University of Ibadan
Journal of Science and Logics in ICT Research

Web-Based Expert System for Childhood Pneumonia Diagnostic and Management

*1 Odufuwa, T.T., [2]Adewole, L.B., [3]Hassan, B.J. and [4]Ogunniyi, O.V.

Department of Computer Science, Federal University Oye-Ekiti, Oye, Nigeria
tolulope.odufuwa@fuoye.edu.ng, lawrence.adewole@fuoye.edu.ng, joshua.hassan@fuoye.edu.ng, modupeolamioluwatoyin@gmail.com

Abstract
This study focuses on developing a web-based expert system to diagnose children with pneumococcal infections. Pneumonia is the most common respiratory disease that causes death in children worldwide, and its diagnosis is challenging due to clinical symptoms similar to other respiratory diseases. As a result, doctors often request multiple tests before deciding, resulting in high costs and longer wait times. The web-based system developed in this study aims to assist doctors and patients in distinguishing between pneumonia and other diseases such as lung cancer, chronic bronchitis, and tuberculosis. The system takes symptoms such as fever, lack of appetite, cough, chills, haemoptysis, and chest pain as input and produces pneumonia as output. The triangular membership function was used to determine the membership level of both the fuzzy logic input and output. The Mandani max-min inference engine was used for logical reasoning, and the fuzzy output was converted back to crisp output in the defuzzification process. The system underwent four development stages: definition of a knowledge system, design, implementation, evaluation, and testing. The evaluation showed a sensitivity of 95%, specificity of 88%, and accuracy of 93% in diagnosing pneumococcal infections in children.

Keywords— Expert system, Fuzzy logic, Pneumonia Web-based system.

1. Introduction

Pneumonia is a disease caused by bacteria, fungi, or a virus that affects the air sacs in the lungs of infected persons. This disease causes individuals diagnosed with it to cough up mucus and have trouble breathing [1,2]. Mortality related to pneumonia is influenced by factors such as the severity of the disease, undernutrition, poverty, inadequate immunizations, and limited access to healthcare [3]. Consequently, children living in impoverished, underprivileged, malnourished, and hard-to-reach areas are particularly vulnerable, highlighting a link between the risk of pneumonia mortality and disparities in healthcare access and preventative services [4].

In recent years, Millennium Development Goal Number 4 (MDG4) of the United Nations General Assembly has become a rallying point for combating childhood pneumonia. This goal aims to reduce the mortality rate of children under five years by two-thirds between 1990 and 2015 [5]. According to the World Health Organization (WHO), pneumonia is the most common infectious disease that causes death in children worldwide [6]. In 2019, pneumonia was responsible for the deaths of 740,180 children under five, accounting for 22% of all deaths among children aged one to five [7]. Although pneumonia affects children and families globally, mortality rates are highest in sub-Saharan Africa and southern Asia [8].

Accurately diagnosing pneumonia requires significant time and money due to the substantial similarity between the clinical signs of respiratory diseases [9]. This similarity often poses challenges for doctors in making an accurate diagnosis, and they may need to conduct multiple tests before reaching a decision. Therefore, it is crucial to have access to the expertise and experience of specialist physicians continuously to ensure the accurate diagnosis and treatment of this condition.

Odufuwa, T.T., Adewole, L.B., Hassan, B.J. and Ogunniyi, O.V. (2023). Web-Based Expert System for Childhood Pneumonia Diagnostic and Management,, *University of Ibadan Journal of Science and Logics in ICT Research (UIJSLICTR),* Vol. 9 No. 1, pp. 131 – 142

Various methods, including computer applications, have been widely adopted to address this issue and support medical decision-reliability of such systems has been the subject of research and discussion in numerous theories, such as Shannon theory, Dumpster-Schafer theory, classical probability, Bayesian probability, and fuzzy sets theory.

The fuzzy set hypothesis, which measures the quality of viewpoints, is associated with a group of items with undefined limits and uses natural language in reasoning. The concept of membership degree describes object memberships in any of these groups [12].

An Artificial Intelligence (AI) program known as an Expert System is built for a particular area of expertise that is clearly defined and imitates the knowledge and analytical abilities of one or more human experts [13]. This makes the system's performance entirely dependent on the right choice of experts. Knowledge engineering is a crucial step in the design of expert systems. A component of the knowledge management procedure is knowledge engineering.

According to Mesher et al. [14], knowledge management is a rapidly developing field that receives great attention. This process has many stages, including problem identification and selection, knowledge gathering and collection, knowledge presentation, knowledge engineering, testing, and evaluation. The steps involved in knowledge engineering are knowledge domain structuring, setting rules for proper access to knowledge, and transferring skills of expert/specialised persons to the expert system. The initial design stage is one of the most important and challenging stages of creating such systems [15].

This study proposes a web-based expert system for pediatric pneumococcal diagnosis. The free e2gLite expert system building tool (shell), which is implemented as a Java applet, is used to build this expert system. A web page that loads the applet and identifies the knowledge base is required to use the expert system. The system can be used without a network connection under the requirement of putting the web page (knowledge.html), the knowledge base (knowledge.kb), and the e2gLite applet archive (making [10]. Expert systems use uncertain information to function, and unreliable information can lead to incorrect decisions and inappropriate medical treatment [11]. The e2glite.jar) in the same subdirectory.

The rest of the paper is organised as follows: section 2 discusses related works, section 3 discusses methodologies, section 4 discusses results, and section 5 concludes the paper.

2.0 Related Works

Expert systems have been developed to diagnose and treat diseases. In 1974, the University of Pittsburgh developed INTERNIST-I as a rule-based expert system for the general internal medicine diagnosis of complex issues [16]. MYCIN, the first well-known expert medical diagnosis system, was developed in 1984 by Shortliffe at Stanford University [17]. It was designed to diagnose and provide remedies for bacterial infections and to help physicians who are not experts in antibiotics to prescribe such medications. MYCIN uses a backward chaining inference procedure. However, its knowledge base needs to be completed because it only covers part of the range of infectious diseases, which is a limitation.

Another medical expert system, known as PERFEX, was developed to assist clinicians in resolving issues they face in evaluating perfusion studies [18]. The knowledge base of the PERFEX system contains over 250 rules developed with the assistance of Emory University Hospital clinicians and researchers. The output of PERFEX is mostly numerical, which is its only limitation.

Djam *et al.* [19] designed a decision support system for diagnosing tuberculosis. They developed a fuzzy expert system to diagnose tuberculosis and serve as a decision-support platform for tropical medicine physicians, researchers, and other healthcare professionals. Additionally, they developed a proposed fuzzy expert system for diagnosing pneumonia in children. The study aimed to create a system that would serve as a decision-support platform for pediatric researchers, physicians, and other healthcare professionals.

Fagbuagun *et al.* [2] proposed a model for pneumonia detection from chest radiographs using transfer learning. The authors utilized the CheXNet model architecture and fine-tuned it on a dataset of chest radiographs to classify them into two categories: normal or pneumonia. The dataset used consisted of 5856 chest radiographs, with 2790 being normal and 3066 having pneumonia. The authors achieved an accuracy of 99.43% and a precision of 99.29% in the classification of chest radiographs. The proposed model can help in the early detection of pneumonia, which is critical in reducing mortality rates associated with the disease.

Alkassar *et al.* [20] developed an automated system for diagnosing childhood pneumonia using modified densely residual bottleneck-layer features in chest radiographs. This system uses a few light-weighted densely connected bottleneck residual block features to extract rich spatial information. Then, four effective methods for reducing data batches into a single vector were used. Adaboost ensemble learning is used to propose an adaptive weight setup, which uses scores generated by each classifier to adaptively set weight for each classifier to maintain low negative rates while achieving the highest true positive rates. The proposed system outperformed other deep network-based pneumonia diagnosis methods with an accuracy of 99.6%.

Amanze *et al.* [21] developed a mobile pneumonia diagnosis expert system that can be used to diagnose patients by taking various check-ups. Either the patient or their assistant could take their medical check-up by using medical peripherals and upload the report by their mobile phone to the server where the expert system could suggest precautionary steps or diagnosis along with patient status. This study uses Object-Oriented Analysis (OOA) with Unified Modeling Language (UML) to analyze and design the pneumonia diagnosis system. PHP was used as a scripting language, while MySQL was used to create the database. The study recommends installing a mobile application directly on mobile phones so that users can access the application quickly.

Leila et al. [22] proposed to develop a fuzzy-based expert system for diagnosing pneumonia. This system identifies and distinguishes between patients suffering from pneumonia and those suffering from other respiratory diseases, such as chronic bronchitis, asthma, lung cancer, embolism, and tuberculosis. The system was developed using a fuzzy expert system, which involved four stages: defining the knowledge system, designing it, implementing it, and testing it using the prototype life cycle methodology. The system's results showed 93% accuracy, 97% sensitivity, and 85% specificity in diagnosing the disease.

3.0 Methodology

In developing this system, the use of structural system analysis and design methodology are adopted.

3.1 Model Formulation

Modeling is done using UML diagrams. jQuery is used for the general programming of the application. Hypertext pre-processor (PHP) is used to implement the server side of the project, it will handle data retrieval and processing. The database server that is used is MySQL.

3.2 System Design

During system analysis, the operation of the present systems is carefully examined and reviewed. All possible information relating to how the current systems operate is gathered and analysed. The data that were collected during the fact-finding procedures serve as the foundation for the design of the new system. In the design phase, various factors were properly looked into which including:

a. Evaluation of data
b. Determining the relationship between different data
c. Organizing the data to meet the end need of the system

3.3 Activity Diagram of Pneumonia Diagnosis System

The activity diagram represents how the user can access the website as shown in Figure 1. Once the user enters the web address and sign in, he/she can easily navigate from one link to another whether to register as a new patient and then view biodata to start diagnosis, then generate the report for the answered questions.

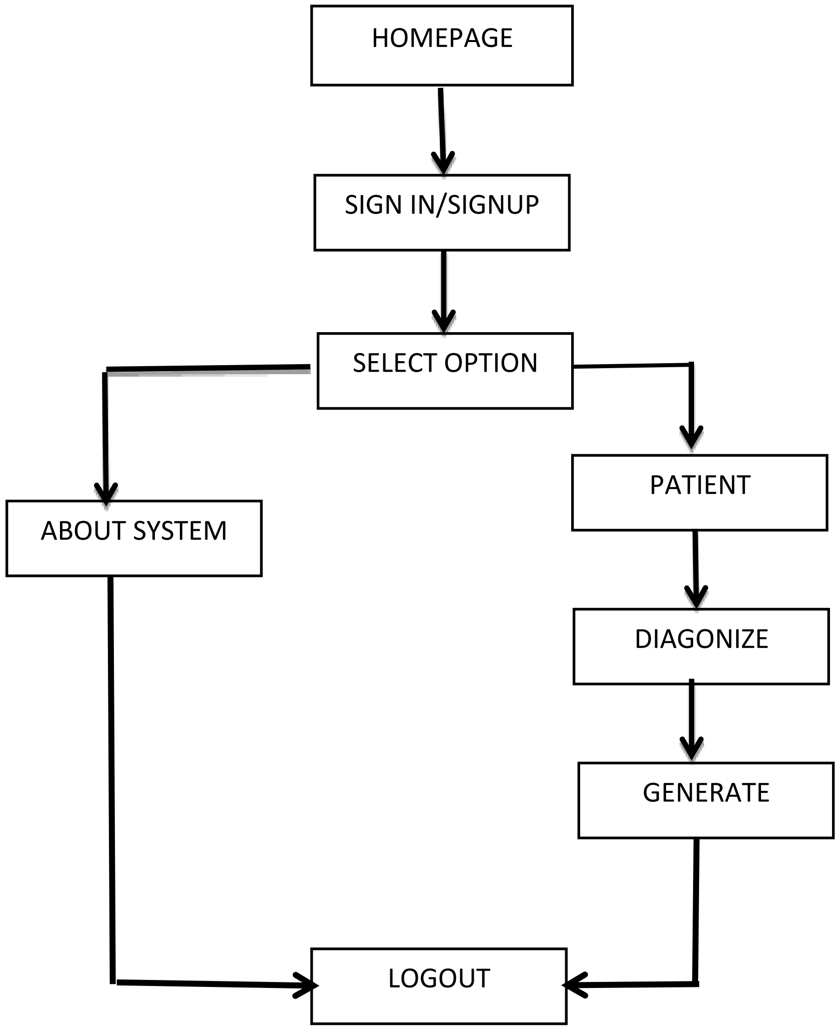

Figure 1: Activity Diagram of Pneumonia Diagnosis System

3.4 Use Case Diagram of Pneumonia Diagnosis System

The user needs to log in or register as a new patient and then view the biodata as contained in the database in Figure 2. After the user has been successfully validated, the patient can now be diagnosed by responding to some symptoms that will later generate a report based on the knowledge engine embedded in the program.

3.5 System Flow Chart

The system will display pneumonia system questions for the user to answer as shown in Figure3. The user will select the answer option from the options available for the question (Yes/No) and then Click submits. Then, the system will display the result from the Fact Database based on the user's answer.

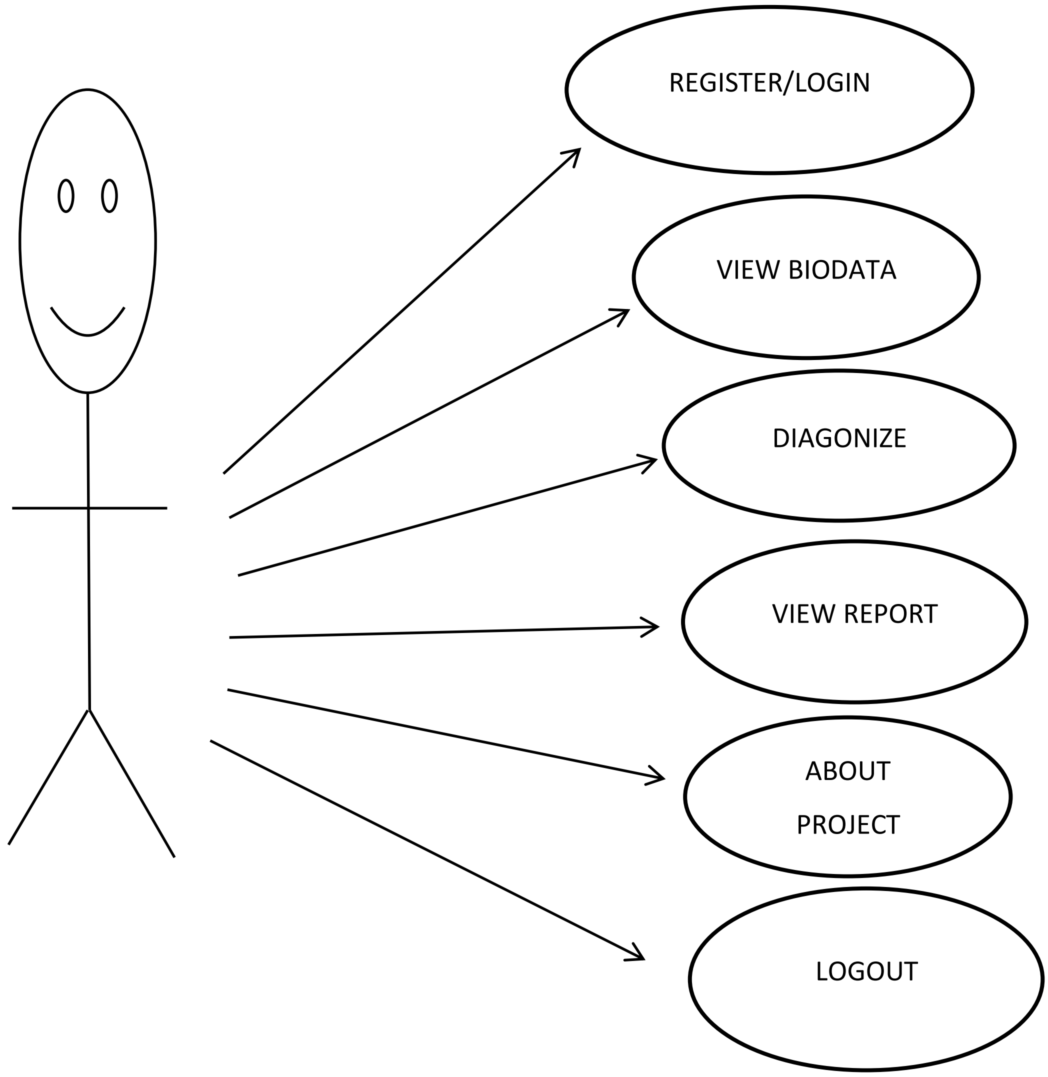

Figure 2: Use case Diagram of Pneumonia Diagnosis System

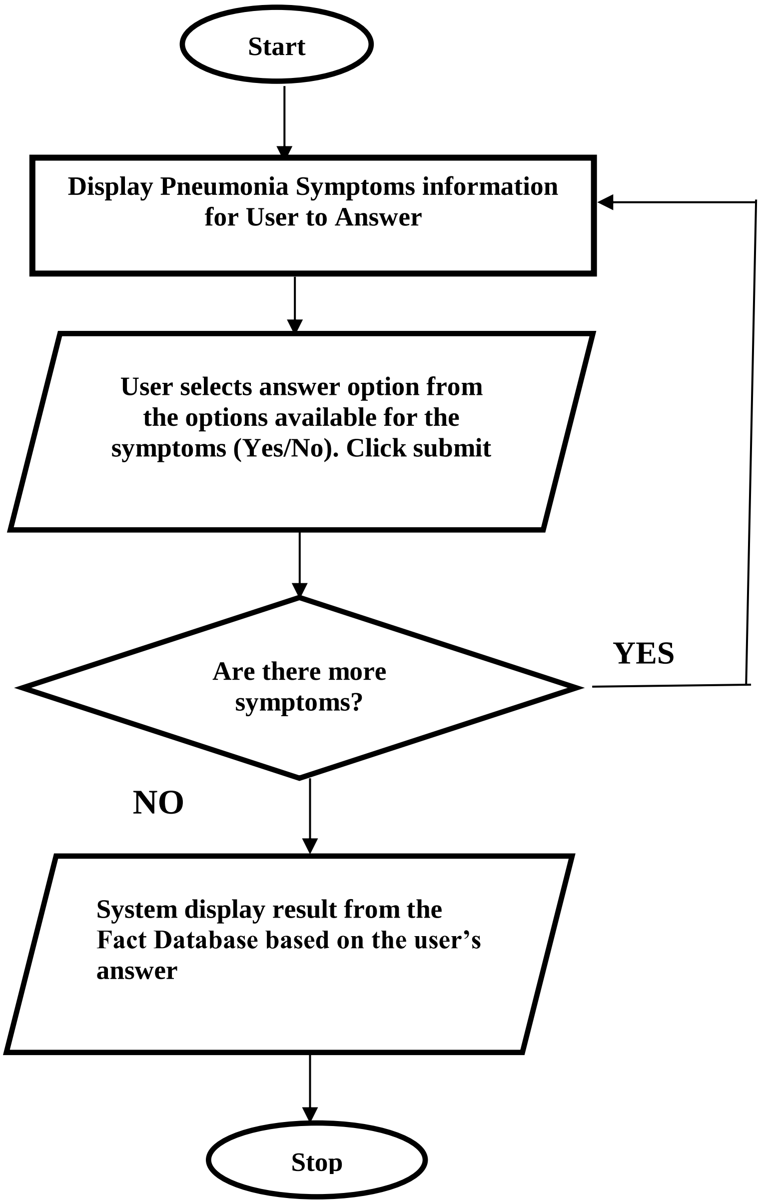

Figure 3. Flow chart of the Pneumonia Diagnosis System

3.6 Input and output variables and membership functions for the fuzzy system

In building the system, various input symptoms were defined. These symptoms include fever, cough, lack of appetite, chest pain, respiratory rate, shortness of breath, fatigue, age, blood pressure, hypoxia, leukocytes, leukocytosis, and lung infiltration. The output variable is the degree of pneumonia.

After defining the variables, a triangular membership function was defined for each variable, corresponding to the degree of severity or intensity of the symptom.

The input variables are as follows: body temperature (350 c for low, 370 c for medium, and 400 c for high), coughing frequency (1 for low, 3 for medium, and 5 for high), shortness of breath (1 for low, 5 for medium, and 10 for high), chest pain (1 for low, 5 for medium, and 10 for high), fatigue (2 for low, 5 for medium, and 8 for high), age (0-17 for childhood, 16-64 for adult, and 63-100 for elderly), respiratory rate (5 for slow, 15 for normal, and 30 for fast), and blood pressure (50 for low, 95 for normal, and 155 for high).

The output variable is pneumonia severity (0 for no pneumonia, 0.5 for mild pneumonia, and 1 for severe or chronic pneumonia).

After determining the membership levels of the input and output variables, fuzzy logic rules were formed to combine the input variable and make a diagnosis or severity assessment based on the degree of membership in the fuzzy set, as shown in Table 1.

Table 1: The If and Then Rule for the Expert System

S/N	IF	THEN
1	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)
2	if (WBC is leukocytes) or (dyspnea is exist) then	(disease1 is pneumonia)
3	If (chest pain is ploretic) or (PO2 is hypoxi) or (wheezing is exist_in_sighs) or (auscutiation_sighsis_decreas) or (respiratory distress is exist) then	(disease1 is pneumonia)
4	If (age is childhood) and (respiratory_ rate is tachypnea2) then	(disease1 is pneumonia)
5	If (age is infancy) and (respiratory_rate istachypnea3) then	(disease1 is pneumonia)
6	If (age is childhood) and (heart_pulse_rate is tachycardic2) then	(disease1 is pneumonia)
7	(age is infancy) and (heart_pulse_rate is taachycardic3) then	(disease1 is pneumonia)
8	If (blood-pressure is low) then	(disease1 is pneumonia)
9	If (temperature_of_body is not fever) and (cough is not severe) and (rales is exist-in-signs) then	(disease1 is not pneumonia)
10	If (cough is severe) or (PO2 is hypoxi) or (dyspnea is exist) then	(disease2 is chronic_ pneumonia)
11	If (age is childhood) and (respiratory_rate is tachypea2) then	(disease2 is chronic_ pneumonia)
12	If (age is infancy) and (respiratory_rate is tachypea3) then	(disease2 is chronic_ pneumonia)
13	If (rates is exist-in-signs) or (wheezing is exist-in-signs) then	(disease2 is chronic_ pneumonia)
14	If (temperature_of_body is fever) or (sputum is purulent) or (chest pain is ploretic) or (auscultation-signs is decreasing) or (CRX is infiltration) or (sputum_culture is positive) then	(disease2 is chronic_ pneumonia)
15	If (age is childhood) and (heart_pulse_rate istachycardic2) then	(disease2 is chronic_ pneumonia)

3.7 Set of rules for knowledge base and the outputs inform of if then else structure

Table 1 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. The system's inference fuzzy engine is a type of Mandani fuzzy model that utilizes fuzzy rules, membership functions, and input variables to measure fuzzy fire and determine the disease severity level. The inference fuzzy engine uses fuzzy rules and membership functions in the hypothesis of each rule to make the number of input fuzzy variables fuzzy and determine a membership degree for each input in the fuzzy set during the fuzzy making stage. The max-min product method and membership functions were used to measure output fuzzy sets for each output variable. The output fuzzy sets generated by the fuzzy rules for each disease were compiled using the Sum function. The Centroid calculation of the DE fuzzy fire method was used to convert the output fuzzy sets into a digital volume between 0 and 1.

4.0 Results and Discussion

4.1 Index Page

Figure 4 shows the starting point of the web presentation. It is the first page seen when visiting the website. It consists of the home button, pneumonia button, diagnosis button and contact us button on the menu bar and the button also links to each other. It gives brief information about pneumonia disease and link to check different types of pneumonia that we have and their symptoms.

4.2. Login Page

Figure 5 accepts the login information of the administrator to gain full access to the program function and features. The program validates the information entered and permits only the valid information

Figure 4: Index page

.

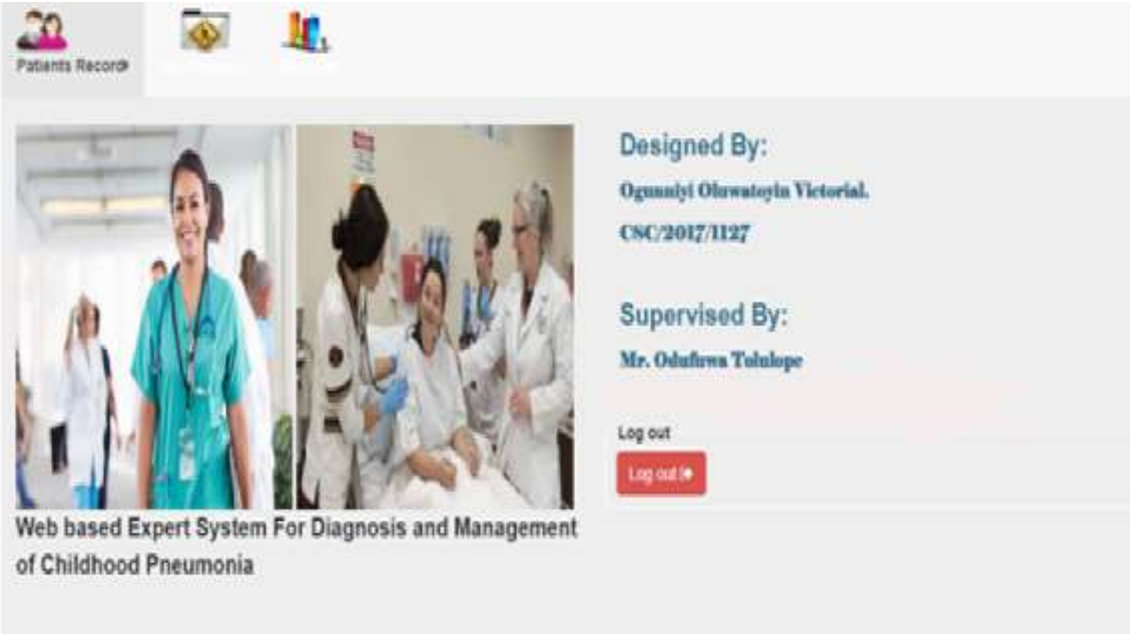

Figure 5: Login Page

4.3 New Patient Registration Page

Figure 6 shows the form page used to store information of a new patient. The information entered includes the patient ID which is generated automatically for each user, surname, other names, phone number, date of birth, gender, address, and next of kin information, etc.

4.4 Expert System Diagnostic Page

Figure 7 allows patients to interact with the expert system diagnostic engine for a few questionings and interaction on pneumonia. The system asks a series of questions and arrives at a conclusion based on the answers provided by the user.

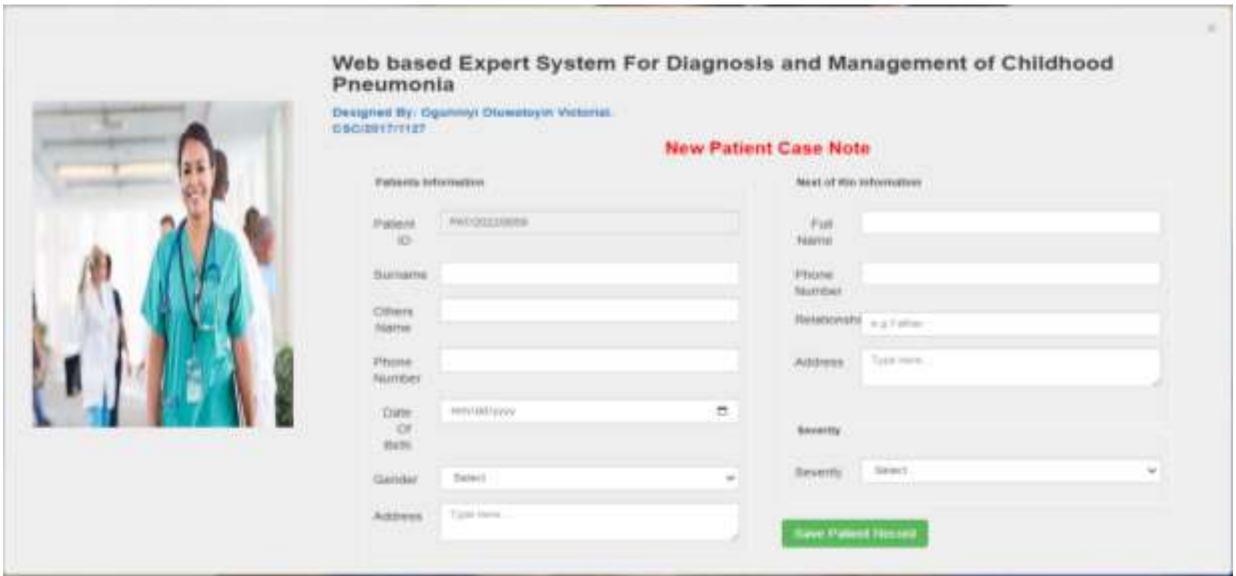

Figure 6: New Patient Registration Page

Figure 7: Pneumonia Disease Diagnoses

4.5 Patient Case Note Page

Figure 8 allows for patient information to be logged into the system for record-keeping purposes. The form, depicted in Figure 4, collects detailed information about their biodata, next of kin, and the disease(s) they have.

4.6 Patient Diagnosis Report Page

The system gives questions to a user in Figure 6. The user can move on to the next question once he has submitted his response. After clicking the "Why ask?" button, the user can see the inference engine´s explanation of the question.

S/N	RegID	Surname	OtherName	PhoneNo.	DateOfBirth	Gender	Address	Severity	NOKNam
1	PAT/2021/0001	AJAYI	ADEGOKE	07016112889	1990-06-12	Male	Ede	Intermidiate	ajayi yusu
2	PAT/2021/0002	AJAYI	ADEOLU	07016112890	1990-01-01	Female	Ede	Mild	ajayi ade
3	PAT/2021/0003	SELIM	ADEKOLA	08076738293	1998-02-20	Male	Ede Osun State	Intermidiate	Akinkunmi
4	PAT/2021/0004	ALAO	MUSTAKEEM	07039848292	1997-03-04	Female	EDE	Intermidiate	AJAYI
5	PAT/2021/0005	selim	adegoke2	07016112891	1998-12-02	Male	EDE	Intermidiate	Akinkunmi
6	PAT/2021/0006	selim	adegoke2	07016112891	1998-12-02	Male	EDE	Intermidiate	Akinkunmi
7	PAT/2021/0007	ABIONA	TAOFEEK	07039402718	2021-05-12	Male	EDE	Intermidiate	AJADI

Figure 8: Patient Case Note Design Page

Figure 9: Patient Diagnosis Report Page (Output)

After answering the questions, the inference engine has enough information to conclude whether the child has pneumonia and the type of pneumonia he/she get. Then the expert system will now give the recommendation that the child has pneumonia or other types of infectious respiratory diseases. As illustrated in Figure 6, some tests were carried out using the system and the system has a sensitivity of 95%, specificity of 88%, and accuracy of 93% in diagnosing the disease.

5.0 CONCLUSION

The "Web-based Expert System for Diagnosis and Management of Childhood Pneumonia" has been designed and implemented to solve issues affecting children under the age of five who require daily medical attention. The system can diagnose various pneumonia causes, improve early diagnosis, and provide better treatment. Additionally, it serves as a temporary aid for those needing immediate help when a professional consultant is unavailable. Moreover, the system has been carefully designed to be user-friendly and accessible to anyone, regardless of their location. This means that users can access the website at any time and from anywhere to manage or diagnose various pneumonia diseases based on their input. Domain experts have validated the system's results after being tested with a domain dataset. This expert system is easy to use and does not require extensive training. The knowledge is represented by IF-THEN rules with forward-chaining reasoning and is developed using E2glite, a rule-based expert system shell. The system has an attractive interface and can be used in DOS or Windows environments with a simple interface.

REFERENCES

[1] Zambare, K. K., & Thalkari, A. B. (2019). Overview on Pathophysiology of Pneumonia. *Asian Journal of Pharmaceutical Research*, *9*(3), 177-180.

[2] Fagbuagun, O. A., Nwankwo, O., Akinpelu, S. A., & Folorunsho, O. (2022). Model development for pneumonia detection from chest radiograph using transfer learning. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *20*(3), 544-550.

[3] Nguyen, T. K. P., Tran, T. H., Roberts, C. L., Fox, G. J., Graham, S. M., & Marais, B. J.

(2017). Risk factors for child pneumonia-focus on the Western Pacific Region. *Paediatric respiratory reviews*, *21*, 95-101.

[4] Wagstaff, A. (2004). *The Millennium Development Goals for health: rising to the challenges*. World Bank Publications.

[5] You, D., Hug, L., Ejdemyr, S., Idele, P., Hogan, D., Mathers, C., ... & Alkema, L. (2015). Global, regional, and national levels and trends in under-5 mortality between 1990 and 2015, with scenario-based projections to 2030: a systematic analysis by the UN Inter-agency Group for Child Mortality Estimation. *The Lancet*, *386*(10010), 2275-2286.

[6] Puumalainen, T., Quiambao, B., Abucejo-Ladesma, E., Lupisan, S., Heiskanen-Kosma, T., Ruutu, P., ... & ARIVAC Research Consortium taneli. puumalainen@ ktl. fi. (2008). Clinical case review: a method to improve identification of true clinical and radiographic pneumonia in children meeting the World Health Organization definition for pneumonia. *BMC infectious diseases*, *8*, 1-7.

[7] Karim, R., Afridi, J. K., Yar, S. R., Zaman, M. B., & Afridi, B. K. (2023). Clinical Findings and Radiological Evaluation of WHO-Defined Severe Pneumonia Among Hospitalized Children. *Cureus*, *15*(1).

[8] Zhi, G., Samsudin, H. B., & Majid, N. (2022). Modeling the length of hospital stay for copd and pneumonia patients in malaysia for 2019. *Journal of Quality Measurement and Analysis JQMA*, *18*(2), 75-85.

[9] Walsh, S. L., Calandriello, L., Silva, M., & Sverzellati, N. (2018). Deep learning for classifying fibrotic lung disease on high-resolution computed tomography: a case-cohort study. *The Lancet Respiratory Medicine*, *6*(11), 837-845.

[10] Fagbuagun, O., Folorunsho, O., Adewole, L., & Akin-Olayemi, T. (2022). Breast Cancer Diagnosis in Women Using Neural Networks and Deep Learning. *Breast Cancer, 16*(2), 152-166.

[11] Chang, B., Chang, C. W., & Wu, C. H. (2011). Fuzzy DEMATEL method for developing supplier selection criteria. *Expert systems with Applications*, *38*(3), 1850-1858.

[12] Quaranta, M. (2013). Fuzzy set theory and concepts: A proposal for concept formation and operationalization. *Comparative Sociology*, *12*(6), 785-820.

[13] Kumar, Y., & Jain, Y. (2012). Research aspects of expert system. *Int. J. Comput. Bus. Res*, *1*(11).

[14] Mesher, A., Abdul-Malak, M. A., Khaled, A., & El-Khatib, S. (2009). Expert systems as a component of knowledge management: A review. Expert Systems with Applications, 36(2), 4768-4775.

[15] Shokouhyar, S., Ataafarin, M., & Tavassoli, M. (2017). Design and implementation of an expert system for diagnosing hearing disorders using fuzzy logic. Computer Methods and Programs in Biomedicine, 141, 143-154.

[16] Kumar, A., Kaur, G., & Kaur, H. (2009). Applications of expert system in medical diagnosis. International Journal of Computer Science and Information Security, 3(1), 78-84.

[17] Buchanan, B. G., & Shortliffe, E. H. (1984). Rule-based expert systems: the MYCIN experiments of the Stanford Heuristic Programming Project. Addison-Wesley Longman Publishing Co., Inc.

[18] Ezquerra, N. F., Acheson, R. M., Carrera, J. M., & Trujillo, M. (1992). An expert system for the interpretation of perfusion studies. Computers in Biology and Medicine, 22(2), 91-101.

[19] Djam X.Y, Wajiga G.M., Kimbi Y.H, & Blamah N.V. (2011). A Fuzzy Expert System for the management of malaria. An International Journal of Pure and Applied Sciences and Technology, 8(3), 84-108.

[20] Alkassar, S., Abdullah, M.A.M., Jebur, B.A., Abdul-Majeed, G.H., Wei, B., & Woo, W.L. (2021). Automated Diagnosis of Childhood Pneumonia in Chest Radiographs Using Modified Densely Residual Bottleneck-Layer Features. Applied Sciences, 11(23), 11461.

[21] Amanze, B. C., Asogwa, D. C., & Chukwuneke, C. I. (2019). An Android Mobile Expert System for the Diagnosis of Pneumonia with Object-Oriented Methodology. International Journal of Computer Sciences and Engineering, 7(4), 39-46.

[22] Arani, L. A., Sadoughi, F., & Langarizadeh, M. (2019). An Expert System to Diagnose Pneumonia Using Fuzzy Logic. Acta Informatica Medica, 27(2), 103-107.