Advances in the diagnosis of ocular diseases: an innovative approach through an expert system

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

Article Info

Article history:

Received Dec 1, 2023
Revised Dec 30, 2023
Accepted Feb 24, 2024

Keywords:

Cataract
Expert system
Glaucoma
Ophthalmology
Visual impairment

ABSTRACT

In the context of ophthalmic care, where early diagnosis of eye disorders plays a crucial role in patients' quality of life, this study focused on the development and evaluation of an expert system based on SWI Prolog. The main objective of this research was to provide an effective method for the preliminary diagnosis of ocular disorders, including cataract, trachoma, uveitis, glaucoma, and presbyopia. For the evaluation of the system, a confusion matrix was implemented and accuracy, sensitivity and specificity were calculated using a sample of 30 cases, of which 20 were positive and 10 negatives. The findings revealed an outstanding accuracy of 95%, with a sensitivity and specificity of 90%. This highlights the potential of the tool as an effective means of early detection of visual problems. In conclusion, this expert system represents a significant advance in ophthalmologic diagnosis, with important implications for clinical care and patients' quality of life, although expansion and validation of the tool in further clinical studies is suggested for its wider and more successful implementation in the field of ophthalmology.

Corresponding Author:

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

1. INTRODUCTION

Visual health is an essential component of people's quality of life. Eye disorders such as cataracts, trachoma, uveitis, glaucoma, and presbyopia. represent a global health concern that spans from childhood to old age, and can significantly affect a person's ability to carry out daily activities and maintain independence. Early detection and accurate diagnosis of these eye problems are crucial for prevention and timely treatment, as these conditions can have a significant impact on the quality of life of affected individuals [1]. In addition, myopia, another common eye disorder, is related to genetic and environmental factors, and can lead to severe visual complications [2], [3]. In older people, eye problems often go unnoticed due to the gradual growth of symptoms [4]. Also, these chronic eye diseases, if not effectively treated, can lead to visual impairment or even blindness. According to the World Health Organization (WHO) there are more than 2 billion people affected worldwide [5].

Despite the importance of eye health, the lack of access to adequate ophthalmologic services and the shortage of specialists in many regions of the world have created a gap in eye care. In addition, early detection of eye problems is often hampered by lack of awareness or knowledge of symptoms, especially in their early stages. Eye disorders not only affect individual health, but also have an impact on economic and social aspects [6]. Glaucoma, for example, is one of the leading causes of irreversible blindness worldwide, and current therapies are often insufficient to prevent its progression [7]. To address these challenges, expert systems have been developed in the field of ophthalmology. However, despite advances in expert system technology, challenges remain in the accuracy and accessibility of the tools available for preliminary diagnosis of vision problems. Many existing systems lack the ability to provide reliable and timely assessments. In addition, adapting these systems to diverse populations and validating their efficacy are critical issues that require continued attention.

To address these challenges, this study aims to develop and evaluate the effectiveness of an expert system for preliminary diagnosis of vision problems based on SWI Prolog, eye disorders such as cataract, trachoma, uveitis, glaucoma, presbyopia, among others. SWI-Prolog, as one of the most popular expert system programming languages, offers a promising approach for the creation of intelligent systems that can aid in the diagnosis and treatment of eye disorders [8], [9]. This expert system will be designed with accessibility and adaptability to different contexts in mind, aiming to provide a useful tool in both resource-limited environments and well-developed urban areas.

This research is highly relevant as it addresses a global public health problem: early detection and accurate diagnosis of eye problems. By developing an accessible and effective expert system, eye care can be improved especially in resource-limited regions and in populations facing barriers to access specialized medical services [10], such as people with rheumatoid arthritis in sub-Saharan Africa [11]. Furthermore, the validation of this expert system will contribute to the advancement of the field of artificial intelligence applied to medicine and ophthalmology, providing an innovative approach to eye care.

2. LETERATURE REVIEW

This section provides a comprehensive review of the proposals made by previous researchers in the field of accurate and early detection of ocular diseases. The detailed review includes innovative strategies and approaches that have played a critical role in advancing this important area of healthcare. This analysis not only highlights the valuable contributions of past research but also provides a solid framework for understanding the evolution and current trends in ocular disease detection.

Vasan *et al.* [12] evaluated the accuracy of the artificial intelligence-based e-Paarvai application for detecting and classifying cataracts from smartphone images. Compared with ophthalmologists' diagnoses, the app showed a sensitivity of 96%, specificity of 25%, and accuracy of 88% in detecting cataracts. It was noted to be effective in detecting immature cataracts with 94.2%, but had difficulties in identifying mature cataracts and other cases. It is suggested that by considering additional information, such as age, sex and visual acuity, diagnostic accuracy could be improved. Although it has certain limitations, e-Paarvai is emerging as a promising tool for diagnosing cataracts in communities that have difficulty accessing medical care, and its incorporation into outreach programs may increase case detection.

Also, using imaging and computer vision technology for automatic detection of the virtual capsulorhexis boundary, Bhat *et al.* [13] conducted a study with the goal of increasing accuracy in cataract surgery. To achieve this, an approach using edge detection, feature extraction, and eye area localization was created in cataract surgery videos. The findings demonstrated the superiority of the proposed operator over other edge detection techniques and a high accuracy of 98.5% in specular reflection point localization.

Ito *et al.* [14] developed an algorithm to detect ocular staphylomas with ultrasound, without the need for a physician. Using local curvature (K), distance to the transducer (L), and location of the staphyloma apex, it was tested on 46 individuals with a variety of ocular conditions such as high myopia or pathological myopia). With an AUC greater than 0.70 for most K parameters, the algorithm proved to be effective in determining ocular shape. In addition, a diagnostic validation score of 0.897 was obtained for the binary classification, demonstrated the exceptional efficacy of the algorithm in most cases, and found the apex with ease and detected staphylomas with accuracy comparable to that of young physicians. However, the algorithm only had an average accuracy of 1.35 ± 1.34 mm in locating the staphyloma apex.

Similarly, Rauf *at al.* [15] developed a machine learning system using a convolutional neural network (CNN) capable of automated identification of pathological myopia in fundus images. They applied a method that performs processing of the eye images and a CNN model is applied to them that extracts attributes and categorizes the images as normal or as signs of pathological myopia. The best CNN model achieves a high AUC score of 0.9845 and a low validation loss of 0.1457, indicating an effective ability to detect pathologic myopia in fundus images. As a result, the most outstanding CNN model achieves a significantly high AUC score of 0.9845 and exhibits a significantly low validation loss of 0.1457, signaling a successful ability in detecting pathologic myopia in fundus images.

Likewise, Faizal *et al.* [16] presented an algorithm designed to aid in the automated detection of cataracts, highlighting the relevance of identifying them early to prevent vision loss. They employed an enhanced CNN model trained with visible wavelength images and validated with medical images of the anterior segment of the eye. The proposed algorithm achieves a high classification accuracy of approximately

95% in cataract detection. It can identify various types of cataracts, such as nuclear, cortical and hybrid cataracts, which contributes to the prevention of cataract-related vision loss.

Similarly, for the purpose of creating an early cataract diagnosis system, Varma *et al*. [17] used a deep learning-based CNN architecture. The technique uses fundus image analysis to accurately classify cataracts into stages of mild, moderate, none, and severe severity (mild, moderate, none, and severe). With the help of an experienced ophthalmologist, fundus images are compiled from various sources and classified. The findings demonstrate that the method outperforms previous state-of-the-art techniques in identifying early cataracts, achieving 92.7% accuracy in cataract classification, with a sensitivity of 98% and specificity of 92.75%.

Also, by using color fundus images, Shamsan *et al*. [18] created computational techniques for early detection of ocular diseases. The most effective of the three suggested strategies is the third one. This approach achieves high accuracy in eye disease classification by combining features from deep learning models with manually created features. The results show an area under the AUC curve of 99.23%, accuracy of 98.5%, precision of 98.45%, specificity of 99.4% and sensitivity of 98.75% which highlights the effectiveness of this method in early detection of eye diseases.

Mayaluri and Lenka [19] addressed a problem in the detection of retinal diseases, such as glaucoma, caused by specularity reflections in fundus images. To solve it, they employed a preprocessing process that separates these reflections and improves image quality. The method includes image segmentation, feature extraction and classification. Experimental results show a significant improvement in image quality in preprocessing and high accuracy in glaucoma detection, with an accuracy of 91.83%, sensitivity of 96.39%, specificity of 95.37% and an AUC of 0.971. This indicates the efficacy of the technique in eliminating reflexes and accurately detecting glaucoma.

Similarly, Varma *et al*. [20] created an automatic cataract diagnosis and classification system using fundus images. A deep convolutional neural network (DCNN) is employed to automatically extract features from these images and then used to classify cataract severity in four stages. The choice of fundus images is based on their ability to accurately capture the internal structure of the eye, essential for early diagnosis. The approach achieves a high accuracy of 92.7% in cataract classification, outperforming other state-of-the-art algorithms, highlighting its efficacy in diagnosing and classifying this visual condition.

Similarly, Kalyani *et al*. [21] investigated how disease detection and prediction in healthcare can be affected by deep learning and CNN technologies. Their main goal is to improve disease detection without medical advice by virtualizing hospital care policies and models. This will improve patient care. CNN and long-term memory neural networks are combined in the deep learning model of the proposed system to identify and categorize eyes with cataracts. The effectiveness of machine learning technology in healthcare and strategic decision making is demonstrated by the astounding 98.5% accuracy of the approach in cataract detection and classification.

In conclusion, different researchers have explored and evaluated different strategies to diagnose eye diseases such as cataracts and myopia using machine learning models and other approaches, with promising results. However, it is important to note that none of the reviewed studies has proposed an expert system-based solution capable of diagnosing more than two types of eye diseases. Therefore, the focus of this study is to implement an expert system using SWI Prolog software for the diagnosis of multiple eye diseases.

3. METHOD

3.1. Buchanan methodology

The study used the Buchanan methodology to create an expert system for diagnosing eye disease. This methodology guided the development process, which included the identification, conceptualization, formalization, implementation, and testing phases, as shown in Figure 1. In the identification phase, the problem (diagnosis of ocular diseases) is identified, the solution is defined, knowledge sources are identified, data is collected, technical constraints are considered, a team is formed, and success metrics are defined, thus establishing the framework of the project. The conceptualization phase focuses on creating the knowledge structure and reasoning logic of the system and defining how the information gathered will be used to make accurate diagnoses. The formalization phase transforms the knowledge into a format usable by the system by developing algorithms, formulating inference rules, and formalizing the representation of medical information and ocular symptoms. Implementation involves creating a functional application using the expert system, developing diagnostic algorithms, implementing user interaction functions, and programming the interface and knowledge base. The testing phase verifies the reliability and efficiency of the system before its clinical implementation by evaluating the accuracy of the recommendations in specific diagnostic situations and correcting possible errors in the reasoning logic and user interface.

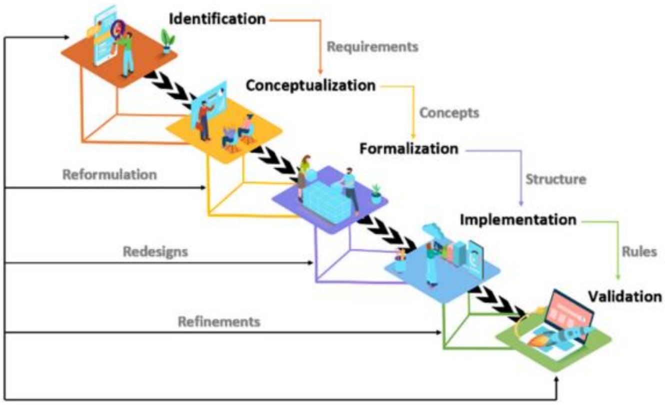

Figure 1. Buchanan methodology adapted from [22]

3.2. Diagnostic inference method

The study used the Buchanan methodology to create an expert system for diagnosing eye disease. This methodology guided the development process, which included the identification, conceptualization, formalization, implementation, and testing phases, as shown in Figure 1. In the identification phase, the problem (diagnosis of ocular diseases) is identified, the solution is defined, knowledge sources are identified, data is collected, technical constraints are considered, a team is formed, and success metrics are defined, thus establishing the framework of the project.

3.3. Evaluation

3.3.1. Confusion matrix

The evaluation of classification algorithms in expert diagnostic systems relied on the utilization of the confusion matrix [23], [24], a pivotal tool for assessing performance. The matrix efficiently categorized classification results into four groups, as illustrated in Table 1. True positives (TP) signified instances where the system accurately identified positive cases, indicating successful identification of actual eye diseases. False positives (FP) highlighted instances where the system incorrectly labeled a case as positive when it was actually negative, resulting in misdiagnoses of eye diseases. True negatives (TN) denoted cases where the system correctly identified negative instances, accurately excluding the presence of a disease. False negatives (FN) identified instances where the system erroneously classified a case as negative when it was, in fact, positive, representing cases where a genuine disease was overlooked.

Table 1. Confusiun matrix

Actual	Predicted	
	Positive	Negative
Positive	TP	FP
Negative	FN	TN

3.3.2. Performance evaluation metrics

To assess the effectiveness of the system, a comprehensive evaluation was conducted, focusing on key metrics such as precision (1), sensitivity (2), and specificity (3). These metrics played a critical role in measuring the overall performance of the system, providing valuable insight into its ability to correctly classify instances, identify true positives, and avoid false positives and negatives. Analysis of these metrics provided a nuanced understanding of the system's ability to handle different scenarios and its reliability in expert diagnostic applications.

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

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

4. CASE ESTUDY

4.1. Identification

This phase is essential in clearly defining both the problem to be addressed and the solution to be implemented. This meticulous process lays the essential groundwork for the successful construction of the system, ensuring a precise understanding of the challenges to be overcome and the objectives to be achieved. The clarity achieved in this phase will facilitate effective implementation and ensure that the expert system is appropriately aligned with the specific needs it is intended to address.

4.1.1. Identification of the problem

In different parts of the world, especially in regions with limited access or difficult medical infrastructure, the main problem centers on correctly identifying and diagnosing ophthalmologic diseases, with special attention to cataracts, trachoma, uveitis, glaucoma and presbyopia in particular. If these medical conditions are not identified and treated in a timely manner, they can significantly affect patients' quality of life. The difficulty arises from the complexity of the clinical and symptomatic characteristics of these conditions, as well as the constant need for a system that can accurately and quickly analyze a patient's symptoms and medical history in order to make a proper diagnosis.

4.1.2. Solution

It is proposed to create an expert system using SWI Prolog software, which will use a substantial medical knowledge base and inference rules to examine the patient's symptoms. Using logical reasoning, the system will evaluate the probability that the patient has one of the ophthalmologic diseases mentioned above. In addition, the system will provide recommendations and, if necessary, refer the patient to a qualified ophthalmologist for further testing. The system will be designed to be adaptable and upgradeable.

4.2. Conceptualization

In this phase, the characteristic symptoms of each of the previously identified ophthalmologic diseases, namely Cataract, Trachoma, Uveitis, Glaucoma, and Presbyopia, are comprehensively collected. This critical stage will focus on the clear definition and systematic organization of the specific symptoms associated with each disease, to be used in the knowledge representation [10] and build a solid knowledge base that will allow the SWI Prolog expert system to make accurate diagnoses. The specific symptoms of each of these diseases are detailed in Table 2 provided by Chua *et al.* [22], and will be used to develop the inference rules and algorithms needed to accurately identify and classify eye diseases.

Table 2. Visual diseases

Diseases	Symptoms
Cataract	Double vision in one eye
	Light intolerance
	Halos around lights
	Increased difficulty seeing at nigh
	Blurry vision
Tracoma	Itching and irritation of the eyes and eyelids
	Ocular discharge
	Eyelid swelling
	Loss of vision
	Eye pain
Uveitis	Redness of the eyes
	Eye pain
	Blurred vision
	Intolerance to light
	Inflammation in sight
Glaucoma	Nausea and vomiting
	Redness of the eyes
	Blurred vision
	Headache
Presbyopia	Ocular Fatigue
	Headache
	Blurred vision
	Difficulty focusing on objects
	Increased difficulty in seeing at night

4.3. Formalization

After having successfully identified and understood the nature of the problem, we proceeded to the formalization phase. During this stage, the main focus was on knowledge creation and practical operation of the expert system [25]. Table 3 presents the formalization of knowledge, which will be fundamental to carry out the implementation and operation of the system.

Table 3. Formalization of knowledge

Then (deases)	If (symptom)
Cataract	The patient has double vision in one eye
	The patient has light intolerance
	The patient has halos around lights
	The patient has increased difficulty seeing at night
	The patient has blurry vision
Trachoma	The patient has itching and irritation of the eyes and eyelids
	The patient has ocular discharge
	The patient has eyelid swelling
	The patient has loss of vision
	The patient has eye pain
Uveitis	The patient has redness of eyes
	The patient has eye pain
	The patient has blurred vision
	The patient has light intolerance
	The patient has inflammation in sight
Glaucoma	The patient has nausea and vomiting
	The patient has redness of eyes
	The patient has blurred vision
	The patient has headache
Presbyopia	The patient has ocular fatigue
	The patient has headache
	The patient has blurred vision
	The patient has difficulty focusing on objects
	The patient has increased difficulty seeing at night

4.4. Implementation

In this phase, the characteristic symptoms of each of the previously identified ophthalmic diseases, namely cataract, trachoma, uveitis, glaucoma, and presbyopia, are exhaustively collected. This exhaustive data collection provides a deep understanding of the clinical manifestations of each disease, facilitating subsequent identification and accurate diagnosis in the development of the expert system. The thoroughness of the symptom collection contributes significantly to the effectiveness of the system by providing a solid basis for informed decision-making in the ophthalmic setting.

4.4.1. User interface

As shown in Figure 2, the focus was on the consideration of multiple dimensions for both the overall design of the interface and the individual elements, including buttons. Careful attention was paid to details of the visual elements, and their precise placement on the screen. Each of these aspects was carefully handled to ensure a seamless user experience.

```
% Start the graphical interface
user_interface :-
    new(Menu, dialog('Ophthalmological Diagnostic Expert System', size(400, 300))),
    new(L, label(name, 'Diagnosis of Eye Disease')),
    new(@txt, label(name, 'Please answer a short questionnaire to obtain your diagnosis')),
    new(@res, label(name, '')),
    new(Exit, button('Exit', and(message(Menu, destroy), message(Menu, free)))),
    new(@btn, button('Start diagnosis', message(@prolog, button))),

    % Change mouse cursor
    send(@btn, cursor, hand2),
    send(Exit, cursor, hand2),

    send(Menu, append, L),
    new(@startbtn, button('Diagnosis')),
    send(Menu, display, @btn, point(85, 370)),
    send(Menu, display, @txt, point(20, 100)),
    send(Menu, display, Exit, point(205, 370)),
    send(Menu, display, @res, point(15, 150)),
    send(Menu, open_centered).
```

Figure 2. User interface design

4.4.2. Fact base

The identified symptoms have been organized as crucial data, forming the fact base for the system's development (refer to Figure 3). This strategic setup allows for the generation of user-directed queries based on the specific symptoms' presence or absence, thereby enabling accurate evaluations. The use of this information as a foundation for queries not only enhances the expert system's interaction with the user but also facilitates a more efficient and tailored appraisal of the patient's ophthalmic afflictions.

```
% Cataract symptoms
symptom_cataract('Double vision in one eye').
symptom_cataract('Light intolerance').
symptom_cataract('Halos around lights').
symptom_cataract('Increased difficulty seeing at night').
symptom_cataract('Blurry vision').

% Trachoma symptoms
symptom_trachoma('Itching and irritation of the eyes and eyelids').
symptom_trachoma('Ocular discharge').
symptom_trachoma('Eyelid swelling').
symptom_trachoma('Loss of vision').
symptom_trachoma('Eye pain').

% Uveitis symptoms
symptom_uveitis('Redness of the eyes').
symptom_uveitis('Eye pain').
symptom_uveitis('Blurred vision').
symptom_uveitis('Light intolerance').
symptom_uveitis('Inflammation in sight').

% Glaucoma symptoms
symptom_glaucoma('Nausea and vomiting').
symptom_glaucoma('Redness of the eyes').
symptom_glaucoma('Blurred vision').
symptom_glaucoma('Headache').

% Presbyopia symptoms
symptom_presbyopia('Ocular fatigue').
symptom_presbyopia('Headache').
```

Figure 3. Basis of facts

4.4.3. Rule

After receiving positive or negative responses from the user, the system uses these responses to make inferences based on specific rules, following a forward-chaining approach. These rules are linked to the symptoms associated with each disease, previously defined as part of the system's knowledge base. When the user indicates that they do not have a particular symptom of a disease, the system intelligently adapts its approach. Instead of continuing with questions related to that specific condition, the system displays the appropriate question related to another possible eye condition. This dynamic adaptation is achieved by using the "assert" function in Prolog, which allows facts or rules to be inserted into the knowledge base at runtime. If the user denies a symptom, the system uses assert to dynamically add a new rule that excludes that particular disease from consideration (see Figure 4).

```
diagnosis(Symptom) :-
    new(Di, dialog('Eye Diagnosis')),
    new(L2, label(text, 'Indicate whether or not you have the following symptoms:')),
    new(La, label(pro, Symptom)),
    new(B1, button(yes, and(message(Di, return, yes)))),
    new(B2, button(no, and(message(Di, return, no)))),

    send(Di, append, L2),
    send(Di, append, La),
    send(Di, append, B1),
    send(Di, append, B2),

    send(Di, default_button,yes),
    send(Di, open_centered),
    get(Di, confirm, Answer),
    write(Answer),
    send(Di, destroy),
    ((Answer == yes) -> assert(yes(Symptom));
    assert(no(Symptom)), fail).
```

Figure 4. Dynamic rule manipulation: using assert

On the other hand, if the user indicates that they are experiencing the symptom, the system fluidly continues the process by presenting additional questions directly related to the condition. This sequential and dynamic approach ensures a comprehensive and personalized exploration of the user's symptoms. Finally, after collecting all relevant responses, the system proceeds to generate a final diagnosis. This crucial stage reflects the synthesis of user responses, disease-specific rules, and expert knowledge embedded in the system. This method ensures an accurate and detailed evaluation, culminating in a final diagnosis that fully and accurately reflects the user's ophthalmic condition.

5. RESULTS

5.1. About the developed diagnostic system

The graphical representation in Figure 5 shows the initial interface that provides a comprehensive platform to begin the process of diagnosing ocular disease. This visual component serves as the gateway to the system, allowing users to begin the assessment of their ocular health in a fluid and accessible manner. Meanwhile, Figure 6 shows the diagnosis process. At this point, the system clearly displays each of the symptoms associated with the eye disease. Patients or users have the opportunity to respond affirmatively or negatively to the initial symptoms they present, marking the beginning of the analysis of their eye health. On the other hand, Figure 7 shows the complete diagnostic result obtained after a thorough examination and analysis of the data collected during the process. This result provides a detailed and accurate understanding of the patient's ocular health status.

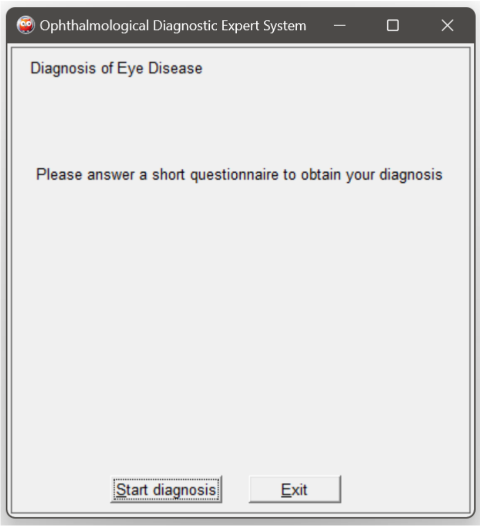

Figure 5. Initial user interface

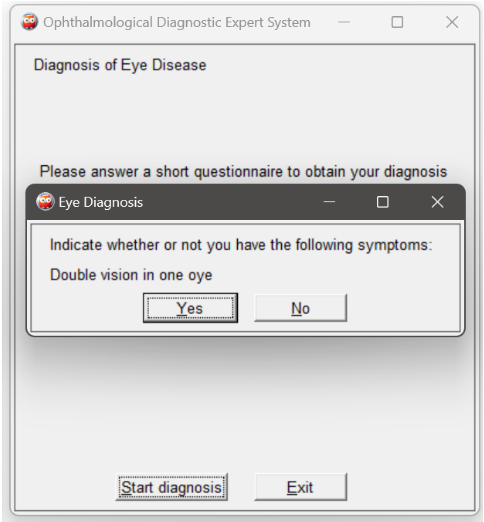

Figure 6. Diagnostic process

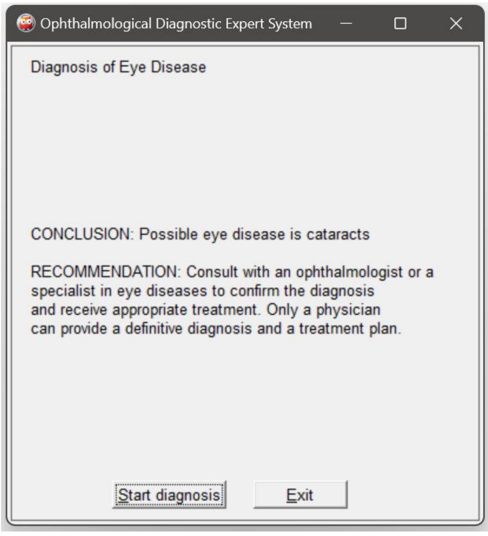

Figure 7. Diagnostic result

5.2. About the interview

The interview questions with individuals experiencing eye problems revolve around various key aspects. They address their experiences with ophthalmological technology, including telemedicine, and any challenges encountered when using such technology. The second set focuses on access to healthcare, inquiring about obstacles in obtaining eye care, participation in mobile care campaigns, and the financial impact of eye care. Lastly, questions on medical training and quality of care aim to gauge the overall state of eye healthcare and ways to enhance the education and training of eye care professionals, especially in underserved areas (see Table 4).

Table 4. Interview questions

Dimension	Question
Technology	Tell me about your experience with the technology used in diagnosing and treating ophthalmological diseases in your area.
	Have you had access to telemedicine ophthalmology services or technologies that have helped you receive a diagnosis or monitor your eye condition?
	What challenges have you faced when using technology in relation to your eye care?
Access to healthcare	What have been the most significant obstacles in accessing ophthalmological services in your community or region?
	Have you participated in mobile ophthalmological care campaigns or community programs to receive care? How was your experience?
	Can you discuss the costs associated with ophthalmological care and how they have impacted your access to it?
Medical training	How would you describe the quality of ophthalmological healthcare you have received in your area?
	Have you noticed improvements in the training and education of ophthalmological healthcare professionals in your region?
	What suggestions do you have for enhancing the training and education of doctors in the field of ophthalmology in areas with limited healthcare resources?

Analyzing the responses of the interviewees, several key themes emerge. First, there is a notable divide in experiences with ophthalmological technology some find it highly beneficial, especially telemedicine services, while others, particularly seniors, struggle with the digital aspects of healthcare. The main obstacle to accessing eye care is the limited availability of ophthalmologists, forcing individuals to travel long distances and incurring financial and physical burdens. Mobile care campaigns have been a lifeline for some, but their infrequency poses a challenge. The cost associated with eye care is a recurring concern, impacting access even for those with insurance. Regarding the quality of care, while some perceive it as excellent and improving, others have encountered inconsistencies. Notably, there is a shared desire for enhanced training, with suggestions including partnerships with larger institutions, incentivizing specialization, and leveraging telemedicine for education. These varied insights emphasize the need for a comprehensive approach to address access, cost, and quality in ophthalmological care, with a focus on improving training and leveraging technology to bridge gaps in underserved areas (see Figure 8). The interview responses underscore the complex and multifaceted challenges within ophthalmological healthcare. While some interviewees have had positive experiences and see potential improvements, the disparities in access, costs, and the varying quality of care are evident. The digital divide in utilizing healthcare technology, particularly among seniors, highlights the importance of making digital interfaces more user-friendly. The infrequency of mobile care campaigns suggests a need for more sustainable solutions to address access issues in underserved areas. The recurring concern about costs underscores the pressing need for affordable eye care options. Furthermore, the desire for enhanced training and education reveals an opportunity for policymakers and institutions to invest in strengthening the capabilities of local healthcare professionals. Overall, this analysis emphasizes the urgency of comprehensive reforms to create equitable and accessible ophthalmological care.

5.3. Evaluation of system effectiveness

To perform a thorough analysis of the confusion matrix and evaluate system performance metrics, tests were conducted using a dataset consisting of 30 meticulously selected cases. This data set covered a variety of ocular conditions of interest: cataract, trachoma, uveitis, glaucoma, and presbyopia. These test cases were meticulously designed to provide a robust and representative assessment of the system's capability.

5.3.1. Confusion matrix analysis

Figure 9 graphically displays the confusion matrix and its detailed classification, providing a comprehensive view of the system evaluation. This visual representation not only provides an immediate insight into the accuracy of the system but also allows a thorough analysis of its diagnostic capacity in relation to the ocular diseases considered. As can be seen, the expert system obtained results indicating good performance in most cases. The system correctly identified 18 cases as positive, demonstrating its ability to make accurate diagnoses. However, two cases were observed in which the system failed to identify the ocular diseases present, indicating a certain limitation in detection. In addition, there was one case of misdiagnosis of a non-existent eye disease. Finally, 9 cases were correctly identified as negative.

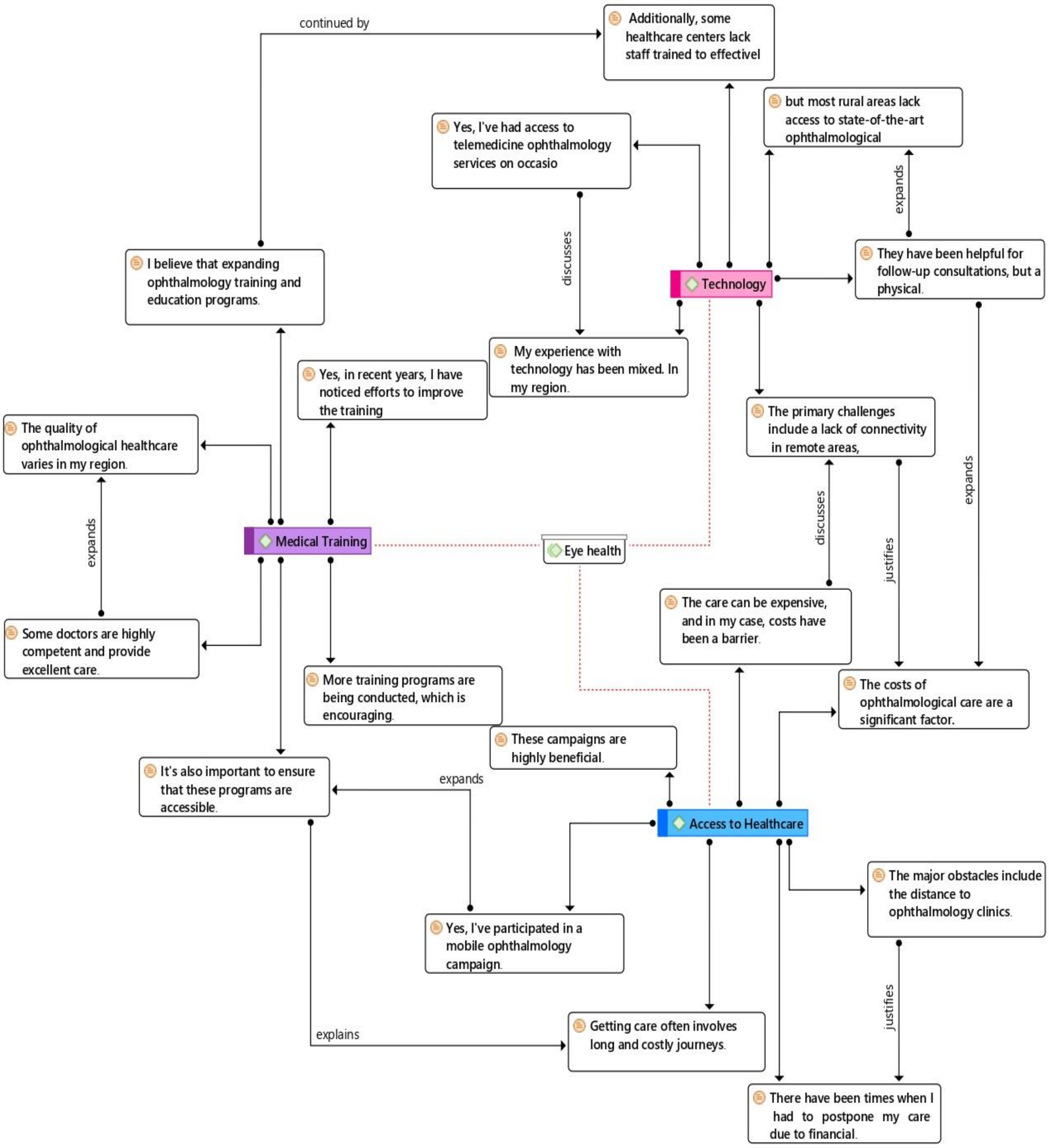

Figure 8. Analysis of the interview with Atlas Ti

5.3.2. Evaluation of metrics

Figure 10 shows the detailed evaluation of key metrics such as accuracy, sensitivity, and specificity. The results show an impressive accuracy of 95%, highlighting the accuracy of the system in the majority of diagnoses made. In addition, sensitivity and specificity of 90% stand out, demonstrating the system's ability to effectively identify both positive and negative cases. These metrics provide a holistic view of the system's performance, highlighting its ability to provide accurate and reliable diagnoses in the field of ocular disease.

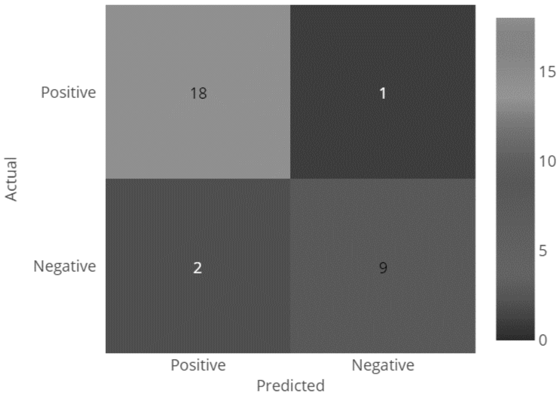

Figure 9. Confusion matrix results

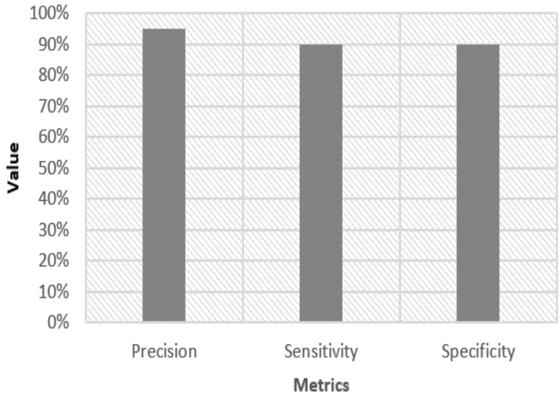

Figure 10. Metric evaluation

6. DISCUSSION

The results presented in studies [14], [17]–[19], offer valuable insights into the development and effectiveness of algorithms and techniques in the field of eye disease detection and visual health assessment. In the following, these results are discussed and compared with those of this research. Ito *et al*. [14] developed an ultrasound algorithm to detect ocular staphylomas with greater than 70% accuracy. However, the location of the staphyloma apex had an average accuracy of 1.35 ± 1.34 mm, which could affect the accurate identification of ocular diseases. On the other hand, Varma *et al*. [17] used deep learning to create a cataract diagnostic system with an impressive 92.7% accuracy, surpassing previous techniques. This highlights the effectiveness of deep learning in early cataract identification, crucial for timely diagnosis and treatment.

Likewise, Shamsan *et al*. [18] excelled in early detection of ocular diseases using fundus imaging and computational techniques. Their approach combined deep learning features, achieving an impressive AUC of 99.23%, accuracy of 98.5%, specificity of 99.4%, and sensitivity of 98.75%. This highlights the effectiveness of their method in the early detection of ophthalmologic diseases by combining features in image analysis. Similarly, Mayaluri and Lenka [19] focused on the detection of retinal diseases, such as glaucoma. The results revealed high accuracy in glaucoma detection, with an accuracy of 91.83%, sensitivity of 96.39%, specificity of 95.37%, and an AUC of 0.971. These results underscore the effectiveness of their technique in eliminating reflexes and improving accuracy in detecting retinal diseases.

In comparison to these studies, the result of this research has achieved an accuracy of 95%, sensitivity and specificity of 90%, respectively, which supports the effectiveness and usefulness of the expert system in the diagnosis of ocular diseases. However, it is important to keep in mind that each of these studies focuses on specific aspects of ophthalmology and uses varied approaches and techniques. The integration of these results into the development of more comprehensive and accurate ophthalmic diagnostic systems could be an area of future research of great relevance. Nevertheless, the results of this research, along with the findings of previous studies, contribute to the advancement of ocular disease detection and diagnosis. Each approach and technique have specific advantages and limitations, highlighting the importance of considering diverse methodologies to improve eye care and eye health.

7. CONCLUSION

In conclusion, the central objective of this research was the creation and evaluation of an expert system based on SWI Prolog for the preliminary diagnosis of a variety of eye disorders, including cataract, trachoma, uveitis, glaucoma, presbytia. The results revealed an impressive accuracy of 95%, along with a sensitivity and specificity of 90%. These findings highlight the relevance of the tool in question for carrying out an effective diagnosis of visual problems, whether in patients with obvious symptoms or in the early stages of ophthalmological diseases. The intrinsic importance of these findings lies in the potential transformation they can bring to ophthalmological care, by providing a precise and reliable tool that can contribute to the early identification of eye conditions. This, in turn, is important for more timely treatments and, ultimately, for a better quality of life for patients. In short, this study highlights the potential of the expert system as a valuable tool for the field of ophthalmology, with prospects for improvement and expansion in the horizon of future research. It is imperative to note that, although the results are promising, as future work it is recommended to expand the database to increase its robustness. In addition, the incorporation of deep learning techniques and the exploration of more advanced image processing algorithms could further enrich their detection capabilities. Finally, additional clinical trials are recommended to validate and further improve the effectiveness of the system in real health care situations.

ACKNOWLEDGEMENTS

The research is thanks to the support that is carried out collaboratively to have the research carried out.

REFERENCES

[1] R. M. Hersi, N. K. Naaman, A. M. Alghamdi, W. A. Alnahdi, Z. M. Bukhari, and H. S. Almarzouki, "Knowledge and attitude toward eye disorders in children among pediatricians and family physicians: a survey study," *BMC Ophthalmology*, vol. 23, no. 1, p. 90, Mar. 2023, doi: 10.1186/s12886-023-02832-5.

[2] G. Zieliński *et al.*, "Exploratory Study on Central Sensitization and Bioelectrical Activity of the Selected Masticatory Muscles in Subjects with Myopia," *International Journal of Environmental Research and Public Health*, vol. 20, no. 5, p. 4524, Mar. 2023, doi: 10.3390/ijerph20054524.

[3] C. Zeitz *et al.*, "Shedding light on myopia by studying complete congenital stationary night blindness," Progress in Retinal *and Eye Research*, vol. 93, p. 101155, Mar. 2023, doi: 10.1016/j.preteyeres.2022.101155.

[4] S. V. M. Kumar and R. Gunasundari, "Computational intelligence in eye disease diagnosis: a comparative study," *Medical & Biological Engineering & Computing*, vol. 61, no. 3, pp. 593–615, Mar. 2023, doi: 10.1007/s11517-022-02737-3.

[5] M. Mostafa, A. Al Fatease, R. G. Alany, and H. Abdelkader, "Recent Advances of Ocular Drug Delivery Systems: Prominence of Ocular Implants for Chronic Eye Diseases," *Pharmaceutics*, vol. 15, no. 6, p. 1746, Jun. 2023, doi: 10.3390/pharmaceutics15061746.

[6] L. M. Rad *et al.*, "The impact of non-coding RNAs in the pathobiology of eye disorders," *International Journal of* Biological Macromolecules, vol. 239, p. 124245, Jun. 2023, doi: 10.1016/j.ijbiomac.2023.124245.

[7] A. Satriano *et al.*, "Neuroprotective Effect of a Nutritional Supplement Containing Spearmint Extract, Forskolin, Homotaurine and Group B Vitamins in a Mouse Model of Transient Ocular Hypertension," *Biomedicines*, vol. 11, no. 5, p. 1478, May 2023, doi: 10.3390/biomedicines11051478.

[8] K. Chen and C.-C. Lin, "Design and Implementation of a SWI-Prolog-Based Expert System to Diagnose Anxiety Disorder," 2022, pp. 165–177. doi: 10.1007/978-3-030-96451-1_15.

[9] V. Sekovanic and S. Lovrencic, "Challenges in teaching logic programming," in *2022 45th Jubilee International Convention on Information, Communication and Electronic Technology (MIPRO)*, May 2022, pp. 594–598. doi: 10.23919/MIPRO55190.2022.9803530.

[10] R. J. Velarde, P. M. Velarde, C. Y. Arias, and L. A. Arenas, "Expert System for the Timely Diagnosis of Infectious Diseases," *International Journal of Engineering Trends and Technology*, vol. 71, no. 3, pp. 215–226, Mar. 2022, doi: 10.14445/22315381/IJETT-V71I3P222.

[11] E. Headcraph *et al.*, "Spectrum of and Factors Associated with Eye Disorders among Rheumatoid Arthritis Patients Attending Tertiary Hospital in Uganda," *Open Access Rheumatology: Research and Reviews*, vol. 15, pp. 103–111, Jul. 2023, doi: 10.2147/OARRR.S413697.

[12] C. S. Vasan *et al.*, "Accuracy of an artificial intelligence-based mobile application for detecting cataracts: Results from a field study," *Indian Journal of Ophthalmology*, vol. 71, no. 8, pp. 2984–2989, Aug. 2023, doi: 10.4103/IJO.IJO_3372_22.

[13] W. A. Bhat *et al.*, "Cataract eye detection by optik image analysis using encoder basis Boltzmann architecture integrated with internet of things and data mining," *Optical and Quantum Electronics*, vol. 55, no. 10, p. 917, Oct. 2023, doi: 10.1007/s11082-023-05038-7.

[14] K. Ito *et al.*, "Automated Classification and Detection of Staphyloma with Ultrasound Images in Pathologic Myopia Eyes," *Ultrasound in Medicine & Biology*, vol. 48, no. 12, pp. 2430–2441, Dec. 2022, doi: 10.1016/j.ultrasmedbio.2022.06.010.

[15] N. Rauf, S. O. Gilani, and A. Waris, "Automatic detection of pathological myopia using machine learning," *Scientific Reports*, vol. 11, no. 1, p. 16570, Aug. 2021, doi: 10.1038/s41598-021-95205-1.

[16] S. Faizal, C. A. Rajput, R. Tripathi, B. Verma, M. R. Prusty, and S. S. Korade, "Automated cataract disease detection on anterior segment eye images using adaptive thresholding and fine tuned inception-v3 model," *Biomedical Signal Processing and Control*, vol. 82, p. 104550, Apr. 2023, doi: 10.1016/j.bspc.2022.104550.

[17] N. Varma, S. Yadav, and J. K. P. S. Yadav, "Fundus image-based automatic cataract detection and grading system," 2023, p. 030001. doi: 10.1063/5.0129359.

[18] A. Shamsan, E. M. Senan, and H. S. A. Shatnawi, "Automatic Classification of Colour Fundus Images for Prediction Eye Disease Types Based on Hybrid Features," *Diagnostics*, vol. 13, no. 10, p. 1706, May 2023, doi: 10.3390/diagnostics13101706.

[19] Z. L. Mayaluri and S. Lenka, "Hybrid glaucoma detection model based on reflection components separation from retinal fundus images," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 9, Jul. 2023, doi: 10.4108/eetpht.9.3191.

[20] N. Varma, S. Yadav, and J. K. P. S. Yadav, "A reliable automatic cataract detection using deep learning," *International Journal of System Assurance Engineering and Management*, vol. 14, no. 3, pp. 1089–1102, Jun. 2023, doi: 10.1007/s13198-023-01923-2.

[21] B. J. D. Kalyani, U. Hemavathi, K. Meena, B. S. Deepapriya, and S. Syed, "Smart cataract detection system with bidirectional LSTM," *Soft Computing*, vol. 27, no. 11, pp. 7525–7533, Jun. 2023, doi: 10.1007/s00500-023-07879-6.

[22] A. B. Chua, K. G. Gonzales, and L. A. Arenas, "Expert Web System: Diagnosis of Visual Diseases," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 18, no. 15, pp. 88–108, Dec. 2022, doi: 10.3991/ijoe.v18i15.33397.

[23] P. Utomo, K. Adi, and O. D. Nurhayati, "Success factors for citizen-based government decision making using K-means fuzzy learning vector quantization," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 32, no. 1, p. 506, Oct. 2023, doi: 10.11591/ijeecs.v32.i1.pp506-516.

[24] U. B. Patayon and R. V. Crisostomo, "Peanut leaf spot disease identification using pre-trained deep convolutional neural network," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 3, pp. 3005-3012, Jun. 2022, doi: 10.11591/ijece.v12i3.pp3005-3012.

[25] R. J. Velarde, P. M. Velarde, C. Y. Arias, and L. A. Arenas, "Evaluation of a Prototype Mobile Application Based on Expert System for the Diagnosis of Diseases Transmitted by the Aedes Aegypti Mosquito," *International Journal of Online and Biomedical Engineering*, vol. 19, no. 13, pp. 72–91, Sep. 2023, doi: 10.3991/ijoe.v19i13.41431.

BIOGRAPHIES OF AUTHORS

Laberiano Andrade-Arenas Doctor in Systems and Computer Engineering. Master in Systems Engineering. Graduated from the Master's Degree in University Teaching. Graduated from the Master's degree in accreditation and evaluation of educational quality, Scrum fundamentals certified, research professor with publications in Scopus indexed journals. He has extensive experience in the University Chair in face-to-face and blended classes at different undergraduate and postgraduate universities in Lima. He can be contacted at email: landrade@uch.edu.pe.

Cesar Yactayo-Arias professional in administration and master in university teaching. Extensive teaching experience in higher education. In addition, experience in educational management. Doctoral study in administration. He can be contacted at email: yactayo@uch.edu.pe.