Preliminary diagnosis of respiratory diseases: an innovative approach using a web expert system

Laberiano Andrade-Arenas[1], Pedro Molina-Velarde[2], Cesar Yactayo-Arias[3]
[1]Facultad de Ciencias e Ingeniería, Universidad de Ciencias y Humanidades, Lima, Perú
[2]Facultad de Ingeniería, Universidad Tecnológica del Perú, Lima, Perú
[3]Departamento de Estudios Generales, Universidad Continental, Lima, Perú

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ABSTRACT

This study addressed the challenge of accurate and timely diagnosis of respiratory diseases such as influenza, asthma, and pneumonia by developing and evaluating a web-based expert system. The objective was to develop and assess both the usability and diagnostic efficiency of a web-based expert system adaptable to mobile devices. A combined methodological approach was used, using the rapid application development (RAD) model to build the system and the user usability system (SUS) to evaluate the usability with the participation of 15 users and 21 simulated cases with a confusion matrix to determine the precision, accuracy, sensitivity, and specificity of the system in diagnosing respiratory diseases. The results showed that the expert system has a considerable capacity to identify and differentiate these diseases, with a precision of 86%, an accuracy of 76%, a sensitivity of 80%, and a specificity of 67%. Furthermore, the usability evaluation using the SUS method yielded an average of 82, indicating a positive perception and good usability by the users. In conclusion, although the results suggest a promising potential to improve the diagnostic process in clinical and community settings, the need for future studies to validate its performance in real clinical settings is recognized.

Corresponding Author:

Cesar Yactayo-Arias
Departamento de Estudios Generales, Universidad Continental
Lima, Perú
Email: cyactayo@continental.edu.pe

1. INTRODUCTION

Respiratory diseases are a major public health problem affecting millions worldwide [1]. These conditions alter lung function, make breathing difficult, and manifest themselves in various 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]. In addition to their impact on quality of life, these diseases are a significant economic burden due to healthcare costs and lost productivity. Among the most common and debilitating respiratory diseases are influenza, pneumonia, and asthma, all of which have significant consequences. In this sense, timely and accurate medical care is essential for the effective management of respiratory diseases. However, accurate diagnosis can be challenging 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 diseases, leading them to self-medicate. This can lead to misdiagnosis or delays in treatment, negatively impacting the health and well-being of patients, especially in settings where resources are limited or access to healthcare is reduced.

In the quest to improve 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 diseases. For example, the system developed in [3] is an expert system capable of diagnosing influenza and the common cold, two of the most common respiratory diseases. Furthermore, Porter *et al.* [4] evaluated an algorithm designed to run on smartphones that aims to detect asthma exacerbations. On the other hand, Burnashev *et al.* [5] developed an expert system that used fuzzy logic to assess the severity of pneumonia. Fuzzy logic is a technique that allows one to deal with uncertainty and imprecision in data, which is particularly useful in the medical field where symptoms and signs can vary in presentation and severity. However, despite the progress made, significant challenges remain in the ability of systems to address different respiratory diseases. Previous studies have developed systems capable of diagnosing only a limited set of diseases, making it difficult to optimally implement them to identify multiple similar conditions, such as influenza, pneumonia, and asthma, in a single diagnostic system. This fragmentation in detecting similar diseases with different systems results in the inefficient use of resources.

To fill this gap, this study develops a web-based expert system adaptable to mobile devices for the preliminary diagnosis of respiratory diseases such as influenza, pneumonia, and asthma. This system is based on the decision tree method, a technique that uses a hierarchical structure of decisions to conclude. Adaptability to mobile devices will allow users to access the diagnostic system anytime, anywhere, making it easier to get quick and accurate medical help when needed [6]. In addition, the use of a decision tree in the diagnostic process ensures a systematic and structured evaluation of symptoms, improving the accuracy and effectiveness of respiratory disease diagnosis.

The main objective of this study is to develop and evaluate a web-based expert system for the diagnosis of respiratory diseases. This system will be designed to accurately and efficiently identify conditions such as influenza, pneumonia, and asthma. The evaluation will focus on the usability and diagnostic efficiency of the system, including parameters such as precision, accuracy, sensitivity, and specificity.

On the other hand, the importance of implementing this expert system lies in its ability to improve access to healthcare, facilitate accurate and timely prediagnosis, and reduce the burden on healthcare systems by preventing serious and costly complications associated with respiratory diseases. Expert systems in medicine play a critical role in providing immediate access to knowledge for physicians and patients. Using algorithms such as decision trees, and expert systems improve the quality and safety of healthcare. They do this by providing computerized clinical decision support not only to clinicians but also to patients and other stakeholders, ensuring that they have access to relevant information and expertise [7]. This capability facilitates more informed decision-making, leading to more accurate presumptive diagnoses and better patient outcomes. It also promotes public education about respiratory health and encourages health self-management, empowering individuals to make informed decisions about their well-being.

2. LITERATURE REVIEW

2.1. Breakdown of respiratory diseases

This section presents a detailed analysis of several respiratory diseases, such as influenza, pneumonia, and asthma. The definitions of each of these diseases have been examined, as well as the characteristic symptoms associated with each. This breakdown allows for a deeper understanding of these respiratory diseases, their clinical manifestations, and their implications for diagnosis and treatment.

2.1.1. Influenza

Influenza is a rapid-onset viral respiratory disease responsible for significant levels of illness and death worldwide [8]. It causes annual winter epidemics and, sometimes, widespread pandemics. Although it is usually mild and self-limiting, it can pose significant health risks, particularly to the elderly or those with underlying chronic health conditions, potentially leading to serious illness or even death [9]. In addition, young children are particularly susceptible to severe influenza virus infections and associated complications [10]. Typical symptoms of influenza include fever, malaise, cough, and body aches [11]. In addition, according to the World Health Organization (WHO) [12], other symptoms may include coughing (usually dry), headaches, muscle and joint aches, severe general malaise, a sore throat, and a runny nose.

2.1.2. 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 [13]–[15]. It is also the leading infectious cause of death in children under five years of age worldwide [16], [17]. Although it is possible to detect and treat pneumonia with simple tools and drugs, detection remains a major challenge in developing countries [18], [19]. 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 [20].

2.1.3. Asthma

Asthma is a chronic respiratory disease that affects a large number of people worldwide [21]. Although there is no cure for asthma, it can be controlled with inhalers and preventive measures to avoid triggers. However, accurate diagnosis of asthma in adults remains a challenge in current clinical practice [22]. In addition, diagnosis in children is a significant clinical challenge [23]. The four most common presenting symptoms are cough, wheezing, shortness of breath, and chest tightness [24], [25]. According to the WHO [26], some people may experience worsening symptoms during cold spells or temperature changes. Other triggers may include exposure to dust, smoke, certain fumes, grass and tree pollen, and contact with animal hides and feathers, harsh soaps, and perfumes.

2.2. Related works

According to Canari *et al.* [3] respiratory diseases have caused high mortality rates worldwide over the years, a situation that was highlighted again during the coronavirus disease 2019 (COVID-19) pandemic. People living in extreme poverty are the most vulnerable to these diseases. To facilitate the diagnosis of respiratory diseases, a mobile health application was designed, allowing patients to register and obtain a diagnosis from the comfort of their homes. The validation of the design, based on functionality, efficiency, effectiveness, and satisfaction, showed high acceptance among users due to its ability to reduce the time needed to obtain a diagnosis.

In the same vein, Arani *et al.* [27] developed a fuzzy expert system framework to diagnose pneumonia and distinguish it from other respiratory diseases such as chronic bronchitis, tuberculosis, asthma, stroke, and lung cancer. The main goal was to provide a decision-support tool for both general practitioners and patients, especially in the diagnosis of pneumonia, a disease with clinical signs that are difficult to distinguish from other respiratory diseases. To develop the system, they used a fuzzy expert system methodology, which was divided into four phases according to the prototype life cycle methodology. The results obtained showed that the system had a sensitivity of 97%, a specificity of 85%, and an accuracy of 93% in diagnosing the disease. This indicates that the developed fuzzy expert system has high performance in detecting pneumonia and differentiating it from other respiratory diseases.

Similarly, Porter *et al.* [4] developed and evaluated the precision of a smartphone-based diagnostic algorithm for detecting asthma. To develop the algorithm, they conducted a prospective, double-blind diagnostic accuracy study and compared the performance of the algorithm with expert clinical assessment and formal pulmonary function testing. Individuals with physician-diagnosed asthma were divided into two categories: those with confirmed exacerbations and those with controlled asthma. The algorithm's performance was then evaluated in relation to clinical diagnosis and patient-reported wheeze detection. Results showed that the algorithm had a positive percentage agreement (PPA) of 89% with expert clinical diagnosis of asthma exacerbations. In addition, the negative percentage agreement (NPA) was 84%. It also outperformed as a detector of patient-reported wheeze with a sensitivity of 63.7%, suggesting its effectiveness in rapidly identifying asthma exacerbations without the need for clinical examination or pulmonary function testing.

Likewise, Gurbeta *et al.* [28] developed and tested a real-time automated telemedicine system with expert diagnosis for asthma and chronic obstructive pulmonary disease (COPD). This system, which integrates a spirometer, a mobile application, and an expert diagnosis system, is based on technologies such as Android, Java, MATLAB, and hypertext preprocessor (PHP). The primary objective was to provide accurate diagnosis and expert advice to patients in remote, rural, and isolated areas, as well as those with limited physical mobility. A prospective study was conducted in three remote primary healthcare facilities and one hospital in Bosnia and Herzegovina. Over six months, 780 patients were assessed and diagnosed using the developed system, for which technologies such as Android, Java, MATLAB, and PHP were used to build the necessary technological infrastructure. The results of the study showed an accuracy of 97.32% in diagnosing asthma and COPD in the evaluated patients. In addition to improving the quality of care, the system provided significant benefits in terms of access to care for patients in remote areas and with limited physical mobility.

Similarly, Burnashev *et al.* [5] developed a fuzzy expert system using fuzzy logic to assess the severity of pneumonia, taking advantage of the inherent uncertainty in medical diagnosis. The knowledge base was built in SWI-Prolog to improve medical decision-making and to contribute to the development of medical software products. They used fuzzy logic to deal with uncertainty and developed a client-server system using Python and Prolog. They used the Django framework for developing the client-side, while the PySwip module was used to manage the knowledge base. In addition, they performed system tests using a graphical interface developed with XPCE, following the system design lifecycle. On the other hand, Amanze *et al.* [29] developed a mobile expert system for the diagnosis of pneumonia using Imo State University Teaching Hospital as a case study. This system, which allows medical checks to be performed through devices connected to Android smartphones and reports to be uploaded to the server, aims to improve the health of users. They used PHP and MySQL for their development, applying object-oriented analysis with the unified modeling language (UML).

3. METHOD

3.1. Rapid application development model

Rapid application development (RAD) is an agile methodology based on active user participation in the development process through iterative prototyping [30]. This approach allows for rapid iteration and feedback, facilitating early identification of requirements and necessary adjustments to the system. By combining iterative development with prototyping, RAD significantly accelerates the software development cycle by reducing the time spent on each phase, from planning to prototype integration [31]. Therefore, the RAD methodology was used to develop the expert system for diagnosing respiratory diseases, as shown in Figure 1, which details the actions performed during its four main phases: requirements planning, user design, construction, and transition. The choice of the RAD methodology for the development of the medical diagnosis expert system is justified by its ability to adapt in an agile way to changing user requirements and its focus on prototyping, which facilitates early validation of the system. Given the medical context, where requirements can be complex and subject to constant change due to scientific advances and user needs, the RAD methodology allows for close collaboration between developers and users, ensuring that the final system is effective, usable, and meets the quality standards required in the healthcare field.

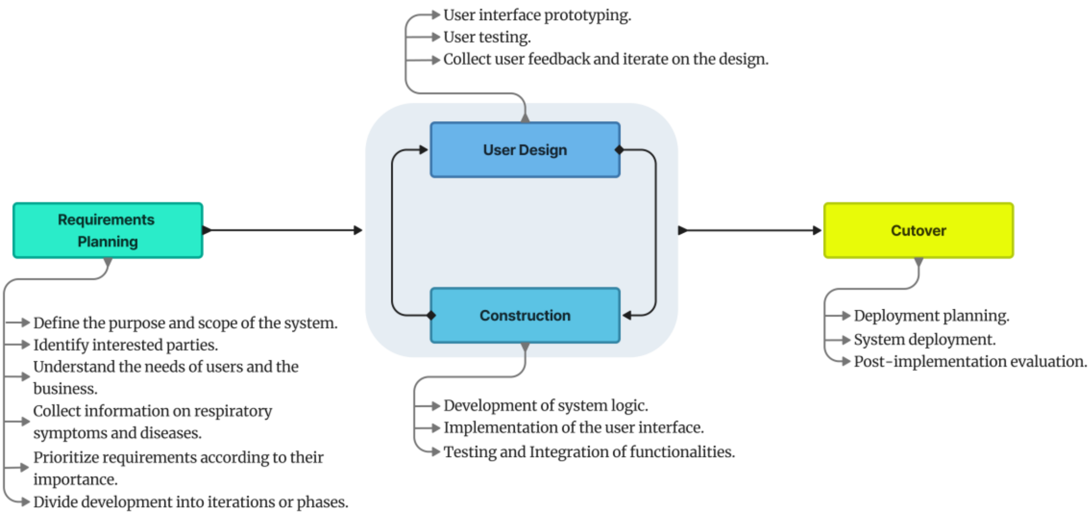


Figure 1. Description of each of the stages of the RAD methodology according to the expert system development study

3.2. System usability scale

To evaluate the usability of the expert system, it was decided to use the system usability scale (SUS), which is widely recognized as the standard for measuring perceived usability [32]. This tool is characterized by its reliability and affordability, making it an ideal option for a comprehensive evaluation of the usability of systems. It is composed of ten simple items that allow obtaining a global view of usability from the user's perspective [33]. This choice was based on the need to obtain an accurate and general evaluation of the user's experience with the expert system, to identify areas for improvement, and to ensure user-centered design for future iterations of software development.

The SUS is a scale consisting of a series of questions designed to assess the perceived ease of use of a system. It consists of a combination of Likert-type questions and 10 forced-choice questions, as shown in Table 1. Users provide feedback on the system by rating a series of statements on a five-point scale, which ranges from strongly disagree to strongly agree. The answers are subsequently utilized to compute a total score that spans from 0 to 100, where higher scores signify a higher perceived usability. This score serves as a measure to assess the system's overall usability.

Table 1. 10 SUS questions

Id	Question
Q1	I think that I would like to use this system frequently.
Q2	I found the system unnecessarily complex.
Q3	I thought the system was easy to use.
Q4	I think that I would need the support of a technical person to be able to use this system.
Q5	I found the various functions in this system were well integrated.
Q6	I thought there was too much inconsistency in this system.
Q7	I would imagine that most people would learn to use this system very quickly.
Q8	I found the system very cumbersome to use.
Q9	I felt very confident using the system.
Q10	I needed to learn a lot of things before I could get going with this system.

3.3. System diagnostic logic

The development of the system's diagnostic method was based on the use of a decision tree approach, starting with the identification of a set of symptoms associated with respiratory diseases such as influenza, asthma, and pneumonia. These symptoms were carefully selected from an exhaustive review of existing medical literature and previous research. To ensure the accuracy and relevance of the selected symptoms, a variety of sources were consulted, including scientific articles. Specifically, symptoms associated with influenza were taken from [9], [10], symptoms characteristic of pneumonia were taken from [18], and symptoms associated with asthma were identified from [22]–[24].

Once the collection of these relevant symptoms was complete, we moved on to the next stage of the process, which was the construction of the decision tree. This decision tree was constructed as a visual representation of the different diagnostic pathways that the expert system would follow depending on the symptoms presented by the patient. Each node in the tree represented a particular symptom, while the branches indicated possible medical conditions associated with those symptoms. This hierarchical structure allowed the expert system to make differentiated and precise diagnoses, adapted to the specific symptoms of each patient.

3.4. Confusion matrix and performance metrics

The confusion matrix serves as a valuable tool to efficiently illustrate the performance of the classifier, with the advantage of direct interpretation of the results. Its simplicity allows effective evaluation of multiple models or algorithms [34], making it a versatile tool for evaluating performance in different contexts and applications. As shown in Figure 2, the four primary components of the confusion matrix consist of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).

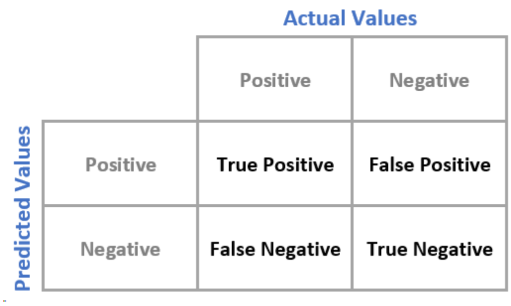


Figure 2. Representation of the confusion matrix

Once the confusion matrix is constructed, the matrix values can be used to calculate various model evaluation metrics, such as precision, accuracy, sensitivity, and specificity. These metrics provide a more detailed understanding of the performance of the model in terms of its ability to correctly classify samples into different classes. The metrics are described in detail below.

Precision, a vital measure of a model's efficacy in correctly identifying positive cases, gains particular relevance in situations where the costs associated with false positives are substantial. It is calculated as the ratio of true positive predictions to the total number of positive predictions generated by the model [35]. It can be calculated using (1).

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

Accuracy, defined as the ratio of correctly predicted cases to the total number of cases in the dataset, is an essential metric for evaluating a model's performance in classification or prediction [35]. This fundamental measure provides a clear view of the model's ability to classify accurately. Accuracy, which considers both correct and incorrect predictions, provides a comprehensive view of the model's predictive ability. It can be calculated using (2).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (2)$$

The sensitivity of a diagnostic test represents its ability to adequately detect positive cases within the total number of true positive cases. A high sensitivity indicates that the test has a lower tendency to generate false negatives, thus increasing its reliability. Sensitivity, by focusing on the detection of true positive cases, is critical in evaluating the effectiveness of a model. It can be calculated using (3).

$$Sensitivity = \frac{TP}{TP + FN} \quad (3)$$

The Specificity of a diagnostic test represents its ability to adequately detect negative cases within the total number of true negative cases. High specificity suggests that the test has a lower propensity to generate false positives, that is, to misclassify negative cases as positive. By focusing on the accurate identification of negative cases, specificity plays a critical role in evaluating the reliability of a model. It can be calculated using (4).

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

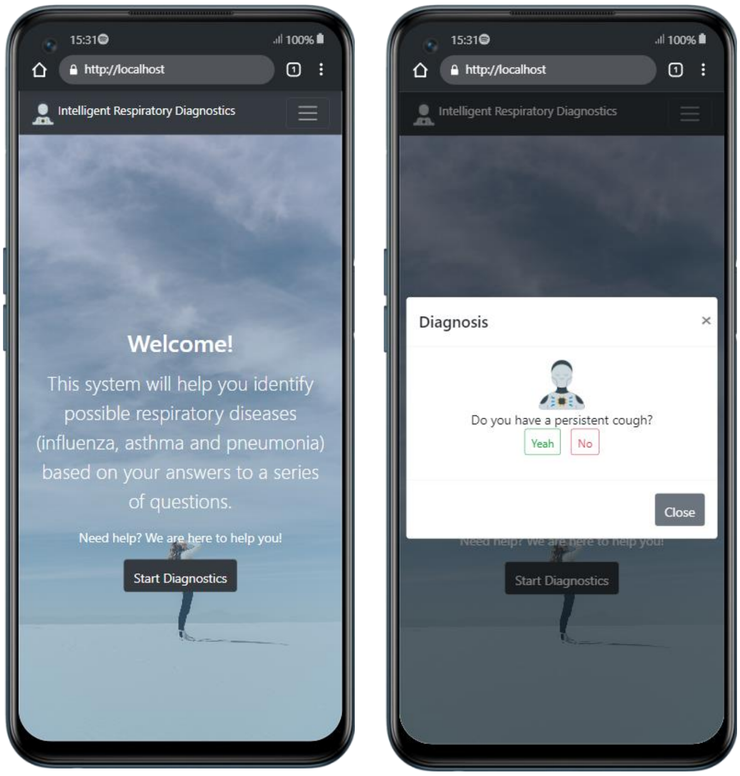
4. RESULTS

4.1. Developed web expert system

Figures 3 and 4 demonstrate the adaptability of the developed web-based expert system for mobile devices, designed to diagnose three specific respiratory diseases: influenza, asthma, and pneumonia. Figure 3(a) shows the initial interface of the system, welcoming the user and providing a brief description of the expert system's functionality. It also features a button that lets the user start the diagnostic process, making it easy to assess their health status. Figure 3(b) shows the diagnostic query process in detail. Each question has two response options: "Yes" and "No." Users should select "yes" if they are experiencing the symptom mentioned in the question and "no" otherwise. It is important to note that the questions are presented automatically as the user answers or selects an option. This interactive approach allows for a fluid and dynamic user experience. As the user progresses by answering the questions, the system makes inferences based on the answers provided and finally displays the final diagnosis result. This web-expert system-based approach not only facilitates the diagnosis process for the user but also provides an effective tool for early detection and management of respiratory diseases.

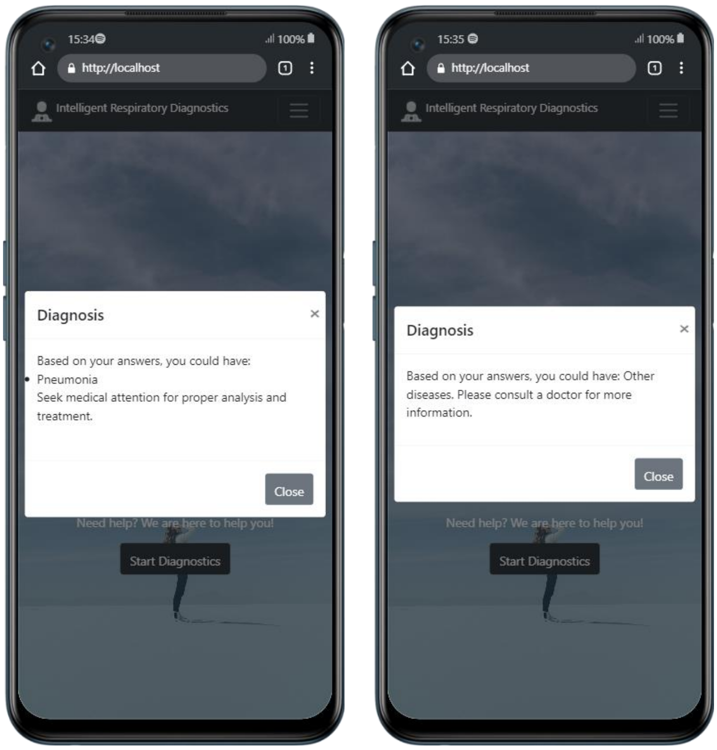
Figure 4(a) shows the result of the diagnosis, which is determined based on the responses provided by the user during the interaction with the system. Once the diagnosis of the respiratory disease in question has been made, the system provides a recommendation to the user, suggesting that he or she seek immediate medical attention at a hospital or specialized health care center. This recommendation is based on the importance of obtaining a thorough analysis and appropriate treatment by health professionals to manage the diagnosed condition and avoid possible complications effectively.

On the other hand, Figure 4(b) shows the result when the system does not identify the specific disease from the answers provided or when the user has indicated that he or she does not have the said symptom. In this case, the system indicates that the condition may correspond to another disease not considered in the initial diagnosis process. As a precaution, the system advises the user to consult a healthcare professional for a more detailed evaluation and personalized guidance. This recommendation reflects the system's commitment to the user's comprehensive health care, ensuring that the user receives the information and support necessary to address any medical concerns with due attention and care.



(a) (b)

Figure 3. Mobile version web expert system in (a) initial system interface and (b) question process for diagnosis



(a) (b)

Figure 4. Mobile version web expert system in (a) preliminary diagnosis result and (b) result when the disease is not identified

4.2. Usability evaluation

A total of 15 users participated in the usability evaluation study. The selection of these participants was done through convenience sampling, which means that those individuals who were easily available and willing to participate in the study were selected based on accessibility and availability criteria. The users evaluated the usability of the system through a specially designed online questionnaire, which consisted of 10 SUS questions, as shown in Table 1.

Table 2 shows the results obtained using the SUS method. These results provide an insight into the user experience when interacting with this digital tool. The scores obtained, which range from 77.5 to 87.5, reflect a generally positive trend in the ease of use perceived by the users. This consistency in the scores suggests a consistency in the perception of the usefulness and effectiveness of the system, indicating a solid and functional design. It is also important to note that the average SUS score obtained was 82. According to the curved grading scale for the SUS [36], this average score places the system in Grade A, within the 90% to 95% percentile range. This result further confirms the high usability perceived by users and places the system in a category of excellence in terms of ease of use. Likewise, this encouraging result not only validates the effectiveness of the current system but also serves as a fundamental starting point for future iterative improvements. It also highlights the importance of a continuous feedback and design refinement strategy focused on ensuring an optimal and satisfying user experience at all stages of interaction with the expert system, which is crucial for its continued success and ability to effectively meet user needs.

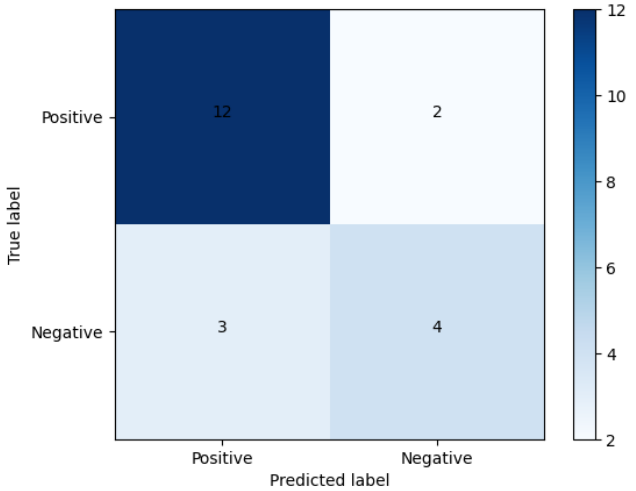
Table 2. Result of the usability evaluation with the SUS

User	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	SUS Score
User 1	3	2	4	1	4	2	4	1	4	1	80
User 2	4	1	4	2	4	2	5	2	4	2	80
User 3	4	2	4	1	4	2	4	2	4	2	77.5
User 4	4	1	5	1	4	2	4	1	4	1	87.5
User 5	4	2	4	2	4	1	4	2	4	1	80
User 6	4	2	5	2	4	2	4	2	4	2	77.5
User 7	4	2	4	1	4	2	5	2	4	1	82.5
User 8	4	1	4	2	4	2	4	1	4	1	82.5
User 9	4	2	5	2	4	1	4	2	4	2	80
User 10	3	1	4	1	4	2	5	1	4	1	85
User 11	4	1	4	1	4	2	4	1	4	1	85
User 12	3	1	5	1	4	2	4	1	4	1	85
User 13	4	2	4	1	4	2	4	1	4	1	82.5
User 14	4	2	5	1	4	2	5	1	4	1	87.5
User 15	4	1	4	2	4	2	4	1	4	2	80

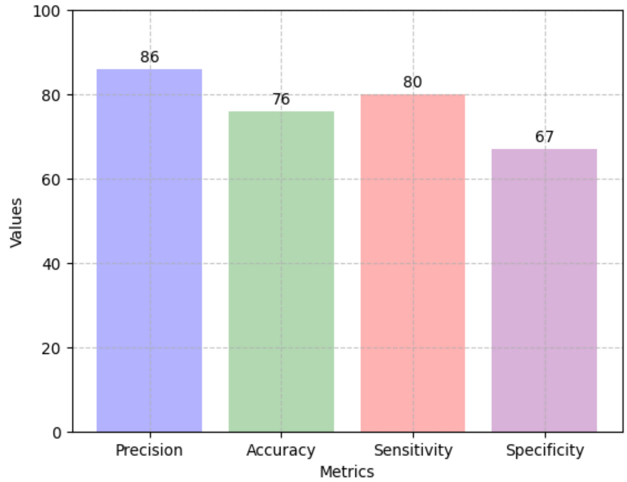
4.3. System performance evaluation

Figure 5(a) shows the variable ability of the system to discriminate between positive and negative cases through an evaluation with a set of 21 carefully designed simulated cases (15 positive and 6 negative), correctly identifying 12 positive and 4 negative cases. This result suggests a promising ability for the early detection of respiratory diseases such as influenza, asthma, and pneumonia, which could have significant implications for clinical management and treatment. However, the presence of 2 cases misclassified as positive and 3 cases misclassified as negative indicates the existence of challenges in the specificity and sensitivity of the system.

Furthermore, the analysis of the system performance parameters provides a complete picture of its effectiveness and accuracy in identifying positive and negative cases. As Figure 5(b) demonstrates, the precision of 86% represents the fraction of positive cases correctly identified by the system, indicating a remarkable ability to minimize false positives and, therefore, reasonable confidence in the validity of the positive diagnoses issued by the system. The accuracy of 76% gives a broader view of the overall performance of the system, considering both positive and negative cases, and thus reflects its ability to correctly classify the majority of the cases evaluated. On the other hand, the sensitivity of 80% highlights the system's ability to detect the presence of respiratory disease in the study population, suggesting a reasonable effectiveness in identifying positive cases. On the other hand, the specificity of 67% shows the proportion of negative cases correctly classified by the system, indicating a certain tendency towards false positives. These results, obtained through a rigorous analysis of the confusion matrix, provide a detailed evaluation of the performance of the system and provide guidance for future improvements and adaptations that could increase its clinical utility and impact on medical practice.



(a)



(b)

Figure 5. Result of performance parameters of the expert system in the preliminary diagnosis of respiratory diseases in (a) confusion matrix of the 21 cases evaluated and (b) performance metrics

5. DISCUSSION

The expert system presented in this study, designed for the preliminary diagnosis of respiratory diseases such as influenza, asthma, and pneumonia, demonstrates a good ability to classify positive and negative cases, as well as a high level of accuracy, as evidenced in Figure 5. Furthermore, Figures 3 and 4 show a mobile-friendly design that improves accessibility for users. These results are encouraging and highlight the effectiveness of our tool to identify these diseases through a mobile-friendly web platform. Furthermore, the usability evaluation using the SUS method yielded an average score of 82, suggesting that the system is perceived as intuitive and easy to use, increasing its potential clinical utility.

When comparing our results with those of previous studies, significant differences are observed. For example, the fuzzy expert system of Arani *et al.* [27] showed a sensitivity of 97%, a specificity of 85%, and an accuracy of 93% in the diagnosis of pneumonia. Although these results are superior to ours, it is important to emphasize that our system demonstrates competitive precision, covers a broader spectrum of respiratory diseases, and is characterized by its ability to adapt to mobile devices, which improves its accessibility and practical utility. Furthermore, the smartphone-based diagnostic algorithm developed by Porter *et al.* [4] showed a sensitivity of 63.7% in the identification of asthma exacerbations, highlighting the effectiveness of technological approaches for the rapid detection of specific conditions. In the same vein, the automated telemedicine system by Gurbeta *et al.* [28] achieved an accuracy of 97.32% in the diagnosis of asthma and COPD, highlighting the importance of technological solutions to improve access to health care. However, the novelty of our system lies in its comprehensive approach and adaptability. Unlike previous studies that focused on one or two specific diseases, our system covers three respiratory diseases. Nonetheless, a significant limitation of our study lies in the utilization of simulated cases rather than real clinical data, potentially impacting the generalizability of the findings to real-world clinical scenarios. However, the system developed with a decision tree approach and its adaptability to mobile devices could broaden the tool's scope and accessibility for preliminary diagnosis, particularly in populations facing geographical or infrastructural constraints.

The findings of this study contribute to the existing knowledge by demonstrating that a web-based expert system can be effective for the preliminary diagnosis of respiratory diseases, with a good perception of usability by users. This extends previous knowledge by including the ability to adapt to mobile devices, which not only improves accessibility but also convenience for end-users. Although our results do not reach the accuracy and sensitivity figures of some previous studies, the accuracy of the developed system is significant. Furthermore, the inclusion of a wider range of diseases and the adaptability to different platforms are important advantages. This study highlights the importance of technological solutions in medical diagnosis and their potential to improve access to and quality of healthcare.

The main purpose of this study was to develop and evaluate a web-based expert system for the preliminary diagnosis of respiratory diseases, with a focus on adaptability to mobile devices to improve accessibility. The results are promising and suggest that the system could be a useful tool in clinical practice. Nevertheless, further research using real clinical data is crucial to validate its performance in clinical settings and improve its diagnostic capabilities. Unanswered questions about its effectiveness under real-world conditions should be addressed in future studies to ensure the reliability and accuracy of the system in everyday clinical practice. Evaluating these factors will not only allow the tool to be improved but will also contribute to the effective integration of new technologies into routine health care.

6. CONCLUSION

The present study succeeded in developing a web-based expert system adaptable to mobile devices for the preliminary diagnosis of respiratory diseases such as influenza, asthma, and pneumonia, evaluating its usability and diagnostic efficiency. Using a methodological approach that combined the development of the system using the RAD model, a decision tree, and its evaluation through a SUS questionnaire and simulated cases, we obtained significant results that highlight the capacity and potential of this tool. The system showed significant accuracy, indicating a considerable ability to diagnose and differentiate between the analyzed respiratory diseases. The usability evaluation, with an average score of 82 in the SUS method, suggests that users perceive the system as intuitive and easy to use. These results are important because they highlight the potential of the system as a viable option for the preliminary diagnosis of respiratory diseases in clinical and community settings. Furthermore, the results of the study provide evidence that web-based and mobile-adaptive expert systems can be effective for the preliminary diagnosis of respiratory diseases, which could transform clinical practice by providing accessible and easy-to-use tools for healthcare professionals, especially patients. This advancement not only improves access to accurate preliminary diagnoses but also has the potential to optimize healthcare resources by facilitating early and timely detection of these diseases. To expand the impact of our findings, it is essential to conduct additional studies that validate the system's performance in real-world clinical settings using real clinical data. The integration of advanced diagnostic techniques, such as machine learning and artificial intelligence, could further improve the accuracy and reliability of the system. Furthermore, although our results are promising, questions remain about the system's effectiveness in real-world conditions, such as its behavior in the face of the variability and complexity of real clinical cases and its impact on clinical decision-making and patient health outcomes. Addressing these questions will require future research to assess the impact of the system in daily clinical practice.

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BIOGRAPHIES OF AUTHORS

Laberiano Andrade-Arenas doctor in systems and computer engineering. Master in systems engineering. Graduated with a master's degree in University Teaching. Graduated with a master's degree in accreditation and evaluation of educational quality. He is a systems engineer. Scrum fundamentals certified, a research professor with publications in Scopus-indexed journals. He can be contacted at email: landrade@uch.edu.pe.

Pedro Molina-Velarde he is a systems engineer, with a master's degree in administration. Software development specialist; he is also an undergraduate teacher at private universities. He can be contacted at email: pmolina@utp.edu.pe.

Cesar Yactayo-Arias is a professional in administration and master's in university teaching, studies in mathematics and statistics. Extensive teaching experience in higher education. In addition, experience in educational management. Doctoral study in administration. He can be contacted at email: cyactayo@continental.edu.pe.