

Expert system for diagnosing learning disorders in children

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ABSTRACT

Given the urgent need for early detection of learning disorders such as dysgraphia, dyslexia, and dyscalculia in children, this study aimed to evaluate an expert system developed in Python to facilitate early diagnosis of these disorders. The background highlights the importance of providing parents, educators, and health professionals with an effective tool for early detection of these disorders. In 21 simulated cases, the system showed impressive performance with an accuracy rate of 95%, a precision of 100%, a sensitivity of 93%, and a specificity of 100%. Furthermore, the acceptability evaluation, conducted with 15 parents selected by convenience sampling, showed a high level of satisfaction, with an overall mean of 4.78 and a standard deviation of 0.45, indicating consistency in responses. In conclusion, this study confirms the effectiveness of the expert system in the early diagnosis of learning disabilities, providing parents, educators, and health professionals with a valuable tool. Despite these encouraging results, the need for additional research is recognized to address limitations and improve the external validity of the system to ensure its widespread utility and adaptability in real clinical settings.

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1. INTRODUCTION

Learning disorders such as dyslexia, dysgraphia, and dyscalculia pose significant challenges to the educational process of children. These learning disabilities affect approximately 10% of children worldwide [1]. Early diagnosis of these disorders is crucial to minimize disruptions in learning development and to provide appropriate treatment. However, current diagnostic methods, which rely heavily on manual assessment by pediatric psychologists, are limited in number and relatively expensive [2]. In addition, dysgraphia, characterized by handwriting difficulties, is a transcription disorder that affects composition and orthographic coding [3]. Its impact on academic, motor, and emotional functioning underscores the importance of early identification [4]. Similarly, developmental dyscalculia, which affects numeracy and mathematical performance, presents additional challenges in assessment. Lack of specificity in assessment measures and detection limits is a significant barrier, particularly in disadvantaged educational settings [5]. Similarly, dyslexia is one of the most common disorders affecting children [6]. Therefore, early identification of problems is crucial, as it may allow children to avoid obstacles in their academic and behavioral progress [7]. Thus, there is a need to explore innovative solutions to improve the efficiency and accessibility of diagnosing these disorders.

Furthermore, diagnosing and effectively addressing the symptoms of dyslexia, dysgraphia, and dyscalculia is a crucial challenge for education and school psychology professionals [8], as well as parents.

These disorders present a complex clinical landscape, making early and accurate diagnosis difficult for the adequate treatment of affected students. The complexity of early identification highlights the need to implement advanced automated solutions, such as expert systems, that can serve as support tools for professionals, educators, and especially parents. These innovative systems could play a fundamental role in identifying learning difficulties, allowing for earlier and more effective intervention. Equipping various education stakeholders with accessible and smart technological tools could significantly improve their ability to address challenges associated with learning disorders.

To address these challenges, this study proposes to develop a diagnostic expert system in Python, taking advantage of its high-level and object-oriented nature. Moreover, nowadays, Python has emerged as a leading programming language due to its versatility and object-oriented approach [9]. Python's flexibility and power have positioned it as the most widely used computer language [10]. Its object-oriented approach and clear structure have made it easy for developers to create logical projects on both small and large scales [11]. In this context, the implementation of the expert system is developed using this programming language, taking advantage of its flexibility and efficiency [12], with the aim of diagnosing learning disorders in children, specifically dysgraphia, dyscalculia, and dyslexia.

The main objective of this project is to develop and evaluate an expert system to provide an early diagnostic tool for learning disabilities in children, which will significantly contribute to the early identification and treatment of these conditions. Given the high prevalence of learning disabilities and the limited availability of specialized professionals, the incorporation of an automated expert system is presented as an innovative and efficient solution to speed up the diagnostic process. This approach will not only optimize the use of resources but also provide broader and more accessible access to specialized assessments. The choice to implement this system in Python is based on its popularity and versatility, ensuring a robust and efficient platform to effectively support the conduct and continued success of this study.

2. LITERATURE REVIEW

In this section, an exhaustive review of the literature will be conducted, focusing on studies related to expert systems and technologies applied to the diagnosis of learning disorders such as dysgraphia, dyscalculia, and dyslexia. Different solutions and techniques implemented in previous research will be explored, highlighting the effectiveness of expert systems in the early and accurate identification of these disorders. Furthermore, the crucial role of technology in this context will be analyzed, examining how the integration of innovative tools contributes to a more holistic and efficient approach in the diagnostic process of learning disorders.

In the study conducted by Ashidiqi *et al.* [13] present a study that treats dyslexia as a condition that affects learning skills such as reading, writing, and arithmetic. A platform was created by them, utilizing an expert system incorporating the certainty factor method, aimed at aiding parents in the early detection of dyslexia and identifying its particular type. The methodology encompasses the assessment of various dyslexia types, including surface, phonological, rapid naming deficit, dysgraphia, and dyscalculia. Findings derived from a transparent system indicate that the platform aligns with anticipated outcomes, showcasing a minimal risk level in identifying dyslexia in children.

Similarly, in another study, they addressed the persistent difficulty in identifying developmental dyslexia in Chinese children by implementing a back-propagation neural network model optimized with a genetic algorithm [14]. Information was gathered from a sample of 399 children spanning grades 3-6, comprising 187 with dyslexia and 212 typically developing individuals, aged between 7 and 13 years. The model demonstrated an impressive predictive accuracy of 94%, underscoring the crucial role of reading accuracy as a decisive factor. Moreover, elements like phonological awareness, pseudo-letter accuracy, morphological awareness, reading fluency, rapid digit naming, and non-letter reaction times were identified as significant contributors to the predictive capability of the model. Using the genetic algorithm to optimize the neural network model not only significantly improved prediction accuracy, reaching 94%, but also suggests the potential of this approach to guide more specific prevention and treatment strategies.

Likewise, the study carried out by Skunda *et al.* [15] presents a method for detecting dysgraphia disorders through the classification of handwritten text. The primary goal of the study is to develop a machine learning-based tool that enables schools to diagnose both dyslexia and dysgraphia, with the aim of applying early detection techniques to improve intervention for affected children. In an experiment with a dataset consisting of 120 school-aged children, 63 of whom were typically developing and 57 of whom had been diagnosed with dysgraphia, an approach based on conventional signal theory was used. A simple algorithm was implemented to preprocess the raw data, followed by the design of a three-layer convolutional neural network to classify the data. During the testing stage, the model demonstrated an accuracy level of 79.7%, demonstrating the feasibility of this approach to classify children into typical and dysgraphia categories.

Similarly, the study conducted by Anggrawan *et al.* [16] addresses the prevailing need for early detection of learning difficulties in children, despite the advanced state of educational technology. The main objective is to develop an expert system utilizing the Certainty Factor and Dempster-Shafer techniques. Lack of knowledge about these disorders can lead to a lack of help for children, affecting their potential and contributing to problematic behavior and mental disorders. The findings indicate that the Certainty Factor approach exhibits greater accuracy than the Dempster-Shafer method when diagnosing learning disabilities in children, achieving accuracies of 90% and 87%, respectively. The unique contribution of this study resides in developing a system for diagnosing distinct types of learning disabilities in children, employing methodologies that have not been previously investigated by other researchers. This approach aims to improve the early detection of learning disabilities, allowing for timely intervention and support for affected children.

Likewise, an additional research effort focuses on dysgraphia as a crucial learning disability impacting writing abilities and potentially exerting adverse effects on the academic performance of children if not identified in the early stages [17]. The main focus is to propose automated methods for the diagnosis of dysgraphia through the analysis of handwriting, specifically using the kinematics and dynamics of writing. The complexity of the diagnosis is highlighted due to the variety of symptoms and the variability in the appearance of the disorder. The study concentrates on creating techniques that utilize a limited set of characteristics to categorize individuals with and without dysgraphia. The assessment of the suggested approaches is conducted using an online handwriting dataset. The outcomes reveal that the proposed method successfully identifies the existence of dysgraphia with a precision rate of 77%, highlighting the effectiveness of this automated and simplified approach for the identification of dysgraphia in its early stages.

On the other hand, the study by Kurniawan *et al.* [18] addresses the problem of students with writing difficulties (dysgraphia) in the learning process, where the majority of regular teachers do not provide adequate assistance. The aim of the study is to deploy an expert system within educational settings utilizing forward chaining for the diagnosis of students. Within this system, forward chaining is employed to detect students with dysgraphia and evaluate the extent of their impairment. The participation of the therapist, teachers, and students with dysgraphia is integrated into the process, and knowledge is gained through interviews and observations. The system underwent testing with a group of 19 elementary school students (grades 3–6), and the test results showed that 97.41% of the system's diagnoses had similarities with the results of diagnoses made by experts.

Similarly, the article proposed by other authors treats dyslexia as a learning disorder characterized by difficulties in reading, spelling, and decoding letters. The central approach is to develop a machine learning model that uses audio recordings to predict the presence of dyslexia in Turkish-speaking children [19]. This model, designed to run on smartphones, is positioned as an alert system that allows children identified as possibly dyslexic to seek evaluations from experts. In the training and evaluation process, a unique dataset was created with audio recordings of 12 dyslexic and 13 non-dyslexic children over a period of 8 months. Different features were examined in the exploration of machine learning algorithms like k-nearest neighbors (KNN) and support vector machine (SVM), including Mel frequency cepstral coefficients, reading speed and accuracy, proportion of missing words, and confidence scores of the speech-to-text process. The results showed an accuracy of 95.63% in detecting children with dyslexia, even with long single-sentence audio recordings, and the model's performance was compared to that of humans.

In summary, the analyses of the reviewed studies show various solutions for the diagnosis of learning disabilities, such as expert systems, machine learning, and deep learning, among others, all of which show positive results. However, the implementation of solutions such as machine learning and deep learning places a significant demand on resources, such as extensive data for model training, and not everyone has such resources and experts for implementation, making it difficult to apply them in regions with limited resources. In response to these findings, this study develops and evaluates a lightweight and adaptable expert system designed for users with different profiles, seeking to overcome the barriers associated with the availability of resources in constrained environments.

3. METHOD

3.1. Buchanan methodology

The methodology used for the development of the diagnostic system for learning disabilities in children is based on the Buchanan methodology, which follows a conventional waterfall life cycle approach divided into five stages, as illustrated in Figure 1, namely identification, conceptualization, formalization, implementation, and test [20]. In the identification phase, the problem is thoroughly analyzed, the system requirements are established, and the solution to be implemented is defined. In the conceptualization phase, a conceptual structure is designed to understand the problem. In the formalization phase, rules and knowledge are codified in an appropriate format. The implementation phase involves the creation of the

system interface and infrastructure, and finally, the testing phase is dedicated to verifying its correct operation and effectiveness in diagnosis.

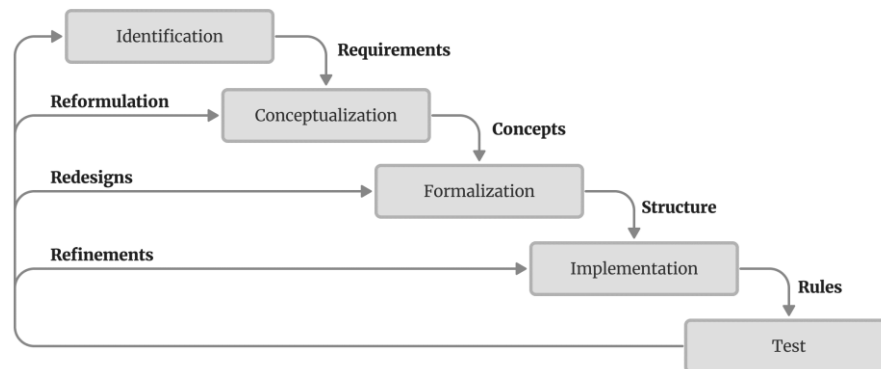


Figure 1. Phases of the Buchanan methodology

3.2. Confusion matrix

The confusion matrix was used as a fundamental tool in the evaluation of the expert system. This choice was based on the need to analyze the performance of the system in a rigorous and precise way, allowing a detailed evaluation of the predictions made. Through the confusion matrix, it became feasible to compare the accurately identified cases (true positives (TP) and true negatives (TN)) with the inaccurately identified cases (false positives (FP) and false negatives (FN)) in an effective manner [21], providing a comprehensive view of the quality of the expert system.

3.3. Performance metrics

Performance metrics were employed to assess the system's efficacy and competence in executing its diagnostic tasks. These metrics provided an objective and quantitative assessment of the system's performance based on its results and the precision of its actions. This allowed them to make informed decisions and improve their operations.

3.3.1. Accuracy

The accuracy metric was used to evaluate the overall proportion of correct predictions made by the system. This metric is calculated using (1), this involves the total of true positives and true negatives divided by the overall number of cases. Accuracy provides an overall measure of system performance in terms of correct predictions over the entire dataset [22].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

3.3.2. Precision

The precision metric was used to evaluate the proportion of correct predictions made by the system. This metric calculates how many of the instances classified as positive were actually positive, providing information about the overall precision of the predictions. In other words, precision is defined as the ratio of true positives to expected positives [23], [24]. This approach provides a more detailed understanding of the accuracy of the predictions, which improves the interpretation of the effectiveness of the evaluated system. It can be calculated using (2).

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

3.3.3. Sensitivity

Sensitivity, alternatively referred to as the true positive rate, focuses on the ability of the expert system to accurately identify positive cases. This metric quantifies the proportion of true positive cases that the system was able to detect and is particularly important in environments where minimizing false negatives is a priority. In simpler terms, sensitivity is the measure of how many of the total positive samples are correctly classified as positive classes [25]. This perspective provides a detailed assessment of the system's

ability to detect true positives, allowing a deeper understanding of its performance in situations where accurate identification is essential. Sensitivity can be calculated using (3).

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

3.3.4. Specificity

The specificity metric assesses the system's capability to accurately recognize negative instances. It is the true negative rate and is calculated as the proportion of true negatives that the system correctly classified as negative. Specificity is critical to reducing false-positives in a diagnostic system. It can be calculated using (4).

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

3.4. Acceptability assessment

A structured questionnaire consisting of 10 questions was used to assess acceptability. Participants were selected by non-random convenience sampling, taking into account the availability and willingness of parents to participate in the research. The questionnaire addressed key aspects of the system, including its usability, understandability, and usefulness as shown in Table 1. The responses collected were subjected to a detailed analysis through the use of descriptive statistical techniques, such as the calculation of the mean and standard deviation (SD), with the purpose of evaluating more precisely the level of acceptance shown by the parents towards the system.

Table 1. Acceptability evaluation results

Id	Questions	Average	SD
1	The information provided by the system is accurate and reliable in terms of diagnosis.	4.67	0.49
2	The system's results are in line with what you would expect from a health or education professional.	4.60	0.51
3	The system interface is intuitive and easy to understand.	4.40	0.51
4	You can navigate the system efficiently and without difficulties.	4.47	0.74
5	The system's functions are easy to use even for someone without technical experience.	4.93	0.26
6	The system adapts to different user profiles (health professionals, educators, parents).	4.80	0.41
7	The information presented by the system is relevant and easily understandable.	5.00	0.00
8	Interaction with the system feels natural and comfortable.	5.00	0.00
9	The time it takes to complete the diagnosis is reasonable.	4.93	0.26
10	The system is accessible to users with different skill levels and needs.	5.00	0.00

4. SYSTEM DEVELOPMENT

4.1. Identification

4.1.1. Problem

The problem addressed in this context centers on the prompt and precise detection of learning disorders like dysgraphia, dyslexia, and dyscalculia in children. The diversity of symptoms and the lack of awareness in the educational community can lead to delays in diagnosis, negatively affecting both the academic performance and emotional health of affected children. The lack of an effective detection system can contribute to these disorders going unnoticed, preventing the timely implementation of interventions and specialized resources. Similarly, the lack of equitable access to specialized services, coupled with the need to consider technological and ethical factors in the diagnostic process, adds another layer of complexity to the problem.

4.1.2. Solution

The proposed solution consists of the development of an expert system for the early diagnosis of learning difficulties in children using Python and based on predefined rules. This system will be designed to analyze specific data, such as children's academic performance and behavioral patterns, provided by the user through an interactive and friendly interface. Healthcare professionals, educators, and parents will be able to enter observed symptoms, and the system will apply predefined rules to generate fast and accurate results. The goal of this solution is to streamline the diagnostic process, enabling early and personalized interventions that significantly improve the educational and emotional prospects of children with learning disabilities.

4.2. Conceptualization

In this second phase of expert system development, a comprehensive collection of information on learning disorders such as dyslexia, dysgraphia, and dyscalculia were undertaken. Key symptoms associated

with each disorder were carefully identified, allowing for an in-depth understanding of the clinical and behavioral manifestations. This phase focused not only on the enumeration of symptoms but also on the exploration of the complex interrelationships between them, providing a solid and precise foundation for the subsequent development of the expert system as shown in Figure 2.

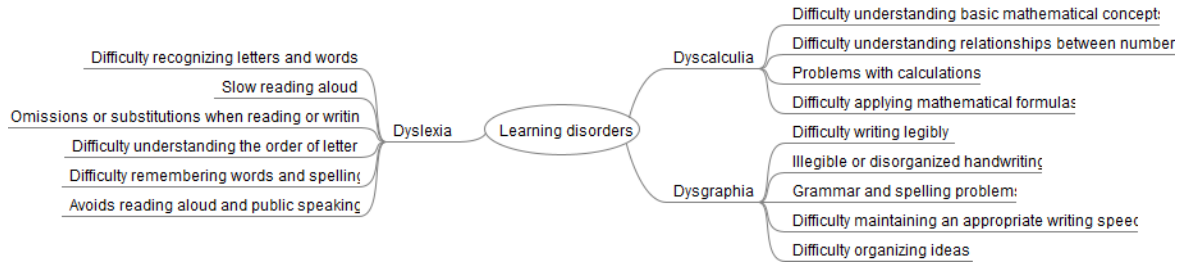


Figure 2. Symptoms associated with each disorder

4.3. Formalization

For diagnosis, a rule base has been built based on the use of if/then logic in Figure 3. The system rule was designed to analyze the symptoms reported by the user by evaluating specific criteria that cover various areas related to academic performance and behavior. The structure of the rules includes conditions (if) that examine the symptoms reported by the user and conclusions (then) that suggest the possible presence of a learning disorder based on these identified symptoms. A wide range of indicators have been considered, such as difficulties in reading, writing, or mathematics, as well as concentration problems and specific behaviors in educational settings identified during the conceptualization phase. The expert system uses this input data to cumulatively apply the rules and generate a preliminary diagnosis based on the relationship between the symptoms marked by the user and the patterns associated with known learning disorders.

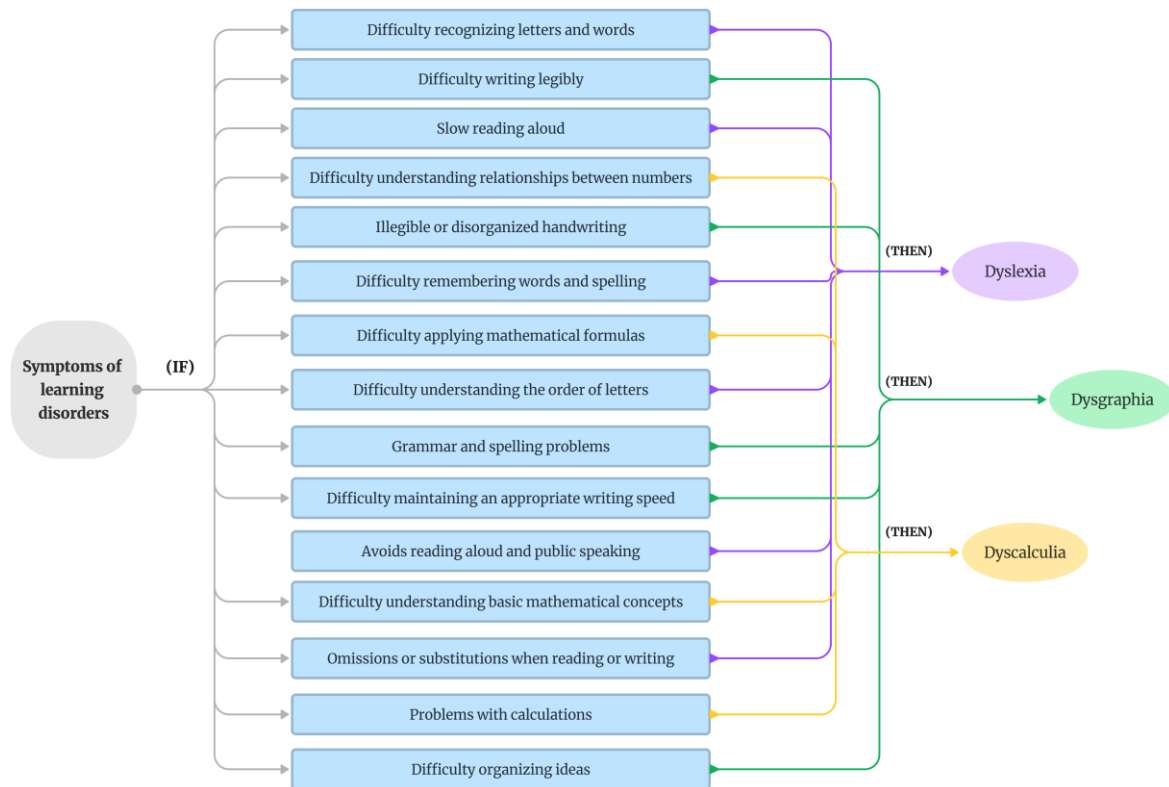


Figure 3. Formalization of knowledge

4.4. Implementation

Figure 4 shows the detailed definition of the symptoms associated with each learning disorder, namely: dyslexia, dysgraphia, and dyscalculia. In this representation, the specific symptoms of each disorder are arranged in checkboxes, with the purpose of facilitating the task of users, such as teachers, parents, and others, to indicate those symptoms that they can observe or identify in children. This visual approach provides an efficient tool for identifying and understanding the characteristic signs of each disorder, thus promoting a more accurate and collaborative assessment by those involved in the educational and care processes.

On the other hand, Figure 5 shows the code structure that represents a condition (if statement) that implements a specific logical rule. In this context, the rule specifies that if the number of symptoms associated with learning disabilities is equal to or greater than 3, then the person is considered to have one of the identified disorders (dyslexia, dysgraphia, and dyscalculia). This rule acts as an identification mechanism, linking the presence of a particular number of symptoms to the classification of a particular disorder.

```

self.dyslexia_checkboxes = [QCheckBox("Difficulty recognizing letters and words"),
                             QCheckBox("Slow reading aloud"),
                             QCheckBox("Omissions or substitutions when reading or writing"),
                             QCheckBox("Difficulty understanding the order of letters"),
                             QCheckBox("Difficulty remembering words and spelling"),
                             QCheckBox("Avoids reading aloud and public speaking")]

self.dysgraphia_checkboxes = [QCheckBox("Difficulty writing legibly"),
                               QCheckBox("Illegible or disorganized handwriting"),
                               QCheckBox("Grammar and spelling problems"),
                               QCheckBox("Difficulty maintaining an appropriate writing speed"),
                               QCheckBox("Difficulty organizing ideas")]

self.dyscalculia_checkboxes = [QCheckBox("Difficulty understanding basic mathematical concepts"),
                                QCheckBox("Difficulty understanding relationships between numbers"),
                                QCheckBox("Problems with calculations"),
                                QCheckBox("Difficulty applying mathematical formulas")]

```

Figure 4. Definition of facts

```

# An empty list called 'disorders' is created.
disorders = []

# It is checked if the number of symptoms is greater than or equal to 3 and the string is added to the 'disorders' list.
if num_symptoms_dyslexia >= 3:
    disorders.append("Dyslexia")
if num_symptoms_dysgraphia >= 3:
    disorders.append("Dysgraphia")
if num_symptoms_dyscalculia >= 3:
    disorders.append("Dyscalculia")

# Then, if the condition is met, the type or types of disorder identified are displayed.
if disorders:
    self.result_label.setText("Diagnosis: " + ", ".join(disorders))
# If the condition is not met, it shows as a result that the type of disorder cannot be determined.
else:
    self.result_label.setText("The learning disorder could not be determined.")

```

Figure 5. Rule to determine the type of disorder

5. RESULTS

5.1. User interface

Figure 6 shows the user interface designed for the assessment of symptoms related to the disorders considered in the study, specifically dyslexia, dysgraphia, and dyscalculia. In this interface, a detailed list of symptoms associated with these disorders is presented, allowing the user to identify those observed or presented by the child in question in order to determine the type or types of learning disorder that he or she might be experiencing. To facilitate user interaction, two distinctive buttons have been incorporated: diagnose, which allows to process the selected information and generate a diagnosis, and new diagnosis, which allows to start a new evaluation process. These interface elements are designed to improve efficiency and ease of use for those using the platform for the early detection of learning disabilities.

Figure 6. User interface

5.2. System performance evaluation

In the evaluation of the expert system, 21 simulated cases were implemented, consisting of 15 positive cases, representing the presence of learning disorders, and 6 negative cases, representing the absence of said disorders. Each of these cases was verified by the expert system, and the results were classified in a confusion matrix. A comprehensive analysis of the system's performance metrics, including accuracy, sensitivity, and specificity, was then performed. This meticulous approach allowed us to comprehensively evaluate the system's ability to correctly identify and classify simulated cases, thus providing a detailed understanding of its effectiveness and reliability in detecting learning disabilities.

5.2.1. Confusion matrix

After analyzing and classifying the results obtained in the confusion matrix as shown in Table 2, it can be seen that the expert system managed to correctly identify 14 true positive cases, indicating the ability to adequately detect and diagnose present learning disorders. Furthermore, the system did not generate any false positives, suggesting a high specificity in its ability to avoid misdiagnosis in unaffected cases. However, a false negative was observed, meaning that the system was unable to detect an existing case of learning disabilities. On the other hand, six true negative cases were recorded, indicating the correct identification of cases where no disorders were present. These results highlight the efficiency of the system in accurately identifying positive cases and its ability to avoid errors in diagnosing the absence of learning disabilities.

Table 2. Result of confusion matrix

Predicted	Actual	
	Positive	Negative
Positive	TP = 14	FP = 0
Negative	FN = 1	TN = 6

5.2.2. Performance metrics

The metric results indicate excellent performance of the evaluated system as shown in Table 3. The 95% accuracy indicates that most of the predictions made by the system were correct. 100% precision means that all predictions classified as positive by the system were in fact positive. The sensitivity of 93% indicates

that the system correctly identified 93% of the positive cases present in the dataset. The specificity of 100% means that the system did not generate any false positives; in other words, it correctly classified all negative cases. These results indicate the high ability of the system to make accurate predictions and to effectively identify both positive and negative cases.

Table 3. Metrics results

Metrics	Value
Accuracy	95%
Precision	100%
Sensitivity	93%
Specificity	100%

5.3. Acceptability assessment

The results of the acceptability evaluation of the disorder diagnosis system show high general satisfaction among parents. On average, the lowest score is found in the question about the intuitiveness and ease of the system interface, with an average score of 4.40, indicating that although the majority of users find the interface easy to understand, there is room for improvement in the intuitiveness. On the other hand, the highest score is found in three different questions, all with a perfect score of 5.00. These questions focus on the relevance and understandability of the information presented by the system, the naturalness and comfort of interacting with the system, and the accessibility of the system to users with different skill levels and needs. These results suggest that users generally perceive the system to be highly reliable, comfortable, and easy to use, with specific areas for potential improvement in the intuitive interface in Table 1.

In addition, the overall average of 4.78 indicates a generally positive evaluation of the disorder diagnosis system by parents. This value, together with the total standard deviation of 0.45, suggests that there is a relatively high level of consistency in user responses, as the standard deviation is relatively low. The low standard deviation indicates that there is consistency in the acceptance of the system among the users surveyed. Although the lowest average was found in the question about the intuitiveness and ease of the interface, the overall consistency and high scores in other areas highlight the effectiveness of the system in terms of reliability, relevance of information, and ease of interaction, providing a solid foundation for future improvements focused on user experience.

6. DISCUSSION

In this study, an expert system for diagnosing learning disabilities such as dyslexia, dysgraphia, and dyscalculia was developed and evaluated. The research addressed the effectiveness of the system by evaluating 21 simulated cases using performance metrics. The results obtained show an accuracy of 95%, a precision of 100%, a sensitivity of 93%, and a specificity of 100%, underscoring the effectiveness of the system in the accurate detection of learning disorders. In contrast, other researchers have implemented an expert system using the Certainty Factor method for the early detection of dyslexia [13]. While this strategy aligns with expectations and carries a minimal level of risk, the results obtained in the present study exceed its performance metrics. The 95% accuracy and 100% precision of the proposed system suggests a significant improvement in diagnostic capability.

Likewise, in comparison with the study [16], which also addressed the detection of learning disorders in children through the certainty factor and Dempster-Shafer methods, their findings revealed a 90% precision for the certainty factor, surpassing the 87% achieved with the Dempster-Shafer method. These differences highlight the improved effectiveness of the rule-based expert system developed in this study for the accurate identification of learning disabilities. The 100% accuracy achieved by the proposed system suggests an additional robustness of the diagnostic capability compared to the results obtained in previous research. These discrepancies underscore the relevance and significant contribution of the rule-based approach to improving the diagnostic accuracy of learning disabilities in the context of the present study.

Similarly, compared to the results obtained in the study [18], where an expert system was implemented for the diagnosis of dysgraphia using forward chaining, the present research presents equally remarkable figures. While in the previous study the agreement between the results of the expert system and the diagnoses made by experts was 97.41%, in the present study the accuracy was 95%. Despite the slight difference in terms of agreement, the 100% accuracy achieved in the present research exceeds the performance of the previous study. Furthermore, the expansion of the focus of the present study to include not only dysgraphia but also dyslexia and dyscalculia adds an integral dimension to the expert system that may be relevant in the early detection and management of a broader range of learning disorders.

This study makes a significant contribution to the field of learning disability diagnosis by demonstrating the effectiveness of the proposed expert system. The expansion of the scope to include multiple disorders is shown to be a distinctive and valuable factor, providing a more comprehensive solution compared to previous research that focused on more specific aspects. The rigorous methodology used in the evaluation of simulated cases supports the reliability of the results, highlighting the solidity of the approach used and allowing early and personalized interventions.

7. CONCLUSION

In conclusion, this study has successfully achieved its main objective of developing and evaluating an expert system to provide an early diagnostic tool for learning disorders such as dyslexia, dysgraphia, and dyscalculia in children. The results of the performance evaluation, based on 21 simulated cases, show a high level of accuracy with an accuracy rate of 95%, a precision of 100%, a sensitivity of 93%, and a specificity of 100%. These metrics demonstrate the effectiveness and reliability of the system for identifying learning disabilities. Furthermore, the evaluation of the acceptability by the users, in this case the parents, yielded an overall average of 4.78, indicating a generally positive evaluation of the diagnostic system. The consistency of user responses, supported by a total standard deviation of 0.45, suggests a uniform positive perception of the system. These findings underscore the importance and perceived usefulness of the tool in the context of early identification of learning disabilities, providing parents, educators, and health professionals with a valuable tool for early identification. However, it is important to consider the limitations of this study, such as the non-random selection of users and the use of simulated cases instead of real patients. These limitations may affect the generalizability of the results to real-world situations. In addition, it highlights the need for future work that expands the external validity of the system by including a more diverse sample and evaluating it in real clinical settings. In the future, the robustness of the system is expected to be improved through continuous updates based on user feedback and the integration of emerging technological advances in the field of learning disorder detection.

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