Diagnosis of Febrile Diseases with Fuzzy Cognitive Map

Subjects: Primary Health Care

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Febrile diseases are fever-based diseases with similar and overlapping symptoms that are often confusable and difficult to differentiate. They are prevalent in tropical and subtropical regions where climatic conditions such as temperature, humidity, and evaporation contribute immensely to promoting the spread. The fuzzy cognitive map (FCM) model to serve as a decision-support tool for medical health workers in the diagnosis of febrile diseases.

fuzzy cognitive map febrile diseases malaria enteric fever laser fever

1. Introduction

The signs and symptoms of a disease distinguish one disease from another. Sometimes, these signs and symptoms are so similar that it becomes a challenge to make a fast and accurate distinction and this could result in an inaccurate diagnosis. Since diagnosis is the bedrock of medical practice [1], an inaccurate diagnosis could lead to complications, and, if not handled properly, could lead to the death of the victim [2]. Febrile diseases are fever-based diseases with similar and overlapping symptoms that are often confusable and difficult to differentiate. They are prevalent in tropical and subtropical regions where climatic conditions such as temperature, humidity, and evaporation contribute immensely to promoting the spread. According to Attai et al. [3], tropical locations around the world are severely affected by infectious diseases.

The knowledge of the symptoms, the etiology of a disease, and the thought process gained during practice help a physician to associate symptoms with a disease. The cognitive mapping operations could be transferred into a machine for more accurate and faster processing than a human physician does. Among many other challenges, the traditional logic of a computer does not support human reasoning as it exhibits exactness in its methodology [4]. This shortcoming of conventional logic becomes more pronounced in medical diagnosis because of ambiguities associated with a patient's medical history, laboratory investigation results, symptom elicitation, etc.

The limitation of conventional logic is overcome with fuzzy logic technology capable of resolving ambiguities and uncertainties through collaboration and aggregation and reasoning with approximation as done by the human physician [5]. With fuzzy logic, transferring the knowledge of the human physician becomes easier as the cognition operation can be mapped with fuzzified datasets and later defuzzified into crisp outputs.

Physicians are prone to errors, and medical diagnostics errors could be life threatening [2]. The errors could be because of a lack of experience, the large volume of data due to an influx of patients requiring services from a limited number of physicians, poor accessibility to patients' previous records to obtain medical history, the inability of patients to express their feelings of a particular symptom, among other reasons. They (physicians), therefore, need a tool that can assist them in reducing these errors. One such tool is the medical decision support system (MDSS), which has been useful in making critical decisions.

One of the main reasons the population, particularly those in tropical regions, cannot get medical care, according to the World Health Organization (WHO), is a lack of medical personnel. According to Mehta et al. [6], African healthcare facilities are vastly understaffed and under-resourced. The WHO [7] report of the 2018 accessibility to medical personnel in Africa is appalling, as the density ratio of 5000 patients is equated to 1 physician and 6 nurses. These statistics justify the need for a decision-support diagnostic tool to aid in curbing the rising cases of mortality caused by, among other factors, the lack of access to medical facilities by an average person living in tropical regions, especially in rural settings and resource-scarce areas.

2. Modelling Differential Diagnosis of Febrile Diseases with Fuzzy Cognitive Map

A disease associated with fever is commonly referred to as a febrile disease. Prasad et al. [8] demonstrated a wide range of pathogens associated with several febrile diseases. However, the distribution of the disease varies by geography, season, age, and immunity of the patient. According to Bell [9], the relative frequency of acute febrile syndrome varies widely with geography, living condition, and occupational exposure. There has been some research on the differential diagnosis of confusable symptoms of febrile diseases. Malaria tends to become the default diagnosis of febrile diseases due to its ubiquity and severity [10][11], such that if a patient presenting the symptoms is tested for malaria and the result is found to be negative, such a patient is left untreated for other diseases by an inexperienced medical doctor with the risk of complications. According to Crump et al. [12], healthcare workers often lack epidemiological information or the laboratory services necessary to support rational diagnostic and management decisions for patients with negative malaria diagnostic test results.

In order to treat a nonmalaria febrile illness properly (keeping in mind that patients may have malaria concurrently with another disease, especially in high endemic areas), the pathogens that cause a febrile disease must be known. If the agent is not identified, knowing the category of the pathogen (parasitic, bacterial, or viral) is useful for deciding on treatment [13]. This requires high-level accuracy of differentiation of the symptoms. Patients with enteric fever develop problems and may require therapy with longer antibi-otics to remove the infection. Enteric fever symptoms include fever, diarrhoea, muscle aches, stomach pain, rash, and others; therefore, certain guidelines are important to assist clinicians in performing the right tests and treating patients with enteric fever [14]. The ability to detect Mycobacterium tuberculosis (MTB) infection, recognize the factors that lead to tuberculosis (TB) disease, receive preventative therapy, and put methods in place to track infections and treatment completion all contribute to better control of tuberculosis [15]. Dengue fever is the most prevalent viral illness spread by mosquitoes; although it is typically moderate, dengue fever can progress into a severe type that can be fatal [16].

A review by the WHO [17] on the different tools used to evaluate acute febrile illness (AFI) in South India shows malaria to be the commonest cause of AFI, followed by dengue, scrub typhus, bacteremia, and leptospirosis. It was also revealed that malaria diagnosed by smear microscopy was more popular than other methods of tests.

Considerable research is undertaken on the alternative diagnostic methods for malaria, tuberculosis, HIV/AIDS, and dengue fever, leaving the other febrile diseases almost neglected. The effect of this is positively felt in malaria, where there was about a 40% reduction in the incidence of malaria between 2000 and 2015 [7]. A significant challenge is the acute shortage of physicians in febrile disease-prone areas. The WHO [7] gave the 2018 report on accessibility to medical personnel in Africa. According to the report, the density ratio of a physician to a 5000 populace is 1, while that of nurses/midwives is 6. This poor accessibility has affected the proper diagnosis and treatment of febrile diseases, thereby increasing the morbidity and mortality rate. The experts have a great role to play in developing systems capable of retaining knowledge and assisting them in their jobs. The medical decision support system (MDSS) has been found useful to medical practitioners in an attempt to increase the accessibility of patients to medical care and reduce the workload of personnel.

Although several approaches are used to enhance processes of improving individual health, the introduction of the fuzzy logic approach seems more human-like because of its ability to deal with uncertainty and ambiguity, which are recurring attributes in medical records. Das et al. [18] adopted fuzzy logic to model doctors'/medical experts' confidence levels in diagnosing diseases in the patient. Their method is composed of the following four steps: (i) the modelling of the antecedent part of the rules, which consists of linguistic assessments of the patient's symptoms provided by the doctors/medical experts with their corresponding confidence levels by using generalized fuzzy numbers; (ii) the modelling of a consequent part, which reveals the degree of association and the degree of non-association of diseases into the patient, by using intuitionistic fuzzy system (IFS); (iii) the use of an IFS aggregation operator in the inference process; and (iv) the application of a relative closeness function to find the final crisp output for a given diagnosis. Nilashi et al. [19] proposed a knowledge-based system for breast-cancer classification using fuzzy logic to assist medical practitioners in their clinical decision support towards their healthcare practice. The proposed knowledge-based system proves to have a better prediction accuracy (0.932) for breast cancer in relation to PCA-SVM (0.867), PCA-KNN (0.823), and decision tree (0.929).

Amjad et al. [20] employed an expert soft sets system (SES) based on the soft sets and the fuzzy set theory to diagnose dengue fever. They calculated the risk percentage of 30 patients with the help of soft sets, and it was noted that 13 patients were suffering from dengue while the other 17 patients had no complaints of dengue fever. Sharma et al. [21] introduced the concept of mediative fuzzy relation between the conventional fuzzy set and the intuitionistic fuzzy set. The mediative fuzzy projection was used in the diagnosis of COVID-19 in post-COVID-19 patients. The results obtained from the study were compared with that of conventional and intuitionist fuzzy projection and found to covary strongly. Magwili et al. [22] provided a preliminary diagnosis for patients suffering from mosquito-borne diseases by comparing the system's preliminary diagnosis with the expert's diagnosis in a total of 80 tests with 20 tests per disease; 71.67%, 83.33%, and 91.67% of the time, the system correctly prediagnosed dengue, chikungunya, and malaria, respectively. For other diseases, the system correctly identified the unlikelihood of having the said mosquito-borne diseases 91.67% of the time. Moreover, a chi-square test was also conducted with a level of significance of 0.05, yielding a *p*-value of 0.464. According to Putra and Prihatini [23], tropical infectious diseases require appropriate treatment with the active participation of a doctor and patients. In their result for defuzzification, they calculated the sequential and combined certainty factor, which represents the belief percentage of disease diagnosis suffered by the patient. The results of the expert diagnosis with the expert system for the given cases indicate the system has similarity diagnosis with the expert at 93.99%.

Ekong et al. [24] demonstrated that information technology and medicine could successfully operate together using differential diagnosis by applying fuzzy logic to medical informatics. The result increased productivity in the grid system by an average of 20%. They suggested the need to apply fuzzy logic because it will help to resolve conflicts that may arise from ambiguity, uncertainty, and imprecision in the investigation of tropical diseases. A fuzzy cognitive map (FCM) is a technique for realizing an efficient MDSS. It is built based on the experience of the domain experts who provide the degree of influence and causal knowledge of one concept to another. This means it relies on what an expert, such as a physician, perceives as the causal relationship of a symptom, such as a headache, to a disease such as malaria. This degree of influence is captured and represented as a link between headaches and malaria. According to Bourgani et al. [25], a fuzzy cognitive map is a soft computing technique used for causal knowledge acquisition and supporting the causal knowledge reasoning process. The FCM modelling approach resembles human reasoning; it relies on the human’s expert knowledge of a domain, making associations along generalized relationships between domain descriptors. Bourgani showed different forms of FCM structures for MDSS, made comparisons, and recommended temporal concepts to be included in the design of MDSS for dynamism and efficiency.

Amirkhani et al. [26] identified the different FCM structures used in MDSS after a thorough analysis of each structure and reviewed various diagnoses and decision-support problems addressed by FCMs to determine their contributions to improving medical diagnosis and treatment. Groumpos [27] explored the concept of causality to model a new state space, advanced fuzzy cognitive map (AFCM) methodology for modelling COVID-19 diagnosis. He noted that correlation does not imply causality while causality always implies correlation. He found that the FCM theories are probably the only ones that explore the causality between the variables of medical problems in a sound mathematical and scientific foundation. In Papageorgiou et al. [28] the diagnosis of the degree of severity of pulmonary infection using 33 symptoms of infectious diseases was carried out using the FCM technique. Hypothetical cases were used for the simulation of the results, showing the calculated severity of pulmonary infection to be above 90%. FCM Expert, a software for FCM modelling, was used to analyze a scenario and perform pattern classification [29].

Mpelogianni and Groumpos [30] modified the conventional FCM to obtain a mathematical model that uses a state-space approach to disaggregate the concepts into state concepts, input concepts, and output concepts. The model was then used to compute a building’s energy consumption and management of its loads. Results of computations when compared with that of the conventional FCM were found to be more accurate. According to Apostolopoulos and Groumpos [31], FCMs are potentially trustworthy because they incorporate human knowledge. Based on the parameters of trust, transparency, and causality, an explainable AI is proposed for FCM-based systems.

The architecture and features of the software were shown and discussed, including the characteristics, such as its ability to improve system convergence. A case study of FCM-based classification for modelling the resistance of HIV-1 mutations was demonstrated using a particle-swarm optimizer. A differential diagnosis of 6 eye diseases with 23 symptoms was undertaken by Obot et al. [32], where 2 independent opticians diagnosed 20 patients each and compared with the results of diagnosis using FCM with the Hebbian learning rule. The results show 65% and 45% accuracy for the first and second opticians' diagnoses, respectively. Apostolopoulos et al. [33] developed a state space advanced FCM to detect Coronary Artery Disease (CAD). The state space concepts consist of the input concepts, the state concepts, and the output concepts, where the state concepts depict the concepts that describe the operations of the system. This was later embedded in diagnostic rules developed by cardiologists. A total of 303 patient datasets collected from the Department of Nuclear Medicine of Patras, in Greece, were used to train and test the developed system. The results, compared with the classical FCM, showed 85.47% accuracy, which is a 7% higher accuracy than the conventional method of diagnosis. Apostolopoulos and Groumpos [34] solved the problems of ambiguity and uncertainty in coronary artery disease diagnosis using the noninvasive method with FCM. The results obtained showed an accuracy of 78.2%, which were reported to be better than what was obtained from other algorithms.

A time unit proposed by Bourgani et al. [35] that can follow disease progression is introduced into FCM to develop a diagnostic tool for differential diagnosis of pulmonary diseases (acute bronchitis and common-acquired pneumonia). Time-based FCM was proposed here because the values of weights and concepts of such diseases change according to the time interval. Uzoka et al. [36] proposed a framework for differential diagnosis of tropical confusable diseases using a fuzzy cognitive-map engine where 11 symptoms of 7 diseases were found to be confusable. The study employed the experiential knowledge of practising physicians and utilized a brute-force algorithmic procedure to mimic the mental algorithm used by physicians in the diagnosis process. A case study of malaria was carried out with 20 datasets, of which 55% matched the physicians' diagnoses, and 85% matched the FCM diagnoses. Uzoka et al. [37] showed a higher (though equally significant) correlation between the FCM results and actual diagnosis (AD), and between initial hypotheses (IH) and AD. The comparative summary showed that the IH by the physicians correctly matched the final diagnosis in 55% of the cases, whereas AD of the FCM was 85%. This also connotes that the correlation between the physician's initial hypothesis and the FCM diagnosis was not significant.

Hoyos et al. [38] used fuzzy cognitive maps to enhance clinical decision-support systems for dengue fever. The developed model showed a good classification performance with 89.4% accuracy and could evaluate the behaviour of clinical and laboratory variables related to dengue severity (it is an explainable method). Their model serves as a diagnostic aid for dengue that could be used by medical professionals in clinical settings and [39] applied a fuzzy cognitive map for geospatial dengue outbreak-risk prediction in tropical regions of Southern India. The accuracy of the proposed FCM-based classification approach is much better than the benchmark machine-learning algorithms, which show a deficiency in working with small datasets and without being able to use experts' knowledge.

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