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Classification algorithm with artificial intelligence for the diagnostic process of obstructive sleep apnea

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ABSTRACT

Obstructive sleep apnea (OSA) is a disease that affects millions of people worldwide, and a large proportion of them remain undiagnosed due to the high cost of polysomnography (PSG) tests. For this reason, it is crucial to develop affordable diagnostic tools to facilitate early detection of this condition. This study aims to analyze how an artificial intelligence (AI)-based classification algorithm impacts the diagnostic process of OSA in Lima, Peru. The algorithm was developed following the Kanban methodology, which guaranteed an efficient and transparent follow-up during the development cycle, which is key in the medical context where software quality and traceability are fundamental. A decision tree (DT) was used for diagnosis and classification, employing a training dataset provided by the National Sleep Research Resource (NSRR), from which six relevant attributes were selected for analysis. The research results indicated that, although the improvement in clinical diagnostic accuracy was minimal at 10.81%, positive results were obtained in other aspects: diagnostic time was significantly reduced by 28.17%, and the number of tests required decreased by 24.07%.

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1. INTRODUCTION

Sleep is a primordial and essential activity in which we invest approximately one-third of our lives [1]. Nowadays, the quality and duration of sleep are significantly affected by people's lifestyles, which can have negative repercussions on long-term health, giving rise to what are known as sleep disorders (SDs) [2]. SDs are a common pathology among people, which depending on their condition can be isolated or associated with other disorders [3]. Since 1979, the international classification of sleep disorders (ICSD) has been in use, which in its first version classified SDs into four groups: dyssomnias, parasomnias, disorders associated with other diseases, and unqualifiable SDs [4], [5]. Thanks to this, more than 80 SDs have been recognized and classified [6]. These disorders negatively affect millions of people worldwide, causing loss of life, and accidents, among others [7], [8]. Among the most severe SDs, is obstructive sleep apnea (OSA), which affects 4% of the world's population [9]. OSA episodes occur when the airway suddenly collapses during sleep, cutting off oxygenation to the body [10]. This condition can last more than 10 seconds and occurs with a concurrence of 5 times per hour of sleep. It affects more men than women between 40 and 50 years of age [11]. OSA is usually divided into three levels of severity: mild, when the incidence is greater than 5 but less than 15 events per hour; moderate, between 15 and 30 events per hour; and severe, greater than 30 events per hour [12].

In the United States, it affects 22% of men and 17% of women, with rates exceeding five episodes per hour [13], [14]. Similar figures are reported in Spain and Hong Kong, while significant increases have been reported in Japan, reaching 37% in men and 50% in women [15]–[18]. In Latin America, prevalence varies by region, with studies highlighting cities such as Montevideo and Santiago de Chile. However, in Peru, the lack of accurate data hinders a clear assessment of the problem [19]. A review of medical records suggests that 29.2% of patients present with mild OSA and 26.7% with severe OSA [20]. These findings reflect a potentially growing public health challenge and underscore the importance of optimizing diagnostic methods. Given the paucity of data in Latin America, especially in Peru, it is crucial to explore new strategies to improve the detection and management of OSA. In this context, artificial intelligence (AI), particularly machine learning (ML), has demonstrated its potential to analyze complex data patterns and improve diagnostic accuracy [21]–[23]. ML algorithms can process sleep data and clinical symptoms more quickly and accurately, facilitating early detection and timely intervention [24]. In addition, the integration of AI into sleep monitoring devices allows for optimized data collection and continuous assessments, which could transform the clinical approach to OSA, especially in resource-limited regions [25]–[27].

The relationship between AI and the diagnosis of OSA represents a promising area that integrates advanced technology intending to improve health outcomes. Deepening this interaction and fostering continued research in this area may lead to innovative developments that transform how SD are diagnosed and treated. In this context, the present study aims to evaluate how an AI-based classification algorithm influences the diagnostic process of OSA in Lima, Peru.

2. LITERATURE REVIEW

This section presents some work related to the topic of study. Almazaydeh *et al.* [28] developed a support vector machine (SVM)-based algorithm that uses electrocardiogram (ECG) data to classify patients with and without OSA, achieving an accuracy of 96.5%. However, this approach focuses only on the analysis of ECG signals, which limits its applicability in more complex clinical scenarios that require the integration of multiple sources of physiological data. In contrast, the present study proposes the incorporation of physiological and clinical data, allowing for greater robustness in OSA detection. According to Luo *et al.* [29], five ML models and two diagnostic schemes were used to develop a low-cost system that detects OSA in real time using snoring recordings and polysomnography (PSG) data, with 97% accuracy. Despite its effectiveness, it does not address the integration of various physiological sources. Similarly, Haidar *et al.* [30] employed convolutional neural networks with respiratory data, achieving an accuracy of 83.5%, although without considering other physiological and clinical variables. Al-Abed *et al.* [31] proposes an algorithm based on textural features extracted from normalized gray-level concurrence matrices (NGLCM) obtained by short-time discrete Fourier transform (STDFT) for OSA detection. Although this approach offers promising results, with an accuracy of 90.16%, it relies on complex mathematical transformations that could make it difficult to implement in clinical practice. According to Kristiansen *et al.* [32], 29 patients with suspected OSA were investigated using a low-cost strain gauge respiratory belt to record various breathing parameters. In the study, various ML-based diagnostic tools were employed, yielding an accuracy of 76.09% and a sensitivity of 78.33%. However, the lower accuracy and exclusive focus on respiratory data are significant limitations. On the other hand, Bouscoulet *et al.* [33] was carried out a comparison of the diagnostic accuracy of portable monitors, evaluating the desaturation index of the respiratory index. In this study, a total of 38 patients were evaluated, achieving a diagnostic confidence of 95%. Although the results are relevant, the study does not explore the use of advanced ML algorithms, a limitation addressed in this work by combining ML techniques with other variables. Finally, Polat *et al.* [34] investigated PSG devices using ML algorithms, achieving 97.1% accuracy in 83 patients. Although robust, this approach focuses on a limited number of variables. Similarly, Kang *et al.* [35] employed snoring sounds in 24 patients, achieving an accuracy of 90.65% for apnea prediction. However, its use of a single acoustic signal limits its applicability. Our study, by contemplating physiological and clinical variables, presents a different approach than other studies, since most previous research tends to focus on the analysis of a single data source or isolated signals, such as ECG, respiratory signals, or snoring sounds. Instead, by integrating both physiological variables (such as breathing patterns, heart rate, or oxygenation levels) and clinical data (medical history, reported symptoms, and patient demographics), this approach allows for a more complete and accurate view of the patient's condition.

3. METHOD

For the development of the classification algorithm with AI, the kanban methodology was chosen. This methodology is a tool of the lean methodology that is widely used in software development [36]. It is a visual system to manage the development of a project; it uses a board divided into columns that represent different stages of the development process [37]. Next, we analyze the activities that we will have to develop

for the creation of the algorithm. The activities were divided into three stages: problem definition, problem analysis, and algorithm design with their respective tasks, as detailed in Table 1.

Table 1. To-do list

Phase	N°	Pending tasks	Description	Priority
Problem definition	T1	Define the problem	We defined the problem of the study.	Media
Problem analysis	T2	Define input data	We define what data the algorithm requires to provide us with the expected results.	High
	T3	Define the output data	We define how the algorithm will express the result after sorting the input data.	High
	T4	Define formulas and methods	We define the formulas and methods required for algorithm development.	Media
Algorithm design	T5	Design the pseudocode	With the information gathered previously, we designed the pseudocode of the algorithm.	Download
	T6	Design the flowchart	As in the preceding task, the flow chart is designed	Download
	T7	Implement the code	We wrote the code with the Python programming language.	High
	T8	Review and optimize the code	We correct and optimize the parts of the code that may cause errors when executing the code.	Media

3.1. Kanban board elements

3.1.1. To-do list

For the correct implementation of the classification algorithm based on AI, the kanban methodology has been used, which allows a visual and structured management of the tasks to be developed. Within this methodology, one of the key elements is the “To-do list”, which groups and organizes the essential activities according to the different stages of the algorithm development. These tasks include defining the problem, identifying and analyzing the input and output data, selecting appropriate formulas and methods, as well as designing the pseudocode, and implementing the code in Python. The organization of these tasks in a list facilitates planning and progress tracking, allowing to prioritize those activities that are most critical and ensuring an orderly and efficient progression in the development of the project.

3.1.2. Board

As part of the kanban methodology, it is necessary to use a board divided into columns to visualize the progress in the development of the algorithm. To carry out this task, we used the digital platform Trello, in which we configured a board consisting of the following columns: task list, in progress, and done, as illustrated in Figure 1. In addition, to facilitate the use of the activity table and the progress of the project, we established the policies or work rules as shown in Table 2.

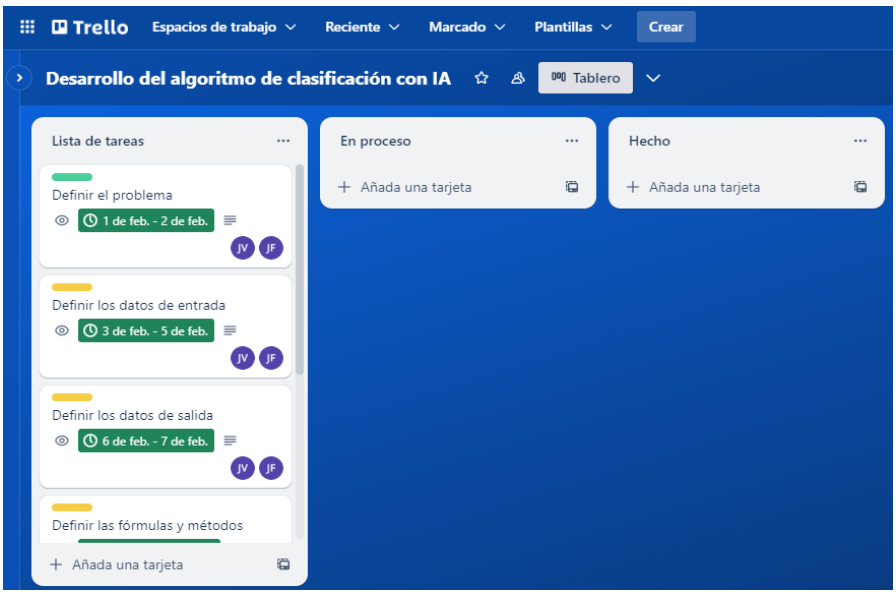

Figure 1. Kanban methodology board

3.1.3. Rules for the use of the board

To ensure efficient project management, specific rules were established for the use of the Kanban board. These rules aim to optimize the workflow, avoid excessive accumulation of tasks in a single stage, and maintain a structured execution of the project. Among the main rules established is the limitation of the number of tasks that can be developed simultaneously, ensuring that no bottlenecks are generated in the process. Likewise, it was determined that the tasks in progress must belong to the same development phase, avoiding the simultaneous execution of activities from different stages, which could generate inconsistencies and delays. These rules are intended to improve productivity, maintain a clear focus in each phase, and guarantee an organized development aligned with the principles of the kanban methodology.

Table 2. Kanban board usage policies/rules

N°	Usage policies
P1	To avoid the bottleneck, only 2 tasks can be performed simultaneously
P2	The tasks to be performed must belong to the same phase
P3	Tasks that belong to different phases may not be developed

3.2. Execution of the tasks

3.2.1. T1-define the problem

For this research work, we proposed the development of a classification algorithm with AI to diagnose OSA. With the analysis of literature related to this disease, we know that for the diagnosis of OSA, the following data are contemplated, the Epworth sleepiness scale, which gives us a diagnosis of clinical suspicion, physical examination, and history of pre-existing diseases. In addition, the sleep apnea/hypopnea index is obtained by dividing the number of apnea events by the hours of sleep (in minutes) and multiplying by 60, but for an apnea event to be considered as such, the airway collapse must be greater than 10 seconds. [38]. To know the number of apnea events suffering during the night, PSG studies are performed, which measure respiration, and heart rate, among others.

3.2.2. T2/T3/T4-defining input data/defining the output data/define the formulas and methods

Continuing with what was addressed in the previous task, we identified the following general information input data such as the age and sex of the patient, in addition, to medical history information such as the presence of snoring, level of daytime sleepiness, hours of sleep, diagnosis of arterial hypertension, body mass index (BMI) and the Epworth index. The algorithm must be able to determine whether the patient suffers from OSA or not. This information can be presented in two ways: in binary form, where it is represented by '1' if the patient has OSA and '0' if he/she does not, or in textual form. Furthermore, considering that the algorithm will be implemented in Python version 3, it was essential to examine the methods offered by the language. It was decided to use the decision tree (DT) classification model as the AI component to diagnose OSA, along with other approaches, such as len(), fit(), predict(), accuracy_score(), and confusion_matrix().

3.2.3. T5/T6-designing the pseudocode/design the flowchart

With the information gathered in the previous tasks, a pseudocode has been designed that covers the reading of the patient's data and their sleep habits. Complemented with the creation of the training and test sets, to preprocess the data and prepare them for the training of the model. Once this stage is completed, we proceed with the creation and training of the model, followed by the prediction phase. The flowchart of the algorithm was also designed considering the pseudocode developed in the previous task. The diagram is shown in Figure 2. Some parts of the flowchart use functions unique to the Python programming language that are impossible to illustrate in the graphic.

3.2.4. T7/T8-implementing the code/review and optimize the code

Based on the work done in tasks 5 and 6, we developed the code. First, we import the libraries train_test_split to split the dataset for training and testing, followed by DecisionTreeClassifier to classify the data, and finally the libraries accuracy_score and confusion_matrix to evaluate the classification accuracy. As input data, there are two blocks, the patient's data and his sleep data. In the patient's data, the patient's age, gender, and the Epworth sleepiness scale are requested, in the sleep data, the duration of sleep and the frequency of apneas per night. Subsequently, we create two lists or tuples for training and testing, each of these tuples stores 3 relevant patient data, such as patient data, sleep data, and diagnosis. For data preprocessing, we must separate the information contained in the tuple 'training_set' into two lists, one containing the first two data (patient and dream data) and the last one the diagnosis. We create the

variable 'model' which instantiates the DT class and with the method 'fit' we train the model with the training liSDs 'x' and 'y'.

```
model=DecisionTreeClassifier()
model.fit(x_training, y_training)
```

As a pre-finalization part, we use the 'predict' method to predict the data, with the 'accuracy_score()' method we calculate the accuracy of the prediction made, and with 'confusion_matrix()' we can see the performance of the method. Finally, the prediction is made, if the prediction of the model is equal to 1 the patient is diagnosed with OSA, otherwise, the condition is discarded. Finally, to optimize the data entry process we have changed the data reading to the read_csv method provided by the 'Pandas' library for reading 'csv' files. This is the only change applied to the algorithm.

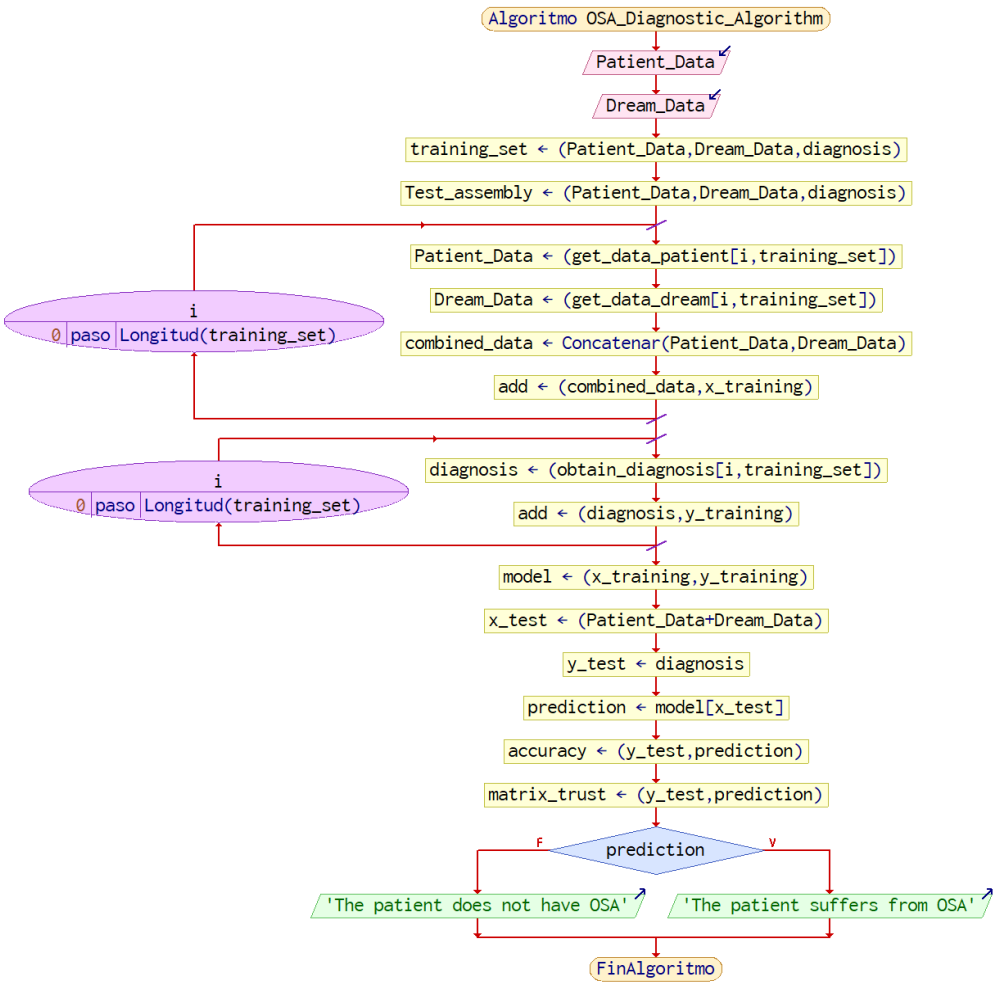

Figure 2. Flow diagram

3.3. Algorithm training

3.3.1. Training data set

For the training of the classification algorithm, access was requested to the database of the National Sleep Research Resource (NSRR), which has a repository of data on sleep, based on questionnaires and trials. Four databases were accessed: apnea positive pressure long-term efficacy study, apnea, bariatric surgery, and continuous positive airway pressure (CPAP) study, MrOS sleep study, and NCH sleep DataBank. After reviewing the four databases, the variables relevant to this project were selected and are described in Table 3. The final version of the training database was made in Excel with the format '.csv'.

Table 3. Training data set

Name	Data type	Description
nsrrid	int64	Patient registration ID
nsrr_age	int64	Age
nsrr_sex	int64	Sex
nsrr_bmi	float64	Body mass index
nsrr_ahi_hp3u	float64	Apnea-hypopnea index
nsrr_ttldursp_f1	int64	Sleeping hours
ess_total	int64	Epworth index
snoring	int64	Snoring
arterial_hypertension	int64	Arterial hypertension
daytime_sleepiness	int64	Daytime sleepiness
diagnosis	Originally object, then modified to int64	Diagnosis of OSA

3.3.1. Training

During the training phase of the model, two different data sets were incorporated. One was composed using data from the NSRR, while the other was created with information collected from a sleep clinic in Lima, Peru, during the first quarter of 2023, involving 39 patients. After completing the algorithm training process, the model generates a DT. In this tree, the main variable guiding the divisions is the Epworth test score. If this score is less than 9.5, the tree branches to the right. In case the result is equal to or greater than 9.5, the bifurcation occurs to the left, considering age as the main variable in this case, as illustrated in Figure 3. Subsequently, test data are loaded to predict and classify the condition of patients, where 1 is diagnosed with OSA and 0 is not suffering from it. In addition, the accuracy of the model is calculated, and the confusion matrix is printed. According to Table 4, we can see that in predicting negative OSA cases the algorithm has an accuracy of 85.71% and recall of 46.15%, in predicting positive OSA cases, the algorithm has an accuracy of 78.12% and recall of 96.15%. With these results, the algorithm has an accuracy of 79.49%. In Figure 4, we can appreciate the crossing of the data to be predicted versus what is being predicted, in the graph the value 0 is equivalent to not having OSA and 1 is equivalent to having it. In row 0, a total of 13 cases without OSA should have been predicted, 6 predictions were correct and 7 were wrong since they were predicted with a negative diagnosis of OSA, but they were positive cases. From row 1, 26 cases with OSA should have been predicted, 25 cases were predicted correctly, and one case was wrong.

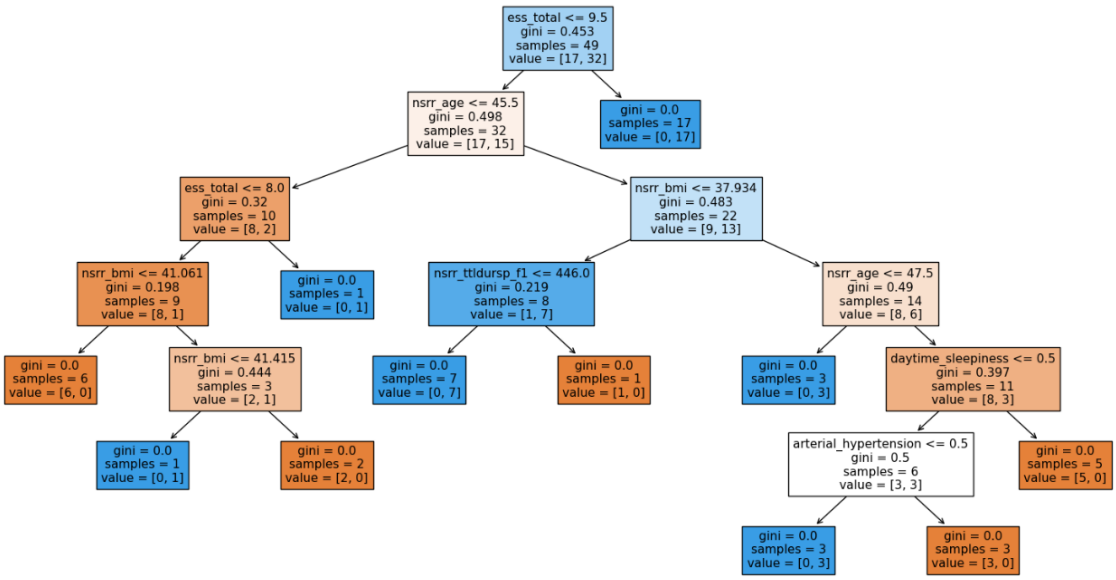

Figure 3. Decision tree graph

Table 4. Training results

	Precision	Recall	F1-score	Support
0	0.8571	0.4615	0.6000	13
1	0.7812	0.9615	0.8621	26
accuracy			0.7949	39
macro avg	0.8192	0.7115	0.7310	39
weighted avg	0.8065	0.7949	0.7747	39

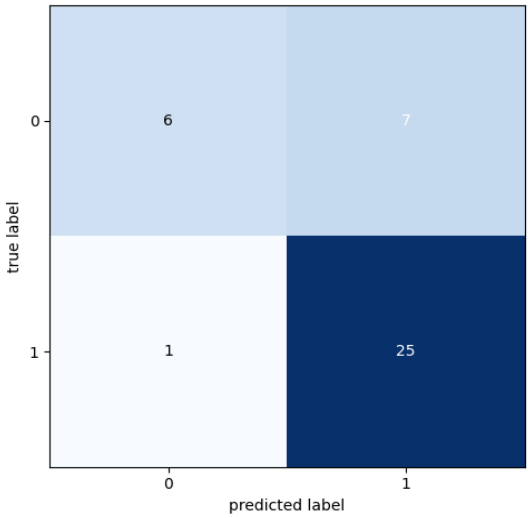

Figure 4. Confusion matrix

4. RESULTS AND DISCUSSION

4.1. Results

This study aimed to determine how an AI classification algorithm influences the diagnostic process of OSA. According to the theory, three key performance indicators (KPIs) were determined that are present in the diagnostic process. Pre- and post-results are detailed in indicator 1 (KPI1) to know the diagnostic accuracy of the clinical evaluation, indicator 2 (KPI2) to measure the diagnostic time, and indicator 3 (KPI3) to determine the number of tests with portable monitors.

4.1.1. Indicator 1 (KPI1)

In this section, we performed a descriptive analysis of the indicator "diagnostic accuracy of clinical evaluation". The contrast was made with the confirmation of cases of successful diagnosis of OSA with the use of clinical assessment, as shown in Table 5. In the pretest, a mean of 0.74 was obtained and for the posttest, it was 0.82. In addition, in Figure 5, we can see that in the pretest there is a percentage frequency of 74.4% of successful diagnoses without the use of PSG, and in the posttest 82.1% of successful diagnoses with the use of the algorithm. At the same time, diagnostic errors decreased from 25.6% in the pretest to 17.9% in the posttest. These results show an increase of 10.81% in the diagnostic accuracy of the clinical evaluation. Regarding the hypothesis test, McNemar's test was applied for qualitative variables. A significance level of 0.508 was obtained, which is greater than the significance level of 0.05, therefore, the null hypothesis (H0) is accepted, and the alternative hypothesis (H1) is rejected. Therefore, a classification algorithm with AI does not significantly influence the clinical evaluation of patients with suspected OSA in Lima-Peru, as shown in Table 6.

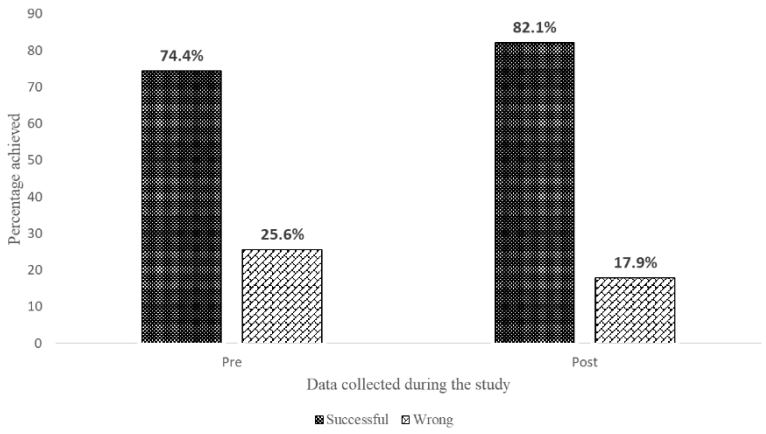

Figure 5. Bar chart of pre and post of KPI1: diagnosis accuracy of clinical evaluation

Table 5. Indicator 1 frequency data

		Pre Confirmation	Post Confirmation
N	Valid	39	39
	Lost	0	0
Media		0.74	0.82
Median		1	1
Fashion		1	1
Standard deviation		0.442	0.389
Variance		0.196	0.151
Minimum		0	0
Maximum		1	1
Sum		29	32
Percentiles	25	0	1
	50	1	1
	75	1	1

Table 6. Specific hypothesis test 1

	Pre Confirmation and Post Confirmation
N	39
Exact significance (bilateral)	.508b
a. McNemar test	
b. Binomial distribution used	

4.1.2. Indicator 2 (KPI2)

According to the results in Figure 6, the significance level in the pretest was 0.050 and, in the posttest, it was 0.021, in this case, one of the values did not exceed 0.05, so we can affirm that the data do not follow a normal distribution. Therefore, the Wilcoxon test is used for hypothesis testing. As shown in Table 7, after applying for the Wilcoxon test, a significance level of 0.001 was obtained, so the alternative hypothesis (H1) is accepted, and the null hypothesis (H0) is rejected. Therefore, a classification algorithm with AI significantly influences the use of PSG in patients with suspected OSA in Lima-Peru. In addition, Figure 7 details the pre and post KPI2: diagnostic time. According to the results, in the pretest, a mean of 12.85 was obtained and for the post-test, it was 9.23. With these results, a 28.17% decrease in diagnostic time is observed.

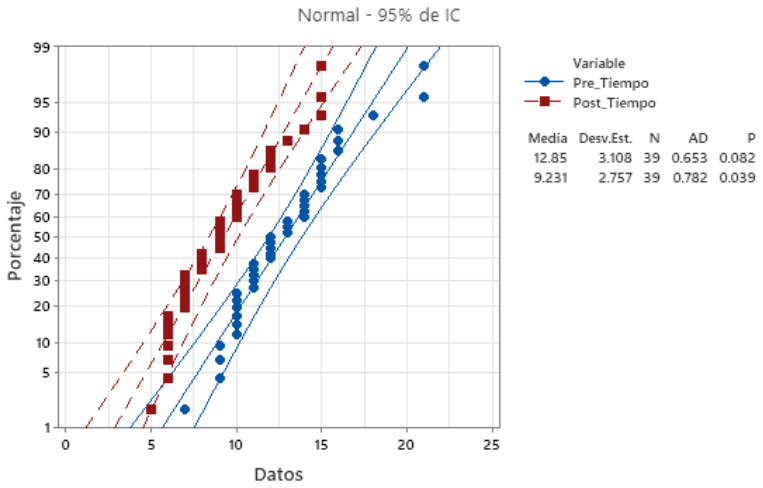

Figure 6. Normality plot of indicator 2

Table 7. Specific hypothesis contrast 2

	Post Time and Pre Time
Z	-4.404b
Sig. asin. (bilateral)	<.001
a. Wilcoxon signed-rank test	
b. It is based on positive ranges.	

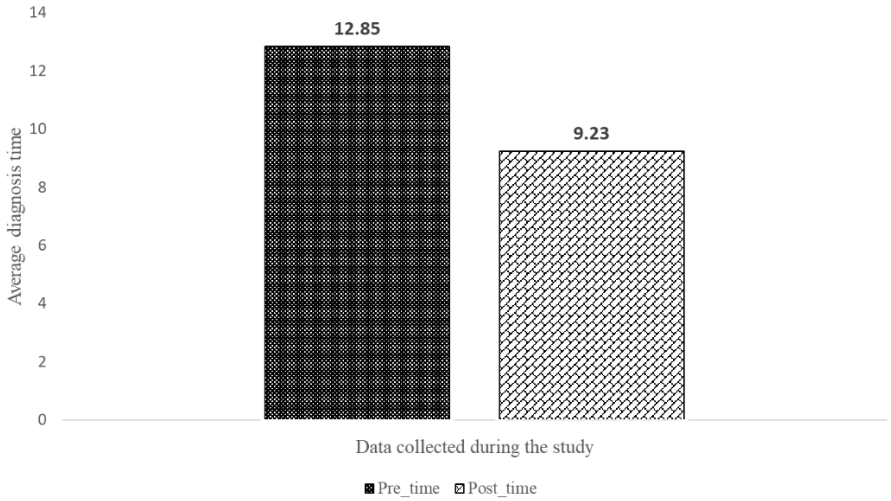

Figure 7. Bar chart of pre and post of KPI2: the diagnostic time

4.1.3. Indicator 3 (KPI3)

For indicator 3, which measures the number of tests with portable monitors for the diagnosis of OSA in patients, the normality test was performed as shown in Figure 8. According to the results, in the pretest, a level of 0.058 was obtained and in the posttest, it was 0.105, since both values did not exceed 0.05, we can affirm that the data do not follow a normal distribution. Therefore, the Wilcoxon test is used for hypothesis testing. According to Table 8, using the Wilcoxon test, a significance level of 0.001 was obtained, therefore, the alternative hypothesis (H1) is accepted, and the null hypothesis (H0) is rejected. Therefore, a classification algorithm with AI significantly influences the use of portable monitors in patients with suspected OSA in Lima-Peru. For KPI3, which measures the number of tests requested for the diagnosis of OSA, a mean pretest of 8.64 was achieved and for the post-test, it was 6.56. These results show a decrease of 24.07% in the number of tests requested with portable monitors, as shown in Figure 9.

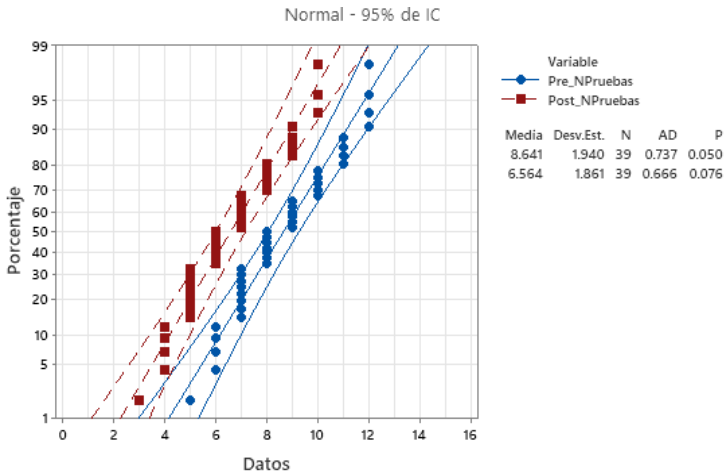

Figure 8. Normality plot of indicator 3

Table 8. Specific hypothesis test 3

	Post_Quantity and Pre_Quantity
Z	-5.889b
Sig. asin. (bilateral)	<.001
a. Wilcoxon signed-rank test	
b. It is based on positive ranges.	

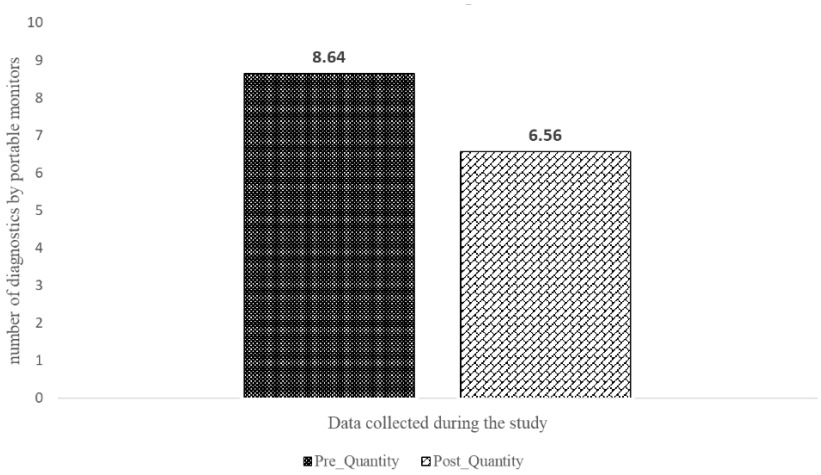

Figure 9. Bar chart of pre and post of KPI 3: number of tests with portable monitors

4.2. Discussion

The results obtained in this study reveal a moderate improvement of 10.81% in clinical diagnostic accuracy, which contrasts with previous studies, such as that of [34], where an increase in accuracy of 17.56% was reported when using ML models in a dataset composed of 83 patients with a mean age of 47 years. This discrepancy could be due to several factors, including differences in the datasets used, such as sample size, patient diversity, and case severity. It is possible that clinical data from patients with more heterogeneous characteristics or with a different distribution of disease severity were used in our study, which could explain a less pronounced improvement. Also, the method applied for algorithm development in this study may have influenced the results. While studies such as [32] observed reductions in diagnostic time between 38.16% and 51.81%, here a reduction of 28.17% was achieved. It is important to note that the algorithms used in [32] were based on different ML approaches, some of which may have been more robust or integrated more historical data, possibly facilitating a greater reduction in diagnostic time. In contrast, in our study, the algorithmic approach was more conservative and focused on improving diagnostic accuracy without significantly increasing computational complexity. In addition, when analyzing the use of portable monitors, this study reported a 24.07% reduction in the number of tests required, which partly coincides with the findings of [33], where 95% effectiveness was observed in the use of these devices compared with traditional PSG. However, a possible explanation for the differences lies in the fact that studies such as [33] used more advanced monitoring equipment or applied more rigorous evaluation criteria. Therefore, it is suggested that the results of this study could be improved by integrating more accurate devices and applying hybrid approaches that combine both algorithmic analysis and clinical experience. Finally, although no studies were identified that explicitly addressed the relationship between reduced diagnostic time and the use of portable monitors, research such as that of [32] suggests that the integration of more sophisticated data collection methods and more advanced models could generate an even greater reduction in the time and number of tests required. This reinforces the importance of exploring more advanced ML methods and considering more diverse databases to achieve better results in future studies.

5. CONCLUSION

The present study has demonstrated that the implementation of a classification algorithm with AI can influence the diagnostic process of OSA in Lima, Peru. Upon review of the results, it was observed that the algorithm had a limited impact on the accuracy of clinical diagnosis, with an improvement of 10.81%. However, a significant reduction in the time required for diagnosis was achieved, with a decrease of 28.17%. This fact indicates a positive impact of the algorithm in this aspect. Likewise, an improvement in the efficiency of requesting tests with portable monitors was observed, with a decrease of 24.07% in the number of requests made. However, the analysis of the confusion matrix revealed difficulties of the algorithm in ruling out false positives in the diagnosis of OSA, which, coupled with the limitations of the training dataset, constructed from multiple databases, indicates the need to explore other ML techniques and improve data quality to optimize model performance. To develop future studies, it would be essential to conduct additional research that focuses on expanding and diversifying the datasets used to train the algorithm, ensuring that they are representative of the population and clinical conditions specific to the region. In addition, the

implementation of active learning techniques, where the algorithm can learn from new data and improve its accuracy over time, could be explored. Finally, the integration of a classification algorithm with AI for the diagnosis of OSA in healthcare systems should be carefully planned. This involves collaboration with healthcare professionals to ensure that the algorithm fits into existing workflows and is used as a complementary tool in the diagnostic process, rather than replacing clinical judgment.

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Michael Cabanillas-Carbonell				✓	✓		✓	✓		✓		✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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