Neuro-Fuzzy Framework for Community-Acquired Pneumonia Severity Diagnosis

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Abstract- Community-Acquired Pneumonia (CAP) is one of the major life-threatening diseases, a syndrome in which acute infection of the lungs develops in a patient within 14 days before the onset of the symptoms. It is one of the most common infectious diseases and a significant cause of mortality and morbidity worldwide before COVID-19 outbreak and often misdiagnosed and inappropriately treated, which also contribute to economic backwardness, mostly within developing nations. Timely and accurate diagnosis of CAP is required to reduce mortality and morbidity rate. Major contributors to high prevalence of mortality of CAP are late diagnosis, insufficient medical personnel and exorbitant treatment cost. This paper presented a proposed neuro-fuzzy framework for diagnosis of CAP severity level, this will aid medical personnel in determining the urgency and type of treatment needed and consequently reduce if not totally eradicate mortality and morbidity rates as a result of CAP.

Indexed Terms- Community-Acquired Pneumonia, Neuro-fuzzy, diagnosis, Severity Level.

I. INTRODUCTION

Medical diagnosis, the process of determining which condition explains a person's signs and symptoms is by nature a complex process involving a lot of vagueness, linguistic uncertainty, hesitation, measurement and imprecision. The information required for diagnosis is often gotten from physical examination, history, and laboratory test results of the patient where several possible explanations are compared and contrasted (Kumar *et al.,* (2011); Wikipedia, (2020)).

Arriving at a medical diagnosis requires clinical skill, hence, there is need to accept the ambiguity present in many clinical situations to make a good decision. With the advent of Science and Technology, intelligent computing has been used in medical experts for qualitative services, thereby reducing the mortality rate and also alleviating the economic burden placed on the society through lost working time due to one ailment or the other. The relations between diagnoses and their symptoms are usually not exclusive; hence, differential diagnoses of diseases that share matching range of symptoms with other diseases is usually difficult to make and observations are usually subjected to errors because of human subjectivity.

Community-Acquired Pneumonia (CAP) is one of the most common infectious diseases in which infection of the pulmonary parenchyma is acquired outside of a health care setting requiring hospital admission in both developed and developing countries before the outbreak of COVID-19 pandemic, with more than 1.5 million adults hospitalized annually. It is a common cause of illness and death from infectious disease both in western and developing countries with high incidence among children less than five years of age and adult age 65 years and above, thereby resulting in high cost of medical expenses. CAP is usually associated with symptoms of acute infection accompanied by the presence of acute infiltrate on a chest radiograph in a patient who has not been hospitalized for more than 14 days before the onset of the symptoms and have not had regular exposure to the health care system but presenting some of the symptoms: cough, sputum production, breathlessness, pleuritic chest pain, dyspnea, fever, headache, and signs such as confusion, dullness to percussion, crackles and rhonchi. CAP as a part of the differential diagnosis of nearly all respiratory illnesses including COVID-19 has often been inappropriately treated due to owing to the high antibiotic-resistant strains of *S. pneumonia* which is the main cause of CAP, hence, it is important to diagnose, assess the severity and treat

CAP on time (Onyedum and Chukwuka, (2011); Watkins and Lemonovich, (2011); Bertsias *et al.*,(2014); Akter *et al.* (2015); Jain a,b *et al.*, (2015); Prina *et al.*, (2015); Tejada *et al*., (2018); Ramirez, (2019); WHO, (2019)).

II. REVIEW OF RELATED WORK

de Miguel-Díez J, *et al*., (2016) carried out study using national hospital discharge data to examine the trends in incidence and outcomes of CAP in Spain from 2004 to 2013; it was observed that CAP in both sexes, increase in occurrence with increasing age with higher occurrence found in men than women in all years and age range; Jain *et al., (2015a;* 2015b) carried out an active population-based surveillance for community-acquired pneumonia requiring hospitalization among children younger than 18 years of age and among adult 18 years and above; it was discovered that CAP affects all age range, but prominent in children under five years of age and elderly of sixty-five years and above. Musher and Thorner, (2014) observed that CAP diagnosis is a very difficult task that needs accurate results as it shared some common symptoms with other diseases such as pulmonary edema and lung cancer which makes it difficult to know the real cause of CAP, as some CAP patients do not display some symptoms due to the comorbid with other diseases. According to researchers, chest Xray is the best accurate system for the diagnosis of CAP but the machine can develop fault at any time and another problem is cost issues. So, various researchers have devised different data mining methods for the diagnosis of various diseases.

Olatunde and Aderinto, (2017) develop a fuzzy model for Osteomyelitis severity prediction using six input variables: Fever, Redness, Stiffness, Irritability, Drainage and Stiffness with one output variable: OsteomyelitisLevel to detects the severity levels of patients categorized into veryMild, mild, moderate, severe and verySevere. (Adewunmi and Adekunle, 2013 and Arani *et al., 2019)* employed fuzzy logic approach in the design of expert system for the diagnosis of pneumonia severity level, the system was able to diagnose pneumonia into various risk levels but lacks the ability to learn and cannot adjust itself to a new environment. Naseer *et al.*, 2020 proposed an intelligent Heart Disease diagnostic system using Mamdani Fuzzy Inference Expert System, using six variables: age, chest pain, electrocardiography, blood pressure systolic, diabetic and cholesterol as input and the intensity of the diagnosis as single output.

Khan *et al.*, 2019 developed artificial neural network approach that accurately predict TB disease based on data collected from TB suspects, guardians or care takers along with samples, TB suspect's variables such as gender, age, HIV-status, previous TB history, sample type, and signs and symptoms served as input to the ANN and a positive/negative outcome as the output. In a way of preventing misdiagnosis which at times happens to medical experts, Olaniyi *et al., (2015)* implemented an intelligent system based on feed forward multilayer perceptron, and support vector machine to diagnose heart disease using the statlog heart disease dataset containing heart disease diagnosed patient's data gotten from UCI Machine Learning.

Sanoob *et al.*, (2016) developed a self-learning intelligent system using Artificial Neural Network (ANN) to identify different stages of pancreas cancer based on some set of symptoms being guided by doctors' disease diagnosis procedures. Result of the study shows that using ANN had advantage of evaluating data in efficient manner the traditional disease diagnosis.

Fuzzy logic and neural networks are natural complementary tools in building intelligent systems. While neural networks are low-level computational structures that perform well when dealing with raw data, fuzzy logic deals with reasoning on a higher level, using linguistic information gotten from domain experts. However, fuzzy systems lack learning ability and cannot adjust themselves to a new environment, while neural networks on the other hand can learn but are not transparent to the user. Hence, there is need to integrate the learning abilities of neural networks with the human-like knowledge representation and explanation abilities of fuzzy systems so as to take advantages of both and addresses their individual limitations, then comes neuro-fuzzy system.

Neuro-fuzzy systems have been developed to assist medical doctors in various medical diagnoses: Obot *et al., (2013)* developed a neuro fuzzy expert system for the diagnosis and therapy of cardiovascular disease and using the same model Obot *et al., (2014)* developed a neuro-fuzzy decision support model for heart failure therapy; Abiyev and Abizade (2016) took advantage of the synergy between fuzzy logic and neural network learning capabilities to develop a Parkinson disease diagnosis system, Shaabani *et al. (2016)* used neuro fuzzy system for the diagnosis of Multiple Sclerosis, Chattopadhyay, (2017) developed an hybrid intelligent system using Mamdani Fuzzy Logic controller on a Feed Forward Multilayer Neural Network that is being tuned by a back propagation algorithm by mathematical modeling of the manual depression diagnosis process using fourteen adult depression symptoms, applied Principal Component Analysis (PCA) to extract the seven major contributing factors to depression with the assistance of psychiatric doctors and the tested using real-world depression cases. Omotosho *et al.,* (2018) developed a neuro-fuzzy based system for classification of lung cells as cancerous and non-cancerous using lung CT scan image downloaded from Cancer Imaging Archive dataset. The system employed neural network tuned with back-propagation algorithm for training and classification of the lung cells while fuzzy inference system was used in determining the stages of lung cancer cancerous cells.

III. RESEARCH METHODOLOGY

The main aim of this study is to develop a reliable neuro fuzzy system for community acquired pneumonia severity level diagnosis. Fig. 1 shows the proposed system research architecture.

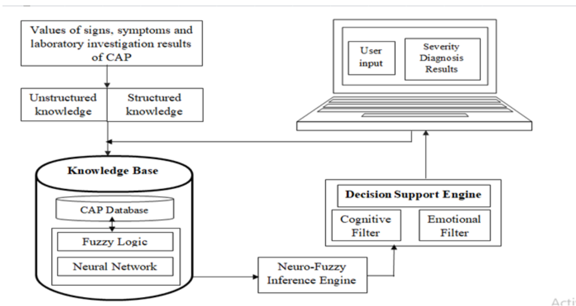

Fig. 1 Proposed Neuro-Fuzzy Based Expert System for Community-acquired Pneumonia Severity

The Components of the proposed framework, as presented in Fig. 1 comprises of signs, symptoms and laboratory investigation results, the structured and unstructured knowledge in CAP diagnosis, knowledge base consisting of Database, Fuzzy Logic and Neural Network, Neuro-fuzzy Inference Engine, Decision support engine (Cognitive and Emotional Filter) and the interface system for entering diagnosis variables and displaying diagnosis severity.

3.1 Knowledge Base

Knowledge Base (KB) stores both structured and unstructured information about the decision variables involved in the diagnosis of CAP and also serves as data repository. The component comprises of CAP Database, Fuzzy Logic of the qualitative knowledge of the medical expert in CAP diagnosis, and Neural Network.

3.1.1 Database

The database consists of both structured information such as Laboratory Investigation results and unstructured such as Physical Examination which are patients' attributes of CAP that are needed for successful diagnosis are stored or retrieved; while the structured database presents information on facts and established knowledge on CAP diagnosis, the unstructured knowledge is gathered through continuous experience, good practices and judgment and it is subjective in nature.

The database model comprises of:

1. Patient-Bio-Data [PatientID, PatientName, PatientAddress, PatientAge, PatientSex, Nationality, MaritalStatus, BloodGroup, NameOfNextOfKin, AddressOfNextOfKin].
2. Lab-Investigation [PatientID, LabTestID, BC, SC, UAT, TestDate]
3. Patient-Radiology-Examination [X-rayID, PatientID, CR, ExaminationDate]
4. Physical-Examination [PatientID, SignID, TP, PR, CH, EP, TC, FV, CC, RC, CL, TF, CK, BB, DP]

3.1.2 Fuzzy Logic

The fuzzy logic component of Fig.1 is described in the following operational sequence:

a) Fuzzification:

It involves a domain transformation where crisp inputs representing CAP features are transformed into fuzzy inputs using triangular membership function.

Given a fuzzy set $T = \{C_1, C_2, C_3, \cdots, C_n\}$ *as* defined in (Eq. (1)), representing CAP diagnosis variables with element denoted by C_i, the fuzzification process involves translating raw input value of each variable into a fuzzy term obtained from set {mild, moderate, severe, very severe} defined over the variables. Such values are derived from functions defined to determine the degree of membership of each variable in the fuzzy set (Eq. (1)).

$$t = \{C_i, \mu_T(C_i) | C_i \in T, \mu_T(C_i) \in [0,1]\} \quad (1)$$

Fuzzification is done using the triangular membership function as shown in eq. (2)

$$\mu_T(C_i) = \begin{cases} 1 & if\ C_i \leq a \\ \frac{C_i - a}{b - a} & if\ a \leq C_i < b \\ \frac{m - C_i}{m - b} & if\ b \leq C_i < m \\ 0 & if\ m \leq C_i \end{cases} \quad (2)$$

where $\mu_T(C_i)$ is the membership function (MF) of C_i in T, μ_T is the degree of membership of C_i in T; a, b, and m, are parameters governing MF triangular shape. Each of the attributes (variables) is described by a linguistic term in the fuzzy set {mild, moderate, severe, very severe} with the assistance of medical experts in CAP diagnosis.

b) Fuzzy Rule Base:

The fuzzy rule base for CAP diagnosis is characterized by a set of "IF-THEN" rules, where the antecedents ('IF' part of the rule) and consequents ('THEN' part of the rule) involve linguistic variables. The collection of these rules forms the rule base for the fuzzy logic sub-system of the fuzzy logic components. The rules are carefully formulated based on the view of medical experts on CAP diagnosis and also consultation of standard literatures. A structure of rules in the rule base is: if ($C_1 = A$) and ($C_2 = B$) and ($C_3 = C$) then ($Y = O$), where C_1, C_2 and C_3 are inputs variables, A, B, C are fuzzy sets of the input variables, Y is the output and O is fuzzy set of the output variable within the fuzzy region specified by the rule. A rule fires if any of its precedence parameter such as *Mild, Moderate, Severe, and Very Severe* evaluates to true or 1, otherwise it does not fire.

c) Fuzzy Inference Engine:

This is the engine of fuzzy logic sub-system that controls how decision is made by applying operations from rule base to values of input variables received to get the expected result. The Root Sum Square (RSS) inferential technique will be used to draw inferences by combining the effects of all fired rules and their respective magnitudes and compute the mean (composite area) whose formula is presented in Equation (3) is adopted in this research.

$$RSS = \sum_{t=1}^{n} R_t^2 \quad (3)$$

where R_t represents a fired rule and t = 1, 2, 3…, n represents the number of fired rules for a particular diagnosis.

Eq. (3) can be expanded into Eq. (4) as depicted below:

$$\sqrt{\sum R^2} = \sqrt{R_1^2 + R_2^2 + R_3^2 + R_4^2 + \cdots + R_n^2} \quad (4)$$

Where $R_1^2 + R_2^2 + R_3^2 + R_4^2 + \cdots + R_n^2$ represents the strength values of different rules.

d) Defuzzifier

The defuzzifier translates the fuzzy output from the inference engine into crisp values which are mostly required by medical experts for efficient interpretation and diagnosis. This study will employ the Centroid of Area (CoA) technique for its defuzzification. This interface receives output from the inference engine and applied Eq. (5) to arrive at the defuzzified output.

$$CoA = \frac{\sum_{j=1}^{n} \mu Y(C_j) C_j}{\sum_{j=1}^{n} \mu Y(C_j)} \quad (5)$$

where $\mu Y(C_j)$ is membership values, while C_j is the center membership value in the function.

3.1.3 Neural Network

The NN component of Fig. 1 learns certain information from the Fuzzy inference system in order to generate the required membership function.

3.2 Neuro-Fuzzy Inference System

The Neuro-Fuzzy Inference System (NFIS) that integrates both the NN and FL components and as well drives the proposed system is presented in Figure 2. The NFIS employs Back Propagation learning techniques and Mamdani's fuzzy logic controller (FLC) has been proposed because it allows knowledge to be illustrated in more perceptive and human-like manner. Triangular membership functions (TMF) are considered for mapping inputs (the symptoms) to the output CAP Severity) with both Inputs and the output arbitrarily assigned class labels – 'mild ('m')', 'moderate ('m')', 'severe ('s')' and 'verySevere ('vS')' within some numeric range.

3.3 Decision Support Engine

Decision support engine component of the proposed framework is made up of cognitive and emotional filter as sub-components; the cognitive filter analyses the alternative output reports of the inference engine on the basis of the established facts of CAP diagnosis; while the emotional filter analyses the output reports of the cognitive filter on the basis of the personal feeling or emotion of human experts in CAP diagnosis acquired through experience.

3.4 User Interface

This is the platform where disease symptoms will be entered and the severity level displayed based on the input.

IV. IMPLEMENTATION

The proposed system implementation will be done using Matlab 2018b, Python and Jupyter Notebook. Python will be used to write the code for the entire system. Jupyter Notebook for the IDE, which is Integrated Development Environment and Matlab will be used in training and testing of the system.

CONCLUSION

In conclusion, a system that combines the capabilities of fuzzy logic and neural network for determining severity level of CAP can go a long way in assisting the medical personnel to timely and accurately diagnose CAP. This in turn will help in curtailing the prevalence of CAP mortality and morbidity.

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