

PRELIMINARY DIFFERENTIAL DIAGNOSIS OF PNEUMONIA DISEASE: AN INNOVATIVE APPROACH USING AN EXPERT SYSTEM BASED ON RULES

Abstract

This study focuses on the development of a rule-based expert system for diagnosing people with pneumonic infections. Pneumonia is the most common respiratory disease causing death worldwide, and its diagnosis is difficult due to clinical symptoms similar to other respiratory diseases. As a result, doctors often order multiple tests before making a decision, leading to high costs and longer wait times. The expert system developed in this study aims to help doctors and patients distinguish between pneumonia and other diseases such as cancer, chronic bronchitis and tuberculosis. The system takes symptoms such as fever, lack of appetite, cough, chills, hemoptysis and chest pain as input and produces pneumonia as output. The system has gone through four stages of development: definition of a knowledge system, design, implementation, evaluation and testing. The assessment showed a sensitivity of 95%, specificity of 88% and accuracy of 93% in diagnosing pneumococcal infections in patients.

Keywords: Expert System, Artificial Intelligence, pneumonia, Exsys Corvid.

INTRODUCTION

Respiratory diseases constitute a major public health problem affecting millions of people worldwide [1]. These conditions impair lung function, make breathing difficult, and manifest in a variety of ways and situations. Initial symptoms, such as a simple cold, may seem harmless but can progress to more serious conditions such as persistent cough, pneumonia, fever, sore throat, and difficulty breathing [2]. Pneumonia is an illness caused by a bacteria, fungus or virus that affects the air sacs in the lungs of infected people. This disease causes individuals diagnosed with mucus and difficulty breathing [1,2]. Pneumonia-related mortality is influenced by factors such as disease severity, undernutrition, poverty, inadequate vaccination, and limited access to health care [3]. Therefore, children living in poor, deprived, malnourished and hard-to-reach areas are particularly vulnerable, highlighting a link between pneumonia mortality risk and disparities in access to health care and prevention services [4].

Accurately diagnosing pneumonia requires a lot of time and money due to the substantial similarity between the clinical signs of respiratory diseases [9]. This

similarity often makes it difficult for doctors to make an accurate diagnosis, and they may need to perform several tests before making a decision.

Therefore, it is crucial to have continuous access to the expertise and experience of specialist doctors to ensure accurate diagnosis and treatment of this disease.

Pneumonia poses a significant health risk¹ with a mortality rate accounting for approximately 30% of all respiratory causes of death.[2] Pneumonia is often misdiagnosed due to similarities with several lung conditions.[3,6] Additionally, the low sensitivity and specificity of diagnostic criteria, radiological and microbiological culture results represent an additional diagnostic challenge.[7]

In addition to their impact on quality of life, these diseases represent a significant economic burden due to health care costs and loss of productivity. Some of the most common and debilitating respiratory illnesses include influenza, pneumonia and asthma, all of which have significant consequences. In this sense, rapid and accurate medical care is essential for the effective management of respiratory diseases. However, accurate diagnosis can be difficult because the symptoms of these diseases can overlap and vary in severity. Not all patients have immediate access to specialized medical services and some people lack knowledge about the symptoms associated with these illnesses, leading them to self-medicate. This can lead to diagnostic errors or treatment delays, negatively impacting the health and well-being of patients, particularly in settings where resources are limited or access to healthcare is reduced. With the aim of improving the diagnosis of respiratory diseases, previous studies have developed various applications, such as expert systems. These are technologies designed to help both healthcare professionals and individuals identify respiratory illnesses.

Efforts have been made to develop systems to help doctors diagnose pneumonia.[8,13]

However, the pneumonia diagnostic knowledge underlying these systems is rudimentary and often sufficient for proof-of-concept demonstration rather than point-of-care use. In recent years, the codification of medical knowledge using ontologies has gained ground due to their ability to represent medical concepts and the relationships between them in a structured and formal manner.[14] Thus, an ontology can help represent complex knowledge, such as that on the diagnosis of pneumonia, by providing a standard vocabulary that helps integrate heterogeneous biomedical data sources.

Research on medical ontologies has grown over the past decade[16], but many developed ontologies suffer from quality and content issues[14,17] which can be mitigated by reusing existing high-quality contents ontologies. An empirical analysis of ontology reuse is described in Ochs et al.[18]

2. Revision of literature

2.1. Pneumonia

Pneumonia is a common and life-threatening disease that requires early detection to prevent further damage to the patient and potentially save the patient's life. [19]–[21] It is also the leading infectious cause of death in children under five years of age worldwide. [22], [23] Although it is possible to detect and treat pneumonia with simple tools and drugs, detection remains a major challenge in developing countries [24], [25]. This disease presents symptoms such as cough, difficulty breathing, increased

respiratory rate, sputum production, and chest pain. It can also cause general symptoms such as fever, fatigue, muscle aches, and loss of appetite. [26]

2.2. Medical Expert System

A medical expert system is a computer-based application employing artificial intelligence and knowledge derived from medical experts to aid in medical decision-making and diagnosis. These systems emulate the decision-making process of human medical experts by analyzing patient data, symptoms, medical history, and other pertinent information [27]. They utilize this information to generate diagnoses, treatment recommendations, and provide medical advice

2.3. Expert systems

Rule-based systems were first developed by artificial intelligence researchers. These early rule-based systems were primarily expert systems. In fact, the term is often used interchangeably with expert systems, although there is a difference. The difference lies in the point of view taken to describe the system: "expert system" refers to the type of task for which the system tries to help replace or assist a human expert in a complex task generally considered to require expert knowledge; "Rules-based system" refers to the architecture of the system in which it represents knowledge explicitly, rather than as procedural code. While the first knowledge-based systems were almost all expert systems, the same tools and architectures can and have since been used for a range of other types of systems. [28-30]

3. Methodology

Generally, an expert system generally includes a user interface, an explanation function, a working memory, an inference engine, a diary, a knowledge acquisition function and a knowledge base. As the meaning of user interface indicates that its function is to maintain communication between the user and the expert system. The function of providing the explanation to the user to understand the necessary knowledge and ability to monitor the operation of the system. Working memory is a collected database of facts used by the system to decide which of the rules can be executed. The inference engine is considered the brain of the expert system that reasons and determines which rules are satisfied by the facts and prioritizes which one is satisfied to execute.

The agenda is a list of satisfied rules produced by the inference engine for execution. The knowledge acquisition function is an optional part of the expert system that provides self-learning capability and the ability for the user to enter knowledge into the system without coding. The knowledge base is the storage of factual and heuristic knowledge. Factual knowledge is knowledge obtained from human experts and literature. On the other hand, heuristic knowledge is mainly individual judgment knowledge that is based on extensive experience, good practices, proper judgment, intelligent guessing, etc. [31, 33].

In the knowledge base, knowledge is not only stored, it is also represented by formalization and organization. Although in practice there are several types of

representation techniques, the most common technique is the production rule which includes the IF and THEN parts. Since the IF part lists a set of conditions in certain logical combinations and in the THEN part its problem solving action is taken, these two parts are also called condition and action. In expert systems, if knowledge is represented as a series (chaining) of production rules, it is called a rule-based expert system.[33]

In a rules-based system, if the facts satisfy the IF part of the rules, the inference engine generates the priority list. In this type of inference, two general problem-solving methods are widely preferred. These are forward chaining and back chaining. In forward chaining, the chaining starts from a set of conditions (inputs) and moves towards a conclusion, while in backward chaining the conclusion (outputs) is known but the path to the conclusion is not known, so backward reasoning is necessary.

In order to obtain a favorable result at the final stage of an expert system, the choice of Exys Corvid software was considered very important. The Exys Corvid expert system was designed to meet the needs of healthcare professionals in the management of complex medical diagnoses. Founded by a team of experts in artificial intelligence and medicine, Exys Corvid was developed with the aim of providing effective diagnostic solutions using advanced rules-based approaches and AI.

The system was initiated in the 2000s, in a context where clinical medicine was gradually moving towards the integration of AI to improve the accuracy of diagnoses. In its early days, Exys Corvid focused its efforts on creating a robust medical database and logical rule structure capable of simulating the decision-making of an experienced healthcare professional. The goal was to create an interface that would allow clinicians to better manage the diversity of pathologies, particularly in primary care environments or in geographic areas with a shortage of specialists.

As it has evolved, Exys Corvid has integrated into several medical platforms around the world, becoming a valuable tool for the management of complex diseases, including pneumonia, heart disease and neurological disorders.

Exys Corvid operates under a rules-based expert system model, a type of computer program designed to mimic human reasoning in specialized areas. Here is an overview of how it works:

1. Knowledge Base:

Exys Corvid's knowledge base consists of a large amount of medical data from various clinical areas. It includes information on symptoms, diagnostic tests, risk factors, possible treatments, and clinical outcomes of different patient cases. This data is constantly updated to reflect the most recent medical discoveries.

2. Diagnostic rules:

The system uses logical rules to associate symptoms, medical history, and test results with potential diagnoses. These rules are created and validated by medical experts, who ensure they are reliable and cover a wide range of clinical scenarios.

3. Inference engine:

The inference engine is the key element of the system. It applies logical rules to a patient's data and generates diagnostic results or recommendations. When a clinician enters information about a patient, such as observed symptoms, test results, or medical

history, the inference engine analyzes this data based on the rules and provides a preliminary diagnosis.

4. User interface:

Exys Corvid provides a user-friendly interface for doctors and clinicians to interact with the system. The interface is designed to be intuitive, easy to use, and effective in a clinical environment. The physician enters relevant patient information and receives diagnostic suggestions or treatment recommendations, along with the underlying logic used to reach those conclusions.

5. Continuous learning and updating:

The system benefits from a machine learning process to refine its predictions based on additional clinical data it collects. Clinical results and physician feedback allow the system to update and improve its effectiveness over time.

6. Validation by experts:

An essential aspect of the functioning of the system is validation by medical experts. Before diagnostic rules are applied in real-world situations, they are thoroughly validated by medical specialists to ensure their relevance and accuracy.

This section displays the rules and actions utilized in constructing the expert system. "Disease1" implies symptoms that are not severe and can be easily managed when diagnosed early, while "disease2" implies a chronic disease that requires urgent medical attention.

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If (temperature-of-body is fever) or (cough is severe) or (sputum is purulent) or (rales
is exist_in_sighs) or (CXR is infiltration) or (sputum_culture is positive)
    then (disease 1 is pneumonia)
If (WBC is leukocytes) or (dyspnea is exist)
    then (disease1 is pneumonia)
If (chest pain is ploreitic) or (PO2 is hypoxi) or (wheezing is exist_in_sighs) or
(auscultiation_sighsis_decreas) or (respiratory distress is exist)
    then (disease1 is pneumonia)
If (age is childhood) and (respiratory_rate is tachypnea2)
    then (disease1 is pneumonia)
If (age is infancy) and (respiratory_rate istachypnea3)
    then (disease1 is pneumonia)
If (age is childhood) and (heart_pulse_rate is tachycardic2)
    then (disease1 is pneumonia)
If (age is infancy) and (heart_pulse_rate is taachycardic3)
    then (disease1 is pneumonia)
If (blood-pressure is low)
    then (disease1 is pneumonia)
If (temperature_of_body is not fever) and (cough is not severe) and (rales is exist-in-
signs) then (disease1 is not pneumonia)
If (cough is severe) or (PO2 is hypoxi) or (dyspnea is exist)
    then (disease2 is chronic_pneumonia)
If (age is childhood) and (respiratory_rate is tachypea2)

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Figure 1:An example of representation by facts and rules.

3.2. System testing with Software Exsys Corvid

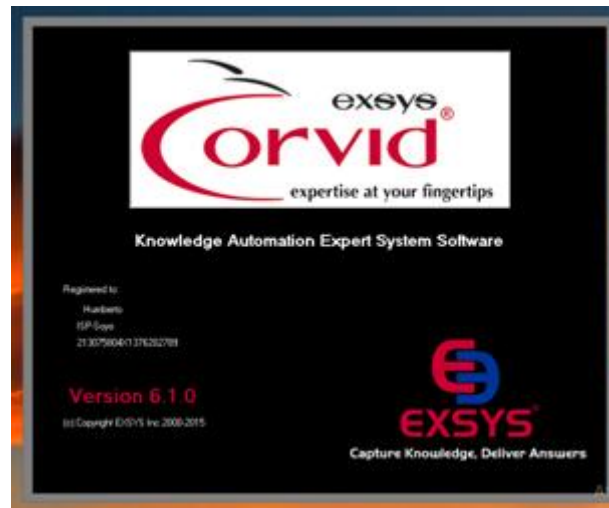


Figure 2: Presentation page

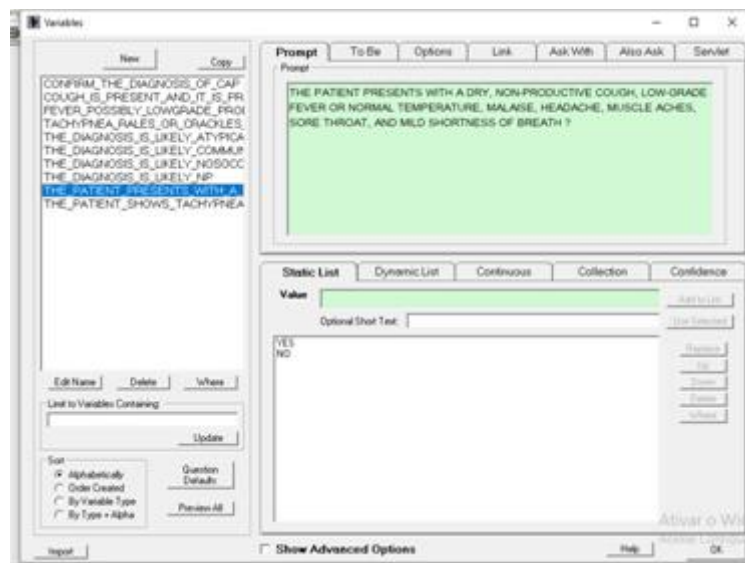


Figure 3: Create variables in system Expert

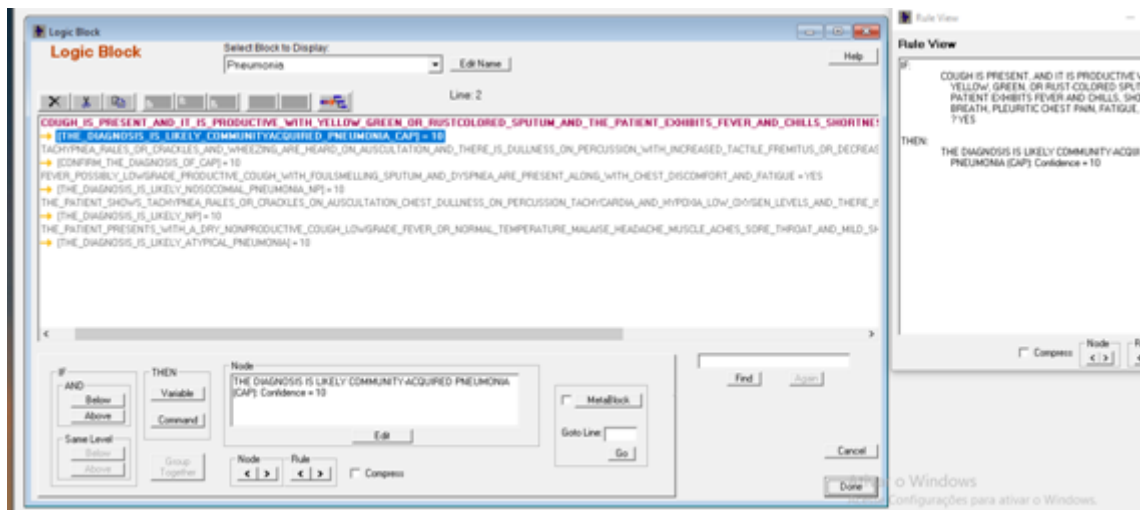


Figure 4: Create rules in system Expert



Figure 5 The diagnostic center interface is shown in Figure



Figure 6: Patient registration page



Figure 7: Report page for the proposed ExpertColera Expert

4. Discussion of Results

In the evaluation phase, the results obtained by the system are compared to the final diagnosis recorded in the patients' medical record and in this regard; The Kappa Cohen method was used.

The volume of K (the degree of correspondence between the system and the doctor's diagnosis) was discussed based on the interpretation table of Landis and Koch (13).

Out of 188 patients' medical records, 176 cases were based on doctor's diagnosis and 12 diagnosis cases were different from doctor's diagnosis and the Kappa test result for variable K was 0/8437. This meant that, based on Table1, the system result was in complete agreement with the final diagnosis recorded in the medical record.

The system created for patients suffering from pneumonia was correct in 131 cases and for 53 patients suffering from other diseases of the respiratory system it was correct in 45 cases. The system has a sensitivity of 97%, specificity of 85% and accuracy of 93%. Pneumonia in this article is 94% obtained using the seventh and eighth relationships.

5. CONCLUSIONS

The “Web-based Expert System for Diagnosis and Management of Childhood Pneumonia” was designed and implemented to solve the problems affecting children under five years of age who require daily medical care. The system can diagnose various causes of pneumonia, improve early diagnosis, and provide better treatment. In addition, it serves as a temporary aid for those who need immediate help when a professional consultant is not available. In addition, the system has been carefully designed to be user-friendly and accessible to everyone, regardless of their location. This means that users can access the website anytime and anywhere to manage or diagnose various pneumonias based on their feedback. Domain experts have validated the system results after testing with a domain dataset. This expert system is simple to use and does not require extensive training. Knowledge is represented by IF-THEN rules with direct chain reasoning and is developed using E2glite, an expert system shell based on

rules. The system has an attractive interface and can be used in DOS or Windows environments with a simple interface.

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