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Diagnosis and treatment of Guillain-Barre using the prolog expert system

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ABSTRACT

This research is mostly about Guillain-Barre syndrome (GBS), a complicated neurological condition with many subtypes that make diagnosis and treatment hard, even though medical care is always getting better. The main goal of this study is to build and test an expert system that can correctly diagnose these subtypes, with a focus on early detection and personalized treatments. The evaluation of the system was carried out using a dataset composed of 20 cases (12 positive and 8 negative). A confusion matrix was used to evaluate key metrics such as precision, sensitivity, and specificity. The findings demonstrate precision and sensitivity of 83% and specificity of 75%. These findings unambiguously demonstrate the efficacy of the system in correctly identifying positive Guillain-Barre cases while substantially reducing false negatives. In conclusion, this expert system offers a potentially useful tool to improve the accuracy of the diagnosis and treatment of Guillain-Barre patients. However, to take advantage of its full potential in clinical practice, it should be used as diagnostic support and not replace the medical staff, and it should be updated periodically to reflect new findings in medicine.

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1. INTRODUCTION

Guillain-Barré syndrome (GBS) is a rare and potentially severe neurological disease affecting the peripheral nervous system. It is characterized by progressive paralysis and decreased reflexes, and it is an autoimmune condition [1]. Generally, this disorder is triggered by a previous infection and can pose a potentially serious threat [2]. Furthermore, it is the leading cause of acute flaccid paralysis worldwide, and in most patients, prior illness, such as respiratory tract infection, is present before manifesting progressive muscle weakness [3], [4]. Leading to ascending muscle weakness and paralysis, which, in some cases, can be life-threatening. First described in 1916 by Guillain, Barre, and Strohl. However, prior to this description, numerous similar cases had been reported under different terms, with less detailed information and various theories regarding their pathophysiological origin [5]. Over the years, medical advances have led to improved diagnosis and treatment of GBS. However, diagnosis and treatment of this disease are hampered by its rarity and variability in how it presents clinically, due to the existence of more unusual and dangerous subtypes of GBS [6], which continue to challenge health care professionals.

It is still hard to quickly and correctly diagnose GBS because its first symptoms are similar to those of other neurological diseases, and it doesn't happen very often in the general population. In addition, the possibility of atypical clinical manifestations can lead to confusion and difficulties in the diagnostic process [7], [8]. Physicians and specialists face difficulties in distinguishing GBS from other conditions promptly, which may result in delays in appropriate treatment and an increased risk of complications for the patient. In addition, the complexity of choosing the appropriate therapeutic approach for each particular case also represents a significant concern.

To address the challenges in the diagnosis and treatment of GBS, we propose to develop an expert system using the Prolog programming language. In the field of medicine, expert systems have been extensively utilized for the diagnosis of various medical conditions [9], [10]. Furthermore, Prolog is widely recognized as one of the most popular programming languages for expert system development [11], [12]. Moreover, it has the ability to work with rules and facts, which makes it an ideal choice for the implementation of a rule-based system and is the basis of artificial intelligence [13], [14]. The Prolog expert system will be designed to process clinical information provided by the physician, such as symptoms presented by the patient, medical history, and diagnostic test results. To figure out how likely it is that the patient has GBS, the system will use a set of rules based on specific medical knowledge or information. The system will also provide recommendations on additional tests that might be necessary to confirm the diagnosis, as well as suggestions for the most appropriate treatment based on the particular characteristics of the case.

The importance of the present research work is to provide a valuable support tool for physicians who are less experienced in the management of GBS, thereby improving the accuracy and quality of care provided. In addition, a well-designed expert system can contribute to general medical knowledge by identifying patterns and trends in the data collected. On the other hand, the main objective of this project is to develop and evaluate a highly accurate, reliable, and accessible expert system that can assist healthcare professionals in the early diagnosis and appropriate treatment of GBS. By providing an effective tool to address this medical challenge, it is expected to significantly improve the prognosis and quality of life of patients affected by this disease. In addition, the expert system will seek to be a source of updated and continuous knowledge in the field of GBS, thus driving future research and advances in clinical neurology.

2. REVIEW LITERATURE

At the intersection of medicine and technology, the application of machine learning (ML) and expert systems to the early diagnosis and treatment of GBS has emerged as a promising approach. This section analyzes how the tools proposed by various researchers are improving the accurate and timely detection of the disease, representing a significant advance in modern medical care. Thus, understanding the impact of these technologies on medical care is essential to advancing the improvement of patients' quality of life.

Alarcón-Narváez *et al.* [15], developed a primary screening tool for the identification of GBS subtypes from clinical variables collected in consultation, without resorting to additional invasive methods. Through experiments involving four classifiers, five filters for feature selection, and six wrappers, along with the one-versus-all (OvA) classification technique, a dataset consisting of 129 patient records from Mexico and 26 key clinical variables was evaluated. The results indicate that the random forest filter excels in diagnosing the four GBS subtypes across all classifiers, and its combination with the support vector machine (SVM) classifier achieves the most outstanding performance (0.6840). Implementation of OvA in conjunction with the SVM classifier achieves a balanced accuracy of 0.8884 for the Miller-Fisher (MF) subtype. This approach shows promise in the early detection and treatment of various GBS subtypes through the efficient application of clinical variables, which could have a significant impact on improving medical care.

On the other hand, they conducted a retrospective study with the aim of evaluating the predictive relevance of various contrast-enhanced imaging patterns in childhood GBS by comparing clinical and therapeutic outcomes [16]. The investigation involves 37 patients who were followed by a pediatric neurology team for 16 years at the University Hospital of Montpellier. The results highlight the presence of muscle weakness, cranial nerve involvement and albumin-cytological dissociation in the patients. Although contrast enhancement is observed in the lumbosacral nerve roots, no significant correlation is found between magnetic resonance imaging (MRI) enhancement patterns and short-term or long-term outcomes. They conclude that contrast-enhanced MRI proves to be a valuable tool in the diagnosis of the disease in children, although its predictive ability in terms of clinical and therapeutic outcomes still requires further exploration.

Also, to identify GBS subtypes, in the study [17], they developed predictive models using ML and compared their performance with ensemble methods. To classify subtypes, one-versus-all and one-versus-one, three classification experiments are created using real data with relevant features. Random forest stands out as the best GBS subtype classifier from a test of a set of 129 and 16 relevant attributes extracted from a real data set. Furthermore, by subjecting each classifier to its own independent 30-fold run, they compared 5

sophisticated ensemble methods with 15 different classifiers. Although no particular method stands out significantly in head-to-head classifiers, individual classifiers generally perform better than ensemble methods in one-to-one classifiers. In conclusion, this study offers a new method for predicting GBS subtypes, using random forests as a viable alternative. This method will help medical professionals and lay the foundation for future research.

Similarly, Torres-Vásquez *et al.* [18], aimed to determine whether balancing an original GBS dataset would improve the ability of current predictive models to recognize GBS subtypes. They created ten binary datasets and used class balancing techniques on records of 129 Mexican patients with various GBS subtypes. In addition, they created predictive models using three different classifiers. The findings showed that balancing the original dataset effectively increases the predictive ability of the models, which can be useful for specialists in providing complementary diagnoses based on relevant features. This contribution aims at the practical application of data balancing techniques in a medical setting, benefiting diagnostic accuracy and timely treatment.

Similarly, they created a comprehensive predictive model to identify the various subtypes of GBS in [19]. They performed a test with 15 classifiers in two situations: four-subtype classification and OvA. In addition, they used data with 16 features and evaluated the performance with ten-replicate cross-validation, identifying the five best classifiers in each case by statistical analysis. The findings show that, when identifying GBS subtypes, approximately half of the classifiers achieve an average accuracy above 0.90. Furthermore, the subtypes with the highest number of instances produce the best results in one-versus-all classification. In conclusion, the study makes a significant contribution to the creation of a reliable predictive model for GBS subtypes, highlighting the value of different classifiers in correctly identifying these subtypes and their potential for improving care and treatment.

On the other hand, Canul-Reich *et al.* [20] conducted the study with the aim of applying three decision tree classifiers (C4.5, C5.0 and random forest) in predicting GBS subtypes in two classification scenarios using real data from 129 patients with GBS to evaluate their performance. In addition, they used nerve conduction test results, clinical and serological data, and serological data. According to the experimental results, the performance of the classifier is comparable across the board, with C5.0 performing marginally better. It is crucial to keep in mind that the study is ongoing and additional experiments are being conducted as part of a growing research project.

Likewise, Hernandez-Torruco *et al.* [21], conducted a study using clinical, serological and nerve conduction test results from 129 patients diagnosed with GBS. They then applied SVM with different cores. In addition, they contrasted the effectiveness of these SVMs with the performance of the C4.5 classifier in the task of predicting GBS subtypes. Experimental results indicate that the performance of both classifiers is similar, with SVMs with polynomial kernel being slightly superior in cross-validation, while SVMs with Laplacian, polynomial and Gaussian kernels outperform C4.5 in the training test. It is emphasized that the study is in progress and further experiments are being conducted as part of an ongoing research project.

In conclusion, it was verified that several researchers presented and evaluated different ML models, such as SVM, decision trees, random forest and other technological solutions, to diagnose GBS, obtaining favorable results. However, it is important to note that so far none has proposed a solution based on expert systems. Therefore, this study focuses on the development of an expert system using SWI Prolog software, with the aim of providing diagnosis and treatment for this disease.

3. METHODS

3.1. Expert system

The development of the expert system encompasses six stages, as shown in Figure 1. i) Identification of the problem and the definition of objectives. During this phase, a precise identification is made of the issue to be addressed by the expert system and the objectives to be achieved through its implementation are established. ii) Knowledge acquisition: at this stage, knowledge is gathered and obtained so that the expert system can make informed decisions. This knowledge may come from human experts, specialized literature, technical documents, databases, among other sources. iii) Representation of knowledge, at this point, acquired knowledge is structured and organized in such a way that it can be processed by the system. This process usually involves the creation of rules, decision trees, semantic networks or other forms of representation. iv) Interface design, the interface through which users interact with the expert system is developed. This interface can be graphical, text-based, or a combination of both, depending on the specific system needs. v) Development and implementation of the inference engine, this process involves implementing reasoning and logic algorithms. The implementation of the expert system is carried out through the use of knowledge representation and the inference engine. vi) Testing and evaluation, the system is subjected to rigorous testing in order to detect possible errors and ensure its proper functioning. This involves comparing the decisions taken by the system with the execution of evidence using real cases. These steps form the process of creating a proposed expert system, ensuring its reliability and efficiency throughout the implementation process.

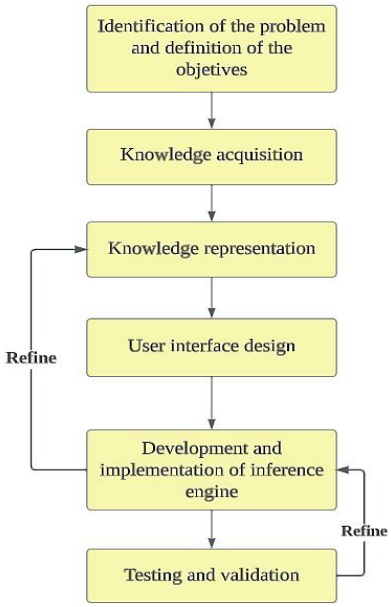


Figure 1. Phases of development of the expert system

3.2. Evaluation of the expert system

In the process of evaluating the effectiveness of the system, we used the confusion matrix, a tool that allowed for a detailed analysis of true positives (TP), true negatives (TP), false positives (FP) and false negatives (FN) [22], as shown in Table 1. We then used these important data to calculate key evaluation metrics, including precision, which assesses the accuracy of predictions, sensitivity, which measures the ability to identify positive cases, and specificity, which measures the ability to correctly identify negative cases. These metrics not only provide a comprehensive understanding of the system's performance, but also create a solid basis for deliberating how well it is performing and how it can be improved in the future.

Table 1. Confusiun matrix

Variable	Actual	
	Positive	Negative
Positive	TP	FP
Negative	FN	TN

4. CASE STUDY

4.1. Identification of the problem and definition of the objective

The diagnosis and treatment of GBS presents a major challenge in today's environment. Although this neurological disease has long been recognized, early identification is made more difficult by the absence of automated resources for accurate and timely diagnosis. In Peru, the situation has reached critical proportions, as the increase in cases has led to the declaration of a health emergency. Although current treatments have a positive effect on the natural course of the disease, some patients may still experience significant residual disability [23]. Furthermore, this condition is a peripheral neuropathy caused by the immune system, and manifests itself through a variety of clinical symptoms [24]. To solve this problem, a new expert system must be created that can identify the four main subtypes of GBS: acute inflammatory demyelinating polyneuropathy (AIDP), acute motor axonal neuropathy (AMAN), acute motor sensory axonal syndrome (AMSAN), and MF syndrome. Given this situation, the objective of the proposed expert system is to enable automated and differentiated diagnosis of these subtypes, improving medical decision making and expediting the implementation of specific treatments to reduce the morbidity associated with this neurological disease.

4.2. Knowledge acquisition

As shown in Figure 2, the general signs and symptoms of each of the four main subtypes of GBS were collected. These symptoms were extracted from reliable sources, specifically from the websites of the Peruvian Ministry of Health and the World Health Organization and the Pan American Health Organization, two entities

with recognized reputations in global health promotion and protection [25]. Each of the identified symptoms was meticulously linked to the potential disease, thus ensuring an accurate correlation. These symptoms take on significant importance to be incorporated into the knowledge representation of the expert system, thus providing a solid basis for informed decision making and early identification of potential GBS cases.

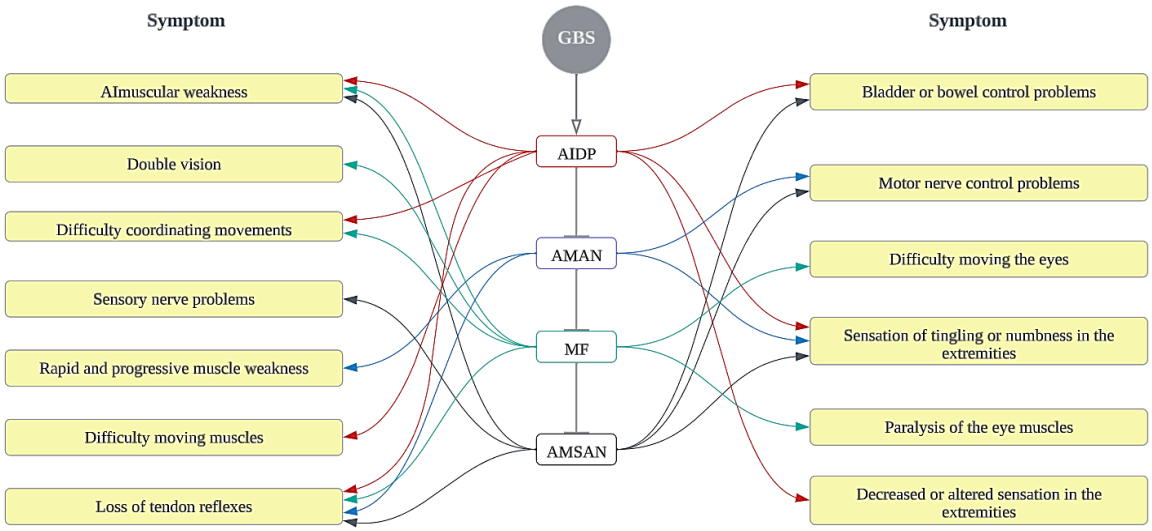


Figure 2. Correlation of symptoms and potential disease

4.3. User interface design

In the process of developing the user interface, as illustrated in Figure 3, priority was given to the consideration of dimensions both for the interface as a whole and for specific elements such as the "Perform Diagnostics" and "Exit" buttons, as well as the background image. Special attention was paid to details such as cursor customization, the strategic arrangement of labels and visual elements, as well as their precise location on the screen. Each of these aspects was meticulously addressed to ensure a consistent, functional and aesthetically pleasing user experience in the expert system.

```
% Start the graphical interface: declaration of dimensions for both the
% interface, individual elements such as buttons and images,
% customization of the cursor, the strategic arrangement of labels and
% visual elements and placement on the screen, etc.
start_interface :-
    new(Menu, dialog('GBS Medical Diagnostic System', size(400, 300))),
    new(L, label(name, 'MEDICAL DIAGNOSTIC SYSTEM - GUILLAIN-BARRE')),
    new(@text, label(name, 'Please answer a short questionnaire to obtain your diagnosis')),
    new(@response, label(name, '')),
    new(Exit, button('Exit', and(message(Menu, destroy), message(Menu, free)))),
    new(@button, button('Start diagnosis', message(@prolog, buttons))),

    % Change button text color
    send(@button, colour, colour(blue)),  % "Test" button in green
    send(Exit, colour, colour(red)),   % "Exit" button in red

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

    % Load the image from a file
    new(Bitmap, bitmap('Sindrome-Guillain-Barre.jpg')),
    new(Fig, figure),
    send(Fig, display, Bitmap),
    new(Size, size(400, 300)),  % resize
    send(Fig, size, Size),
    send(Menu, display, Fig, point(100, 80)), % image position

    send(Menu, append, L),
```

Figure 3. Launching the user interface

4.4. System development and implementation

In the process of building the knowledge base of the system, previously collected symptoms were used, as shown in Figure 4. These symptoms were established as fundamental facts, with the purpose of then

converting them into questions to be answered by the user to indicate the presence or absence of such symptoms in the patient. The "Yes" or "No" answers provided by the user are then used by the system to make inferences based on specific rules. According to these answers, the system follows a series of logical and contextual rules based on questions, as shown in Figure 5. Depending on the type of disease detected, the system proceeds to present a conclusion based on the information collected and offers personalized recommendations for the treatment of the disease in question. This comprehensive approach, which encompasses the collection of symptoms, their transformation into questions, rule-based reasoning, and the provision of diagnoses and recommendations, establishes a sound structure for the effective and consistent operation of the expert system.

```
% Facts
% Symptoms
gbs_aidp :- s_aidp,
                symptom('Muscular weakness'),
                symptom('Tingling or numbness'),
                symptom('Loss of tendon reflexes'),
                symptom('Difficulty moving muscles'),
                symptom('Difficulty coordinating movements'),
                symptom('Altered sensation'),
                symptom('Bladder or bowel control problems').

gbs_mf :- s_mf,
                symptom('Difficulty coordinating movements'),
                symptom('Paralysis of eye muscles'),
                symptom('Loss of tendon reflexes'),
                symptom('Muscular weakness'),
                symptom('Difficulty moving eyes'),
                symptom('Double vision').

gbs_amsan :- s_amsan,
                symptom('Motor nerve control problems'),
                symptom('Sensory nerve problems'),
                symptom('Muscular_weakness'),
                symptom('Tingling_or_numbness'),
                symptom('Loss of tendon reflexes'),
                symptom('Bladder_bowel_problems').

gbs_aman :- s_aman,
                symptom('Tingling or numbness'),
```

Figure 4. Definition of facts

```
question(symptom) :-
    new(D, dialog('Medical diagnostic')),
    new(Lbl2, label(txt, 'Indicate whether or not you have the following symptoms:')),
    new(Lbla, label(prb, symptom)),
    new(Btn1, button(yes, and(message(D, return, yes)))),
    new(Btn2, button(no, and(message(D, return, no)))),

    send(D, append, Lbl2),
    send(D, append, Lbla),
    send(D, append, Btn1),
    send(D, append, Btn2),

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

Figure 5. Rule based on question

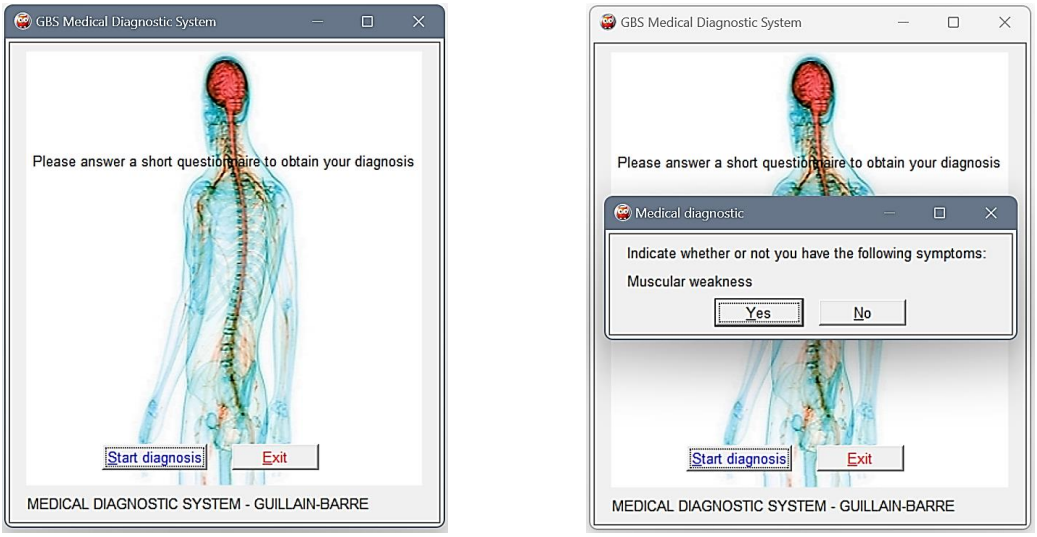
5. RESULT

5.1. User interface

Figure 6 shows the startup and diagnostic user interfaces. Figure 6(a) shows the main interface of the system, highlighting the presence of two essential buttons: perform diagnostics and exit. It is important to note that the exit button performs the function of conveniently closing the system. The perform diagnostics button, on the other hand, triggers a crucial dynamic by opening a pop-up window, as illustrated in Figure 6(b). Within this window, the possibility of answering the established questions is offered, with an exhaustive consideration of the symptoms present. This interaction is characterized by a yes or no checkbox, allowing the user to provide crucial information for diagnosis.

The uniqueness of the system lies in its ability to adapt and adjust the diagnostic approach based on the answers provided. As the user progresses through the answers, the system bifurcates and modifies its trajectory to address specific questions related to the GBS disease subtype being evaluated. This adaptability and customization are key to ensuring that the questions and analysis are relevant and effective for each individual case.

Finally, once all questions have been answered, the system culminates its process and presents the diagnostic result as shown in Figure 7. This result not only includes a conclusion about the possible disease, but also provides valuable recommendations for appropriate management and treatment. This cycle of interaction and analysis, as illustrated throughout Figures 6(a), 6(b), and 7, demonstrates the effectiveness of the system in directing users through a structured and guided process to arrive at a conclusive and evidence-supported assessment.



(a) (b)

Figure 6. User interface (a) main menu and (b) diagnosis of the disease

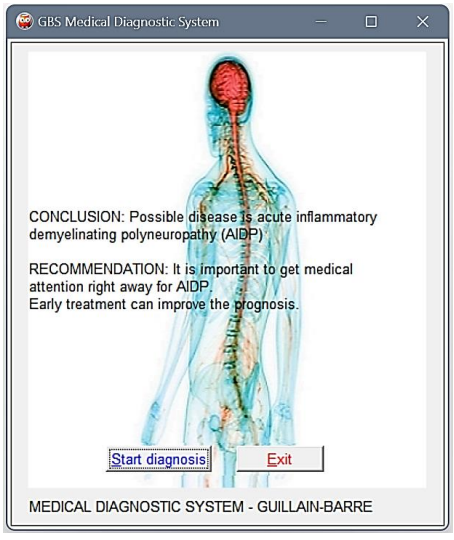


Figure 7. User interface: diagnostic result

5.2. Evaluation of the effectiveness of the system

In the context of the diagnosis of GBS subtypes, the evaluation was performed on a set of 20 cases, consisting of 12 positive and 8 negative cases. Each case represents a distinct clinical case, with distinct features

and symptoms that were analyzed and evaluated by the diagnostic system. These cases represent a variety of clinical presentations and symptom clusters, illuminating the complexity and variability of GBS in real clinical settings. This representative sample of cases allowed us to obtain a robust picture of how the diagnostic system behaves in different clinical scenarios and provides a basis for evaluating its effectiveness in accurately identifying GBS subtypes. This representative sample of cases provided a robust picture of how the diagnostic system performs in different clinical scenarios and provides a basis for evaluating its effectiveness in accurately identifying GBS subtypes.

5.2.1. Analysis of the confusion matrix in GBS subtype classification

The confusion matrix presented in Table 2 reveals four categories of results. The TP reflects the system's success by accurately identifying 10 cases as belonging to the GBS subtype, and they indeed were. On the other hand, the FP points out the occasions in which the system made an error by misdiagnosing two cases as belonging to the GBS subtype when in fact they were not. The TN indicates that the system was able to correctly identify six cases that do not correspond to the GBS subtype, and in fact they did not. Finally, the FN shows that the system failed to adequately detect two cases that were of the GBS subtype, incorrectly classifying them as not belonging to that subtype. These results underline the system's ability to accurately identify between positive and negative cases while highlighting small improvements in its diagnostic ability.

5.2.2. Evaluation of performance metrics in the diagnosis of GBS subtypes

Table 3 shows the evaluation metrics, the outstanding sensitivity of 83% indicates that the system is highly capable of adequately capturing and discerning GBS positive cases within the evaluated set. This quality is essential in the medical context, as it ensures effective detection and early approach to patients with GBS symptoms. In contrast, a specificity of 75% points to a good ability to discern negatives, although there is scope for greater accuracy in this regard. The remarkable precision of 83% points to a significant ability to make accurate diagnoses in the positive cases identified by the system. However, the challenge lies in finding a more robust balance between accurately identifying positives and ensuring the correct exclusion of negatives. These results highlight the continued need for optimization and refinement of the system to achieve a more comprehensive and reliable diagnostic evaluation in the detection of the various subtypes of GBS.

Table 2. Result of confusiun matrix

Predicted	Actual	
	Positive	Negative
Positive	TP=10	FP=2
Negative	FN=2	TN=6

Table 3. Metrics results

Metrics	Value
Precision	83%
Sensitivity	83%
Specificity	75%

6. DISCUSSIONS

In this comparative analysis, three distinct approaches to the diagnosis of GBS subtypes, presented by [13], [15], [18] and the proposed in this research for the diagnostic of GBS subtype, are evaluated, exploring the diverse perspectives that emerge in the convergence of medicine and artificial intelligence. While the four approaches share the fundamental objective of diagnosing GBS subtypes, they differ significantly in terms of evaluation methods, development tools, and results obtained. While Sekovanic and Lovrencic [13] and Alarcón-Narváez *et al.* [15] apply ML techniques and classification algorithms one against all and one against one, the proposal in this research developed in Prolog provides an approach based on logical rules and matrix of confusion to evaluate the effectiveness of the expert system. Each approach seeks to address critical metrics such as sensitivity, specificity and accuracy in the precise identification of GBS subtypes, with methods that vary in their abstraction and applicability. As for development tools, previous studies resort to ML algorithms such as random forest and SVM, leveraging their ability to manage a variety of clinical and serological data. In contrast, the proposed solution stands out for its logical approach and explicit rules, prioritizing explainability and understanding in medical decision-making. Moreover, ML-based approaches, such as those presented by [13], [15], [18], yield solid results in terms of sensitivity, specificity and accuracy, demonstrating their effectiveness in the diagnostic task. On the other hand, the solution proposed in the present research in Prolog provides an essential nuance by focusing on the interpretability of the results, providing a deeper and reasoned understanding of diagnostic decisions. While other researchers present more automated solutions based on ML techniques, which can offer solid performance in classification problems. However, the combination of these diverse approaches could contribute to a more solid and accurate diagnosis of GBS subtypes, benefiting medical practice and health research.

7. CONCLUSION

This study represents a crucial turning point in the ongoing mission to significantly improve care for patients with GBS. A very careful process was used to make and test an expert system that can recognize the four main subtypes of this complicated neuromuscular disorder. With a precision and sensitivity rate of 83% and a specificity of 75%, the results are very encouraging. These data clearly demonstrate the system's ability to accurately distinguish positive cases and significantly reduce false negatives, two features necessary for efficient medical decision-making. The incorporation of subtypes of GBS into the expert system is the most innovative aspect of this study. By addressing the unique requirements of each disease variant, this feature gives the tool a crucial level of sophistication and personalization. By better adjusting treatment to the unique characteristics of each patient, this crucial differentiation has the potential to revolutionize health care. However, on this path to medical excellence, we recognize that there are always opportunities for improvement. For future work, it is recommended that the system be subjected to a more comprehensive clinical validation, in which the system is tested in real-world situations to assess its effectiveness and safety in the healthcare environment. The system must also be kept up-to-date with the latest discoveries in science and medicine in order to maintain its applicability in patient care.

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