an ample amount of time wasted while waiting on a queue to see the doctor.

RELATED WORK

The use of computers to aid health care givers and patients have been available as far back as 1970s with the design and deployment of MYCIN, a medical expert system for diagnosing ailment and based on rule base reasoning (Shortliffe, 1976) that are premised on certainty factors of symptoms present in patients. CASNET was also designed to help medical personnel to detect ailments and diseases in patients by considering the most significant result of tests. It uses semantic network representation formalism, having nodes which represent disease states with attached weights to determine how they relate under some appropriately defined relationship. Due mainly to the dynamic nature of diseases occurrence (Reddy, 2002), complexity in its spread and sensitive factors involved in treatment and isolation these Expert systems could not really capture the vagueness in patient reported symptoms. This is coupled with a dearth in professional expertise needed for building, verifying, defuzzifying and deploying tools for patient diagnostic purposes. The recent (2014) outbreak of the Ebola Viral Disease (EVD) in West Africa where standard health procedures could not prevent the death of the healthcare givers who probably due to the fact that EVD was not rampant and with symptoms similar to high fever, malaria, pains, etc which are not contagious may have initiated very low alert levels in dealing with the case. However, an ICT supported healthcare system using expert system's artificial intelligence and capability to analyze huge and mostly vague data in real-time will provide the necessary large database that can contain all possibility of the symptoms of a disease including Emerging infectious diseases (EIDs). A daunting task awaits data mining in making sense from huge data as EIDs continue to emerge even with variants for which (Vrbova et al., 2009) and (Friedl and Ceccato, 2010); puts the number of EIDs to be increasing globally over the past 50 years. The sources estimates that the proportion of EIDs that involve pathogenic transmission from animals to humans, or *zoonoses* to be ranging from 60% to 75% of contagious diseases. Although the number according to (Vrbova et al., 2009) of "Emerging zoonoses can become devastating if they become transmissible from person to person, it could lead to disease outbreaks. For example, the complete genetic characterization of the pandemic (in) 1918 (of the) "Spanish Flu" virus suggests it not only originated from an avian influenza virus, but that the pandemic virus was in fact an adapted avian influenza virus; these findings show that zoonotic agents can result in severe impacts with minimal genetic changes, in this case increased severity and facilitated human to human transmission, some of which are already present in the current circulating avian viruses." EVDs zoonotic agents include bats, monkeys, apes and duikers (African antelopes). Vrbova et al., (2009) further went on to point out that "society would be better prepared to detect and prevent EIDs if we can get 'ahead of the curve:' if we are able to identify risky situations before the first cluster of cases in humans are identified in hospitals". The increasing use of ICT and its tools has witness an unprecedented growth in almost all areas including security and crime detection (Badiru et al., 2006), in teaching and learning (Reamon and Sheppard, 1997) and healthcare cannot be left behind.

The role of approximate reasoning in a medical expert system which was developed by (Hudson and Cohen, 1992) and called EMERGE uses a rule-based expert system for the analysis of chest pain in an emergency room environment to provide rapid decision making by utilizing certainty factors to indicate the seriousness of the patients illness. The EMERGE according to developers however lacked the ability to record nuance (high distinction) and did not intuitively appear to follow the same processes as the human reasoning process. Though our intent is purely to serve as an alternative to help advance diagnosis of diseases especially contagious ones in our healthcare system and to draw attention to this area of scientific support to the healthcare system we however state that the result of this work or the conclusion from the diagnostic software cannot serve as a substitute for the advice, diagnosis or treatment by a doctor or other trained health professionals.

METHODOLOGY

The diagnostic software designed is based on a mathematical model that allows application of rule-based fuzzy models to obtain a relationship between variables that interfere as signs and symptoms to collectively determine the state of a patient by representing these variables by means of if-then rules with vague or imprecise (ambiguous) predicates, such as:

If body temperature is High then Malaria susceptibility is High.

If body pressure is Low then Fever susceptibility is Low.
 If Weight Loss is High then Chronic Condition is High.

This defines in a rather qualitative way the relationship between the patient's body temperature, pressure and weight and the disease causative mechanism. However, due to the fact that human reasoning and response to data entry or collation is based on heuristics and ambiguity; for example, temperature may be reported as high, slightly high or very high. Pressure could be reported as normal or abnormal and weight loss could be interpreted as high, slightly high or severe. Thus to make such a model operational, the meaning of the term 'high' or 'low' must be defined more precisely. This is done by using fuzzy sets, that is, sets where the membership is changing. The Mamdani model was chosen for this project over the Takagi–Sugeno Model due to the ability of the model to deal with linguistic fuzzy since the latter is more adapted for data driven identification.

Mamdani Model.

In this model, the antecedent (if-part of the rule) and the consequent (then-part of the rule) are fuzzy propositions:

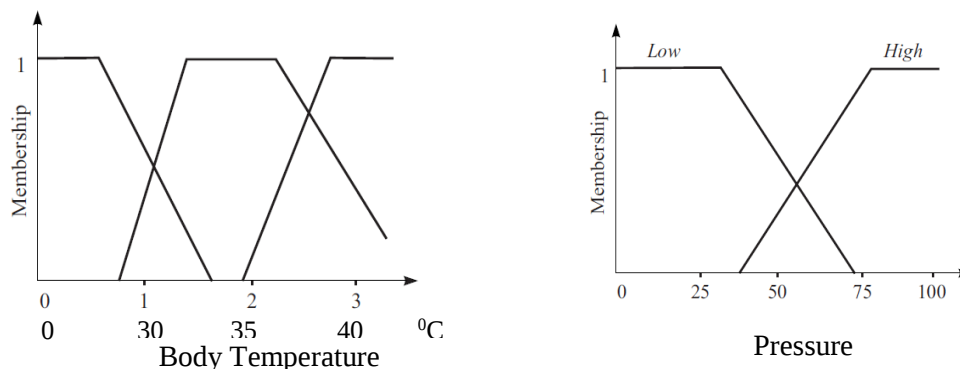
$$R_i: \text{If } x \text{ is } A_i \text{ then } y \text{ is } B_i; i = 1, 2, \dots, K \quad \dots\dots\dots 1$$

Here A_i and B_i are the antecedent and consequent linguistic terms of patients' symptoms as present (such as 'Normal', 'Slightly large', 'Very High' etc.), represented by fuzzy sets, and K is the number of rules in the model.

Fuzzy Inference Systems (FIS).

A FIS according to (Ardil and Sandhu, 2010) "is a way of mapping an input space to an output space using fuzzy logic. A FIS tries to formalize the reasoning process of human language by means of fuzzy logic (that is, by building fuzzy IF-THEN rules)." The Mamdani-type inference expects the output membership functions to be fuzzy sets whose output, after the aggregation and defuzzification process is a single spike rather than a distributed fuzzy set. This output which is a singleton output membership function of the pre-defuzzified fuzzy set corresponds to the efficiency of the defuzzification process and the computation of the centroid of a two-dimensional function. This linguistic fuzzy model is useful for representing qualitative knowledge based on available or visible symptoms and belief that the respondent, that is either the patient or nurse is giving accurate report of patient symptoms. These uncertain and ambiguous linguistic variables or 'qualifying adjectives' contain more information than 'crisp' values of true or false, high or low, hot or cold thus aiding prompt disease detection which depend more on the degree of causative elements in the patient's body. For example early stages of a disease will manifest fewer symptoms compared to later and final states with each stage having its own unique signatures. By using membership functions the degree or extent of viral, pathogenic, bacterial, etc involvement, their stage of development, population, etc present in the patient's immune system (the host) can be more understood.

For example, a membership function mapping of body temperature and blood pressure is shown below in Fig.1.



Since the input–output data of the body system under study are available, the membership functions can be constructed or adjusted automatically with the stringent rule that the qualitative relationship given by the rules is usually expected to be valid for a range of health conditions.

Fuzzy Expected Interval, (FEI).

To handle the fuzzy population distribution in the proposed inference system the equation below which was obtained from reference (Kandel, 2002) was used to obtain the upper and lower bounds in the computation of

the Fuzzy Expected Interval, (FEI) from which a Fuzzy Expected value was computed of the reported symptoms.

$$UB_j = \frac{\sum_{i=j}^n \text{MAX}(pi1, pi2)}{\sum_{i=j}^n \text{MAX}(pi1, pi2) + \sum_{i=j}^{J-1} \text{MIN}(pi1, pi2)} \quad \dots\dots\dots 2$$

$$LB_j = \frac{\sum_{i=j}^n \text{MIN}(pi1, pi2)}{\sum_{i=j}^n \text{MIN}(pi1, pi2) + \sum_{i=j}^{J-1} \text{MAX}(pi1, pi2)} \quad \dots\dots\dots 3$$

Software Implementation (SOSI Clinic)

A screenshot of the graphical user interface (GUI) that accepts patients' real-time symptoms is shown in Fig.2. The GUI as shown is designed to capture the uncertainty of fuzziness and ambiguity or vagueness in responses of the patient under investigation (not diagnosis) in real-time. The resultant conclusions of the software or the administering healthcare personnel such as the nurse on duty that is using the Expert system is however not the final deciding factor of whether patient will be admitted or rejected but only give a clue to the severity of the new case.

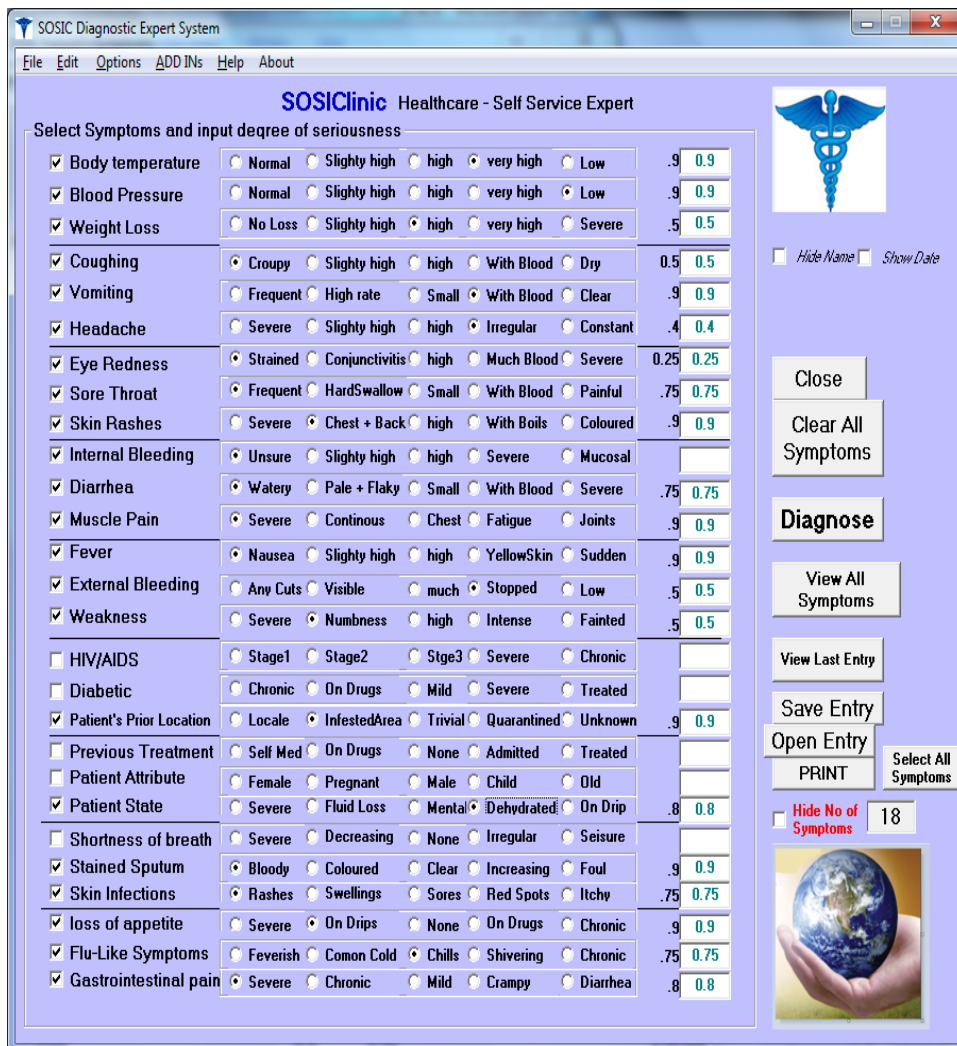


Fig. 2: shows the SOSIC diagnostic console for inputting symptoms

In using this tool, the user will have to select the degree of presence of symptoms as visible on the patient or as reported by the patient under investigation. These selected actions directly ‘fire’ the respective membership functions in the fuzzy Expert system by creating a membership function set. The software based on the selected fuzzy inputs and generated membership functions uses its fuzzy inference system to obtain a unique value which depicts mathematically the state or condition of the patient. This value then serves as a contributor to the final decision of the system after considering all contributing values.

RESULTS AND DISCUSSION

Fig.3 shows a screenshot of the window showing the results of the diagnosis by the SOSIC expert system for which fictitious values have been previously inputted; recall in Fig.2 above. The hypothetical cases or inputs were used to diagnose a severe case of typhoid and quarantine was not recommended since it was not directly contagious but due to the severity of the ailment, admission was recommended.

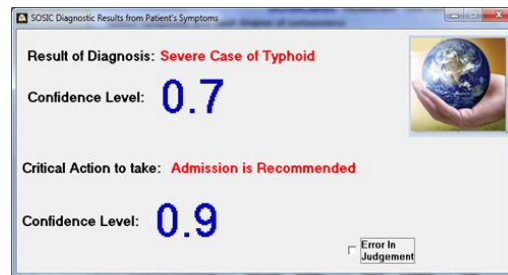


Fig.3: Results of diagnosis of a Typhoid case

However in Fig. 4 below a severe condition of EVD was detected and quarantine was recommended for the patient. The Error in Judgment (EIJ) is further computed by the software to show the degree of its conviction and premise. The EIJ is an optional information source that users or trained personnel can use to further validate the result of the investigation.

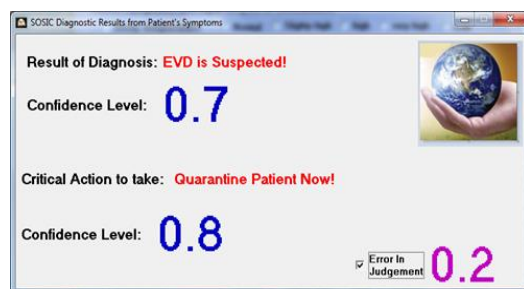


Fig. 4: Results of diagnosis of a contagious EVD case

The EIJ is based on the number and degree of symptoms fed into it by the patient or/and healthcare personnel. For example, a patient reporting internal and external bleedings may get a computation of suspected EVD or Lassa fever but with a high 0.8 EIJ value. This high EIJ or error function value as generated points out that the two symptoms are not enough to conclude such a critical judgment. However, if other symptoms such as the prior locality of the patient or the presence of high fever were inputted in the Expert system’s reasoning the EIJ will drop significantly to say 0.2. Validation data based on demographic characteristics and symptoms in confirmed and probable Ebola cases in Guinea, Liberia, Nigeria, and Sierra Leone as documented by (WHO, 2014) showed that over 90% of the cases were established or confirmed by the SOSIC Expert system.

CONCLUSION

We have presented a novel application of fuzzy sets and fuzzy logic in this work for transforming largely vague responses of patients and their symptoms directly into alert levels with verifiable level of confidence and error in judgment. The results of the hypothetical and real cases used to validate this Expert system’s based model produced very promising results with over 90%. The SOSIC software as an Expert system has allowed the modeling of complex interacting biological systems in patients to produce a unique solution for a line of action by depending on heuristic and intuitive information readily available from ill patients in real-time. This has helped to mitigate the window period of contagious disease spread as it makes its first

appearance in the public domain through healthcare facilities. This is by efficiently detecting and isolating the index case and raising a red flag to curtail further spread. The importance of this tool cannot be overemphasized in our present highly mobile and complex society.

RECOMMENDATION

It could be appropriate if concerned authorities could collaborate and further develop this tool and adopt the outcome of the research as a standard clinical procedure for the healthcare system irrespective of whether the patient will be admitted, referred or rejected. This will definitely help nip in the bulb cases that would have hitherto claimed lives especially the healthcares' due to very low alert levels as history has continue to show that diseases take advantage of man's low alert levels.

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