A Mobile Application for the Early Detection of ADHD Using Random Forest: The Case Study of Primary School Students in Peru

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ABSTRACT

Attention Deficit Hyperactivity Disorder (ADHD) is often underdiagnosed in schools due to the need for lengthy clinical assessments and a reduced number of specialists. Therefore, many children are not identified in time to receive support, especially in resource-scarce educational environments. This study developed a mobile application for the early screening of ADHD in primary school students, based on a Random Forest (RF) Machine Learning (ML) model trained with school-based data. The proposal was conducted in two stages: adaptation of the predictive model to the educational context and construction of the application with modules for digital questionnaires, longitudinal monitoring of each student, and visualization of the assessment results. To validate the proposal, the application was tested in a real school context and compared with the traditional clinical assessment method, where three main indicators were measured: time per student, completion rate of evaluations, and positive predictive value. The application reduced the average assessment time from 12 min to 4 min per student, maintained 100% completion rate of evaluations, and obtained a 100% positive predictive value. Overall, these results support the proposed application as a viable, effective, and reliable alternative for early ADHD screening in a school setting.

Keywords-Attention Deficit Hyperactivity Disorder (ADHD); Machine Learning (ML); Random Forest (RF); educational environment; behavioral data

I. INTRODUCTION

Attention Deficit Hyperactivity Disorder (ADHD) is one of the main challenges for learning, behavior, and school coexistence from the early years. In Peru, the Clinical Practice Guideline of the National Institute of Child Health San Borja estimates a prevalence close to 5% in the general population, with a higher proportion in boys (5–8%), which highlights the urgency of accessible and applicable screening strategies in the educational context [1]. In response to this challenge, various studies have explored the use of Machine Learning (ML) to support the diagnosis of ADHD. Authors in [2], using functional Near Infrared Spectroscopy (fNIRS) and Stroop tasks analyzed with Regularized Linear Discriminant Analysis (RLDA), were able to clinically distinguish between children with and without ADHD. Studies using resting-state functional Magnetic Resonance Imaging (fMRI) showed in [3] that transfer learning improved optimization in small samples, whereas in [4] improved classification performance was achieved using dynamic connectivity and deep learning models. In [5] and [6], the analysis of Electroencephalography (EEG) data using deep networks and Convolutional Neural Networks (CNNs) increased diagnostic accuracy. In adults, authors in [7] used multimodal physiology with wearable devices to detect patterns associated with ADHD. In pediatrics, authors in [8] combined time and frequency domains with deep learning, whereas authors in [9] proposed retinal biomarkers for non-invasive screening. Less costly alternatives include eye tracking with portable devices [10], mHealth applications with eye-tracking [11], and the combination of eye-tracking and Continuous Performance Tests (CPTs) [12], improving diagnostic performance. In [13], interpretable models such as Random Forest (RF) using clinical and school data showed good performance, whereas authors in [14] evaluated model fairness for use in school environments. Furthermore, authors in [15] and [16] applied deep networks to behavioral data and Go/NoGo tasks, supporting the validity of these approaches for ADHD classification.

In parallel, mobile applications have also been successfully used in the Peruvian educational context, for example to support English learning with virtual reality and gamification [17]. Finally, in a previous study [18], we compared ML algorithms on a set of questionnaires administered to primary school students, where the RF algorithm showed the best performance. On this basis, the present work proposes the development of a mobile application that implements this model to support early ADHD screening in the school environment.

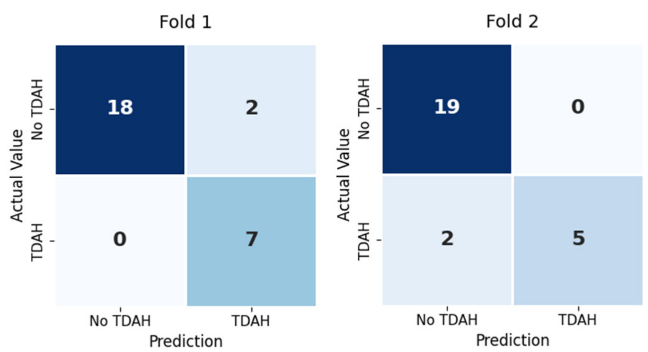
II. MATERIALS AND METHODS

A. Random Forest Analysis

According to the previous study [18], we worked with 116 complete records from an initial total of 139 respondents in a school context, using an instrument with 33 Likert-type variables covering five clinical dimensions and three control variables. Feature selection was performed in two stages: first, the importance of each variable was evaluated through permutation importance in a RF model, and then redundancy was eliminated by preserving, among highly correlated variables, those with greater importance, lower missing data rates, and better clinical interpretability.

This process reduced the feature set to 12 key variables related to impulsivity, social relationships, inattention, motor hyperactivity, and age, including indicators such as difficulty waiting for turns, interruptions, sensitivity to criticism, conflicts with peers, motor restlessness, and adaptation to new rules. These variables were prioritized based on clinical relevance and contribution to model performance.

The RF model was trained and evaluated using 5-fold stratified cross-validation, with fixed hyperparameter settings across all folds. The class distribution was: No ADHD = 85 (73.3%) and ADHD = 31 (26.7%), with a mean age of 8.42 ± 1.64 years (51.7% female). The RF model achieved the highest performance among the evaluated algorithms, reaching an accuracy of 93.3% (Figure 1).



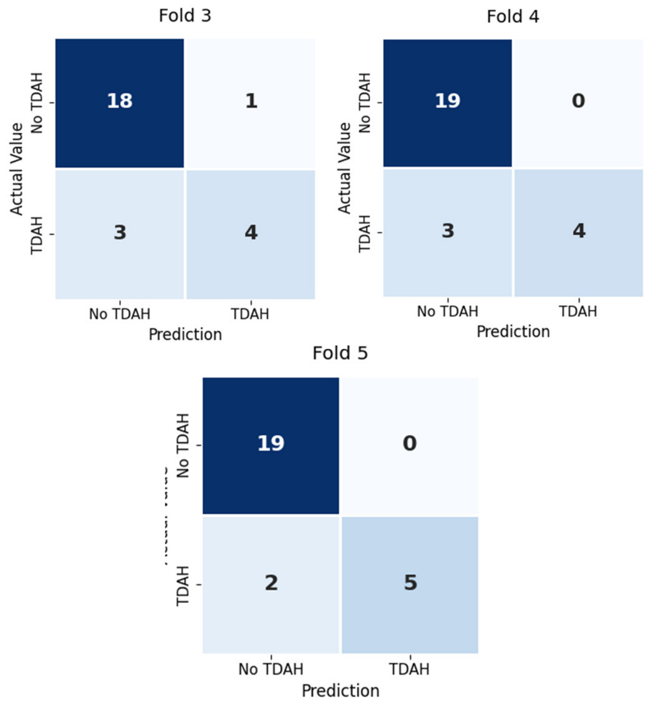


Fig. 1. RF confusion matrices (5-fold cross-validation).

B. Mobile Application Development

1) System Architecture Design

Figure 2 shows the logical architecture used, organized into four blocks: Front End, Security, Back End, and ML Model and Database components. The Front End corresponds to a mobile application developed in Flutter that captures questionnaire responses and consumes backend services. Client access is routed through an Application Programming Interface (API) gateway and an isolated Virtual Private Cloud (VPC), where access control policies and encryption in transit are applied. The application includes real-time validation, session management with short-duration tokens, and retry mechanisms for network interruptions, ensuring a consistent experience on Android and iOS devices.

The Database is implemented as a managed service within the VPC, separating transactional and analytical storage to optimize performance and costs. Transactional storage saves responses and metadata in a normalized, encrypted schema with restricted access, whereas analytical storage uses a columnar store for queries and model monitoring. Communication between services and databases uses secure connections and retry policies, and automatic backups and versioned migrations help preserve integrity and traceability.

The Back End consists of stateless microservices that orchestrate the data flow between the client, storage, and inference service. Implemented as serverless functions, these services scale automatically, reduce latency during usage peaks, and optimize resource consumption. The business layer normalizes and validates responses, persists records with metadata, and publishes events to an internal queue to decouple model invocation and improve resilience.

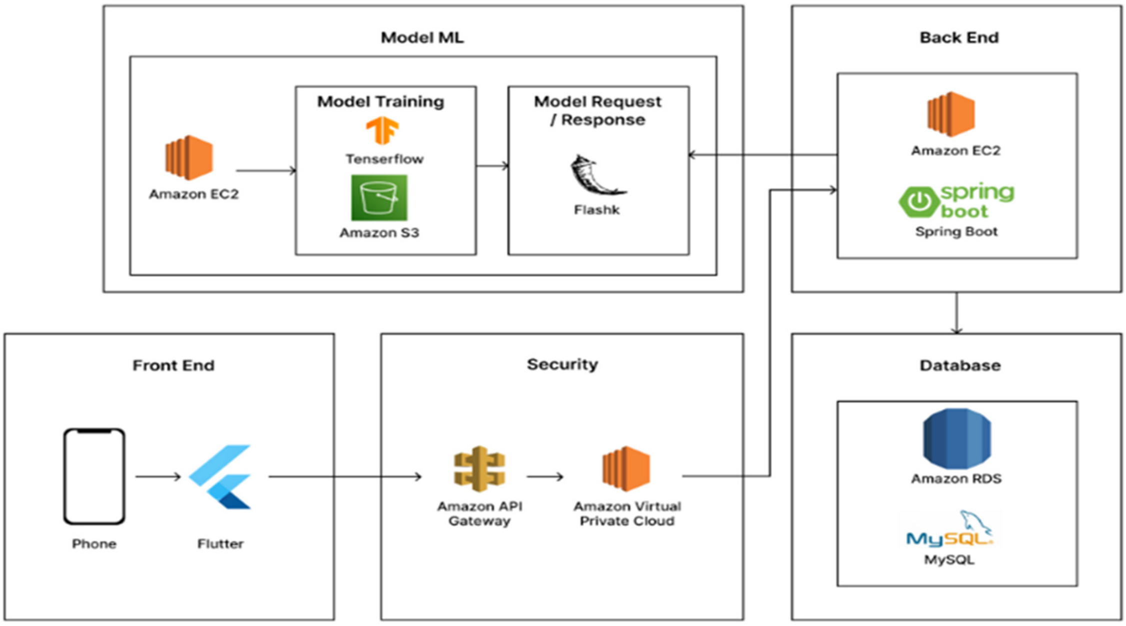


Fig. 2. Logical architecture of the application

The ML model is deployed as a versioned inference service accessible through a private endpoint within the VPC. The prediction pipeline receives the 12 preprocessed input variables, applies the same transformation schema used in training, and executes the RF algorithm to generate the class and its associated probability.

Security is implemented end-to-end through token-based authentication and authorization, TLS encryption, and traffic control policies. Within the VPC, segmented subnets and access control lists restrict access, and input validation helps prevent injections. Data at rest are encrypted with managed keys, sensitive information is anonymized, and audit logs are maintained to support compliance.

2) *Definition of Functionalities*

The main functionalities of the mobile application are as follows: add students, add teachers, add a guardian to a student, perform the ADHD test on a student, visualize student's results over time, view the details of a taken test, visualization of the score obtained in each section, edit teacher details, and edit student details.

III. EXPERIMENTATION

The validation of the proposal was carried out through two controlled experiments, comparing the traditional clinical method (E1) with the assessment assisted by the mobile application (E2) for ADHD screening. Both experiments were conducted with a sample of 30 primary school students, with the participation of 1 psychologist and 2 teachers, and were evaluated using 7 key metrics to determine their effectiveness and efficiency (Table I).

Figure 3 shows the sequence diagram corresponding to Experiment E1. This process is carried out entirely manually, involving the psychologist and the student, with information recorded on physical forms. The procedure is divided into four phases: initiation and preparation, standardized questionnaire, manual processing, and closure and report. The psychologist explains the procedure to the student (1) and conducts an interview to collect background information (2), while the student responds and provides clinical data. Then, the psychologist administers the paper-based questionnaire (3). In the manual processing phase, the psychologist transcribes the responses (4), checks for consistency and omissions (5), calculates scores (6), and interprets the results (7). Finally, they record observations (8), communicate results and recommendations (9), and close the case with the clinical report (10).

Figure 4 shows the sequence diagram of Experiment E2, which uses the proposed tool for ADHD detection. The teacher logs in and accesses the student module (1), while the application loads the list of students (2). The teacher selects the student and opens the digital test (3), and the student answers the questions by dimension (4). The application validates item completeness (5) and saves the responses upon completion (6–7). Subsequently, it sends the responses to the ML Service (8), which processes the data using ML (9) and generates a binary result and dimension scores (10). The results are automatically stored in the student's history (11), displayed instantly to the teacher (12), and notified to guardians (13). Finally, the teacher decides whether to administer another test (14–15) or log out (16).

TABLE I. EXPERIMENTAL DESIGN

Experiment	Subjects	Metrics
Standard clinical assessment (E1)	30 students, 1 psychologist	TS, CR, Sensitivity, Specificity, Accuracy, NPV, PPV
Clinical assessment with the application (E2)	30 students, 2 teachers	

Note: TS = Time per Student, CR = Completion Rate, NPV = Negative Predictive Value, PPV = Positive Predictive Value.

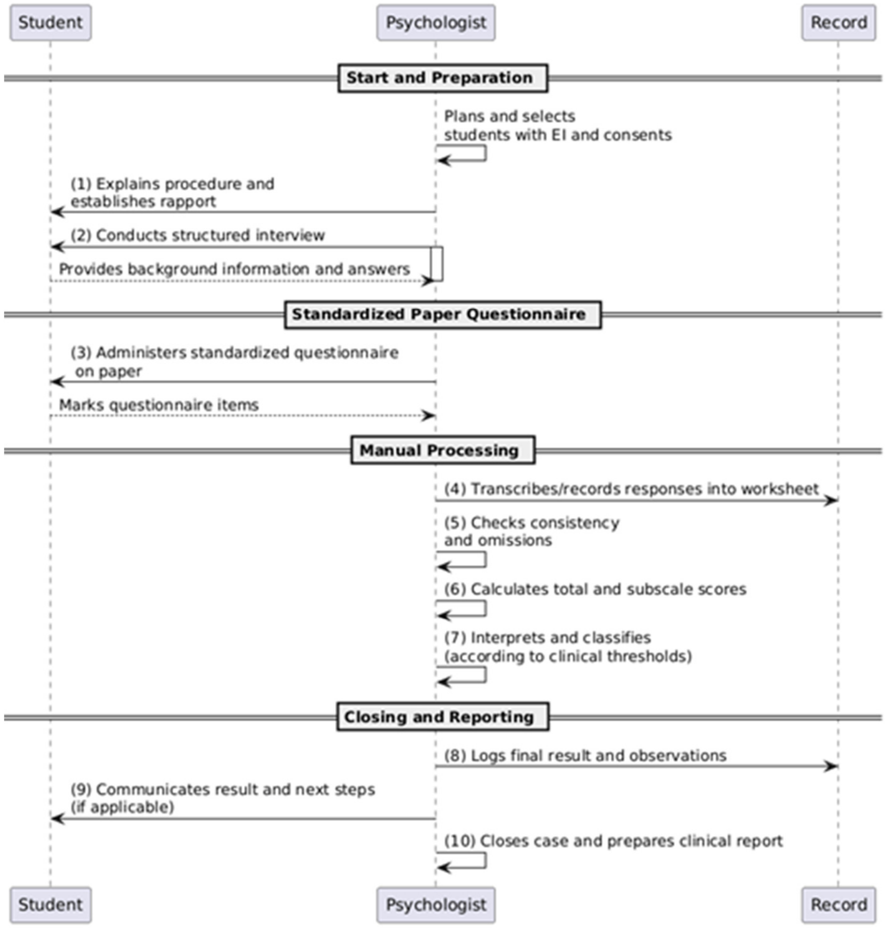


Fig. 3. Sequence diagram of Experiment E1.

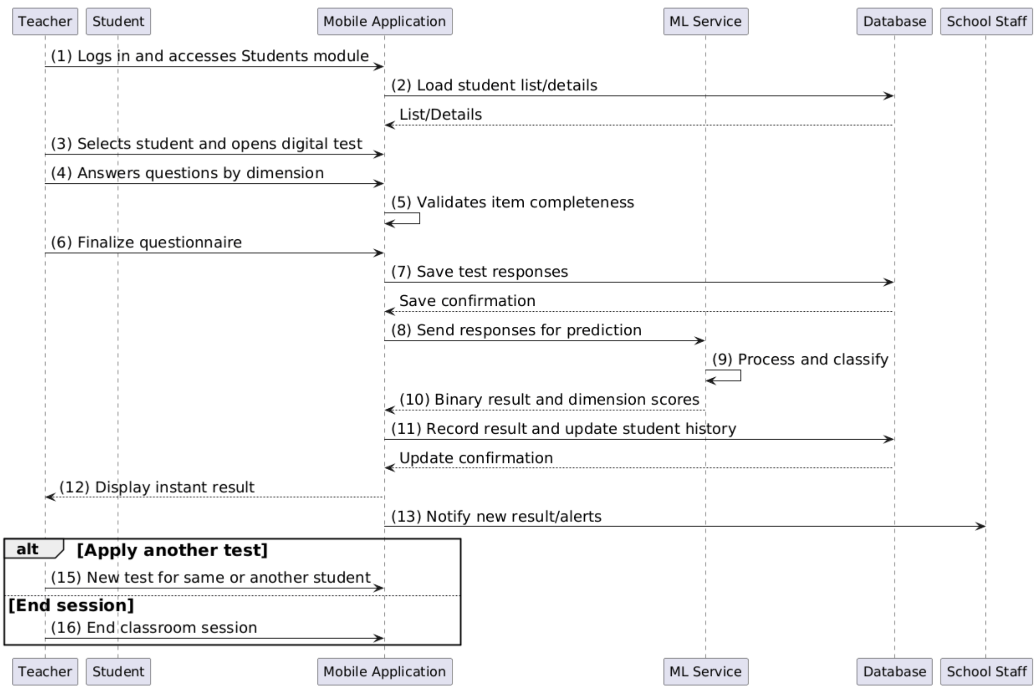


Fig. 4. Sequence diagram of Experiment E2.

The metrics used to evaluate the performance of the proposal were as follows:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \times 100 \quad (1)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \times 100 \quad (2)$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \times 100 \quad (3)$$

$$\text{PPV} = \frac{\text{TP}}{\text{TP+FP}} \quad (4)$$

$$\text{NPV} = \frac{\text{TN}}{\text{TN+FN}} \quad (5)$$

$$\text{TS} = \text{EE} - \text{SE} \quad (6)$$

$$\text{CR} = \frac{\text{NCE}}{\text{TNSE}} \times 100 \quad (7)$$

where:

- TP = app and psychologist agree on "Yes".
- TN = app and psychologist agree on "No".
- FP = app says "Yes" but psychologist says "No".
- FN = app says "No" but psychologist says "Yes".
- NPV (Negative Predictive Value) = proportion of cases classified as negative by the app that are truly negative according to the clinical reference.
- PPV (Positive Predictive Value) = proportion of cases classified as positive by the app that are truly positive.
- TS = time per student.
- CR = completion rate.
- EE = end of the evaluation.
- SE = start of the evaluation.
- NCE = number of completed evaluations.
- TNSE = total number of scheduled evaluations.

On the other hand, to assess the overall perception of the mobile application, a five-point Likert scale survey was designed (1 = Strongly disagree, 2 = Disagree, 3 = Neither agree nor disagree, 4 = Agree, 5 = Strongly agree). The questionnaire included 23 questions grouped into five categories with the aim of capturing users' actual experience during the administration of the tests (Table II).

IV. RESULTS AND DISCUSSION

A. *Experiment E1: Traditional Clinical Evaluation*

Figure 5 illustrates Experiment E1 conducted with a psychologist and a student through an interview. Table III presents the results for the 30 evaluated students, including the clinician's diagnosis and the time per case. Four students (8, 14, 24, and 30) were classified as showing signs of ADHD, whereas the remaining 26 showed no indications according to the clinical criteria. In terms of operational performance, evaluation times ranged from approximately 10 min to 15 min per student, with an average time close to 12 min. These results indicate a consistent and comprehensive evaluation process, with a 100% completion rate for all cases in the experiment.

TABLE II. QUESTIONNAIRE QUESTIONS

Ease of Use	
Q1	Was the application easy to learn after a brief explanation?
Q2	Were you able to navigate between the application's screens without difficulty?
Q3	Were the steps to administer the test to students clear?
Q4	Did you need additional help to complete the assessment?
Q5	Was navigation between the main sections (Home, Students, Settings) clear and not confusing?
Work Efficiency	
Q6	Does the application allow you to administer the test in less time compared to traditional methods?
Q7	Was the system's response time (when saving or processing data) adequate?
Q8	Do you consider the system's response time (less than 5 s to process tests) satisfactory?
Q9	Did you find the feature that allows administering multiple tests to the same student useful for tracking their progress?
Clarity and Presentation	
Q10	Were the test questions written clearly and easy to understand?
Q11	Was the visual design of the application (colors, icons, buttons) clear and appealing?
Q12	Was the information displayed on screen (results, messages) easy to interpret?
Q13	Do you think the progress charts and results timeline add value for monitoring students?
Application Features	
Q14	Was the visualization of results by clinical dimensions (inattention, hyperactivity, impulsivity) clear and easy to understand?
Q15	Were you able to register students with all their data (personal, academic, and photograph) without difficulty?
Q16	Did you find the student detail screen useful, as it centralizes tests, results, and available actions?
Q17	Did you receive mobile device notifications about results or alerts properly?
Q18	Were the visual alerts and notifications (when a high probability of ADHD is detected) timely and easy to identify?
Reliability and Satisfaction	
Q19	Do you trust that the results generated by the application reflect students' performance?
Q20	Did you feel comfortable administering the assessment using this tool?
Q21	Would you recommend the use of this application to other teachers?
Q22	Would you like to continue using the application in your classes?
Q23	Did you feel confident about the protection of personal and academic data when using the application?

TABLE III. RESULTS OBTAINED FROM EXPERIMENT E1

Student	ADHD	Time	Student	ADHD	Time
1	No	10:34	16	No	11:03
2	No	14:18	17	No	12:19
3	No	11:55	18	No	14:36
4	No	13:07	19	No	10:15
5	No	10:09	20	No	13:40
6	No	12:41	21	No	11:44
7	No	11:12	22	No	12:58
8	Yes	14:59	23	No	14:00
9	No	13:23	24	Yes	10:52
10	No	10:48	25	No	13:11
11	No	12:01	26	No	11:27
12	No	11:30	27	No	12:35
13	No	14:05	28	No	14:47
14	Yes	10:22	29	No	10:06
15	No	13:50	30	Yes	13:33

Fig. 5. Traditional clinical evaluation.

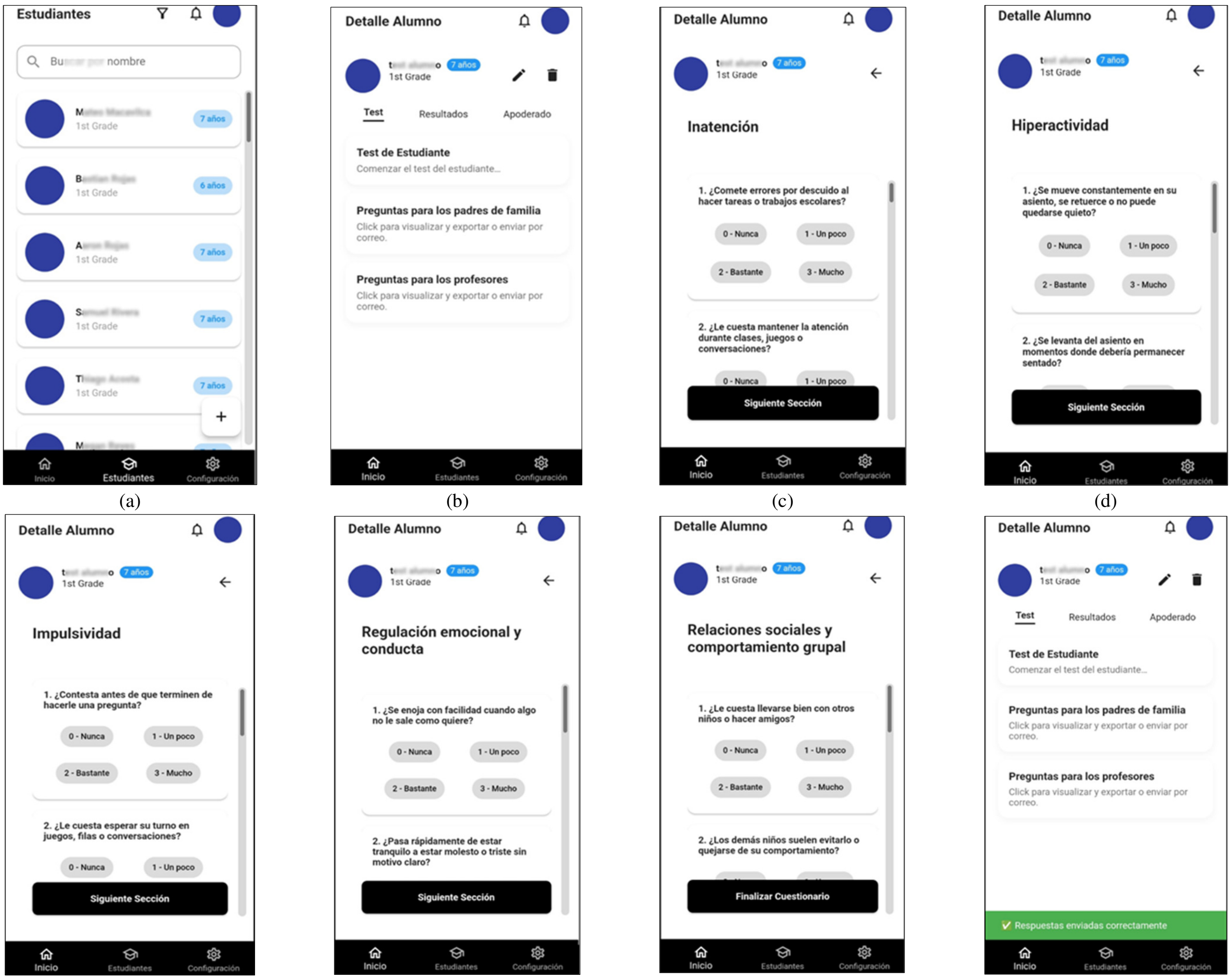
The data obtained were analyzed clinically, classifying participants according to the presence or absence of behaviors compatible with ADHD. Of the 30 students evaluated, four (13.3%) showed traits compatible with the disorder, characterized by manifestations of inattention, impulsivity, or disruptive behaviors observed in the classroom. The remaining 26 students (86.7%) did not present significant indicators.

B. Experiment E2: Clinical Evaluation with the Application

Figure 6 shows one of the teachers during the training session for the use of the application.

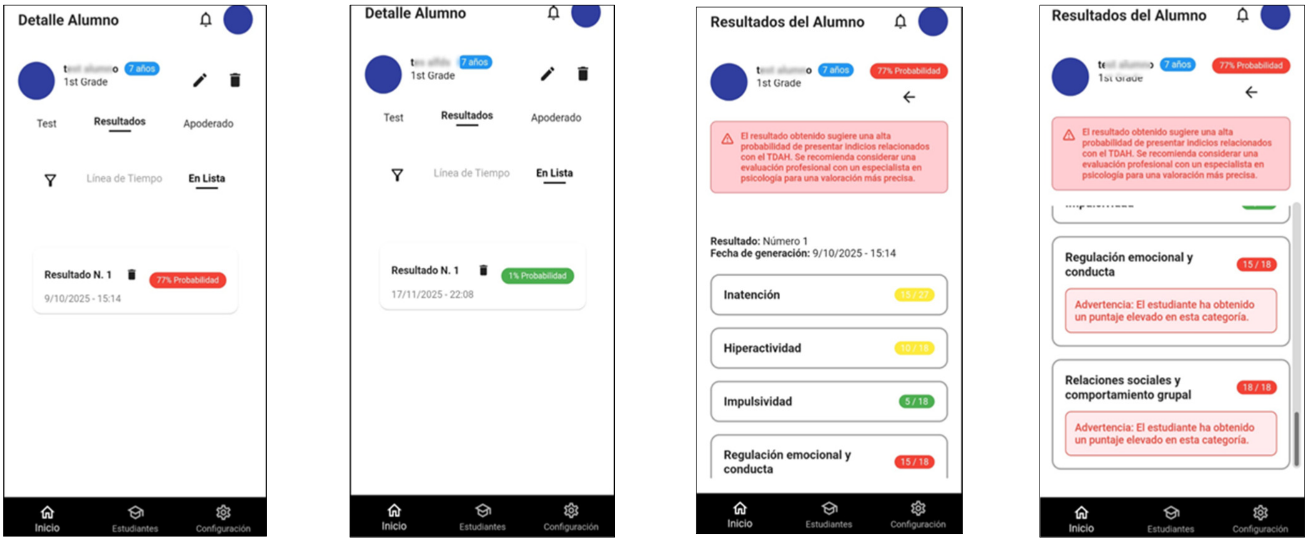
Fig. 6. Teacher during the training session for the use of the application.

Figure 7 illustrates the flow followed by the teacher within the application to administer and review an evaluation test for a student. The teacher accesses the Students screen (Figure 7(a)) and selects the student by clicking on their name. The detail screen is displayed (Figure 7(b)) with three views: "Test" to administer a new test, "Results" to review previous evaluations, and "Guardian" to assign a responsible adult. From "Test", the teacher accesses "Student Test" to start the evaluation.



(a) (b) (c) (d)

(e) (f) (g) (h)



(i) (j) (k) (l)

Fig. 7. Sequence of use of the mobile application during the administration of the digital test by the teachers: (a) Students screen, (b) student detail view, (c) inattention section, (d) hyperactivity section, (e) impulsivity section, (f) emotional regulation and behavior section, (g) social relationships and group behavior section, (h) completion confirmation, (i, j) results overview (detailed view), (k) test summary, and (l) dimension-level responses. (Note: The application interface is shown in its original Spanish version as used in the Peruvian school context.)

The questionnaire is organized by clinical dimensions: inattention (Figure 7(c)), hyperactivity (Figure 7(d)), impulsivity (Figure 7(e)), emotional regulation and behavior (Figure 7(f)), and social relationships and group behavior (Figure 7(g)). Each section is navigated vertically, and the system prevents moving forward without completing all questions. At the end, the teacher selects "Finish questionnaire", and a success message is displayed (Figure 7(h)).

To review the results, the teacher accesses the "Results" tab (Figures 7(i) and 7(j)), where students with probability of ADHD are shown in red and those without indications in green. When a test is selected, an overview is displayed (Figure 7(k)), and upon choosing a specific dimension, the individual responses are shown (Figure 7(l)).

Table IV presents the results obtained for the 30 students evaluated in Experiment E2, including the diagnosis generated by the model and the time required for each evaluation. In total, two students (students 14 and 30) were identified as having signs of ADHD. Evaluation time showed high efficiency, with an average close to 4 min per student.

Table V summarizes the impact of the mobile application on the operational efficiency of the screening process. First, the TS was reduced from 12 min in the traditional method to 4 min with the use of the application, indicating a substantial optimization in the duration of each evaluation. This improvement was achieved while maintaining a CR of 100% in both experiments, meaning that all scheduled evaluations were effectively carried out. In addition, the PPV of the application remained high, indicating that the cases identified as positive by the system correspond to students who actually present signs of ADHD, which reinforces the practical usefulness of the tool in school contexts.

TABLE IV. RESULTS OBTAINED FROM EXPERIMENT E2

Student	ADHD	Time	Student	ADHD	Time
1	No	03:45	16	No	04:48
2	No	04:12	17	No	03:36
3	No	03:08	18	No	04:19
4	No	04:59	19	No	03:03
5	No	03:21	20	No	04:52
6	No	04:33	21	No	03:25
7	No	03:50	22	No	04:10
8	No	04:01	23	No	03:58
9	No	03:15	24	No	04:04
10	No	04:40	25	No	03:18
11	No	03:29	26	No	04:44
12	No	04:07	27	No	03:30
13	No	03:55	28	No	04:27
14	Yes	04:22	29	No	03:06
15	No	03:11	30	Yes	04:55

TABLE V. COMPARISON OF PERFORMANCE METRICS BETWEEN EXPERIMENT E1 AND EXPERIMENT E2

Metric	Experiment E1	Experiment E2
TS (min)	12	4
CR (%)	100	100
Sensitivity (%)	100	50
Specificity (%)	100	100
Accuracy (%)	100	93.3
NPV (%)	100	92.8
PPV (%)	100	100

Taken together, the results show that the application offers a fast and efficient evaluation process, with high reliability metrics that position it as a robust tool for early ADHD screening.

Although the application demonstrated high specificity (100%) and overall accuracy (93.3%), sensitivity reached 50% in the experimental validation. This implies that, among the four students clinically identified as presenting ADHD indicators, the application correctly identified two. In the context of early screening tools, false negatives are particularly critical, as missed cases may delay referral and intervention. It is important to note that the experimental sample included a small number of positive cases (n = 4), which increases variability in sensitivity estimates. During cross-validation in the training phase, the RF model achieved an average recall of approximately 0.71 for the ADHD class, indicating more balanced performance under stratified conditions. However, real-world deployment with limited positive instances may reduce observed recall.

Future improvements will focus on increasing sensitivity through threshold adjustment strategies, cost-sensitive learning approaches that penalize false negatives more strongly, probability calibration techniques, and expansion of the dataset with a larger and more balanced sample. It is also emphasized that the proposed application is intended as a screening support tool rather than a diagnostic replacement. Students classified as negative but presenting persistent behavioral concerns should still be referred for professional clinical evaluation.

C. Survey

Figure 8 shows the results of the usability survey administered to the teachers regarding ease of use (Figure 8(a)), work efficiency (Figure 8(b)), clarity and presentation (Figure 8(c)), functionalities (Figure 8(d)), and reliability and satisfaction (Figure 8(e)), obtaining an average score of 4.70 ("strongly agree").

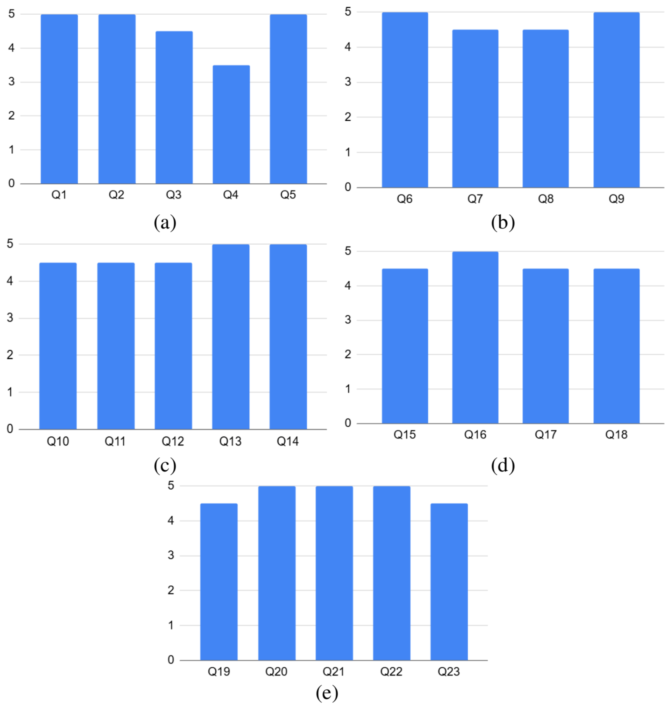


Fig. 8. Survey results: (a) ease of use, (b) work efficiency, (c) clarity and presentation, (d) functionalities, and (e) reliability and satisfaction.

D. Comparison with Other Studies

To contextualize the results, Table VI compares the proposed study with previous works on early ADHD detection [4, 7, 10, 12] using three attributes: low technological cost (A1), accuracy greater than 90% (A2), and use of non-invasive data or data without specialized equipment (A3). While several studies reach high accuracy or use advanced technologies, most are conducted in clinical or controlled environments and depend on specialized equipment, which limits their implementation in school settings.

TABLE VI. COMPARISON WITH SIMILAR WORKS

Work	Attributes		
	A1	**A2**	**A3**
Proposal	×	×	×
[4]	–	×	–
[7]	×	–	×
[10]	–	–	–
[12]	–	×	×

In contrast, the proposed system integrates an RF model into a low-cost mobile application, achieving high accuracy (93.3%) and using non-invasive observational data. It is the only approach in Table VI that simultaneously meets A1, A2, and A3, positioning it as a viable alternative for early screening in school contexts. However, the observed sensitivity indicates that further optimization is required to improve the identification of positive cases.

V. CONCLUSIONS

In this study, a mobile application was developed for early Attention Deficit Hyperactivity Disorder (ADHD) screening in school settings, based on a Random Forest (RF) model trained with observational data from the previous study [18]. The proposal was structured in two phases: (A) RF analysis and (B) mobile application development.

For validation, the traditional clinical method was compared with the assessment assisted by the mobile application through two controlled experiments with the same sample of students, using metrics such as Time per Student (TS), Completion Rate (CR), sensitivity, specificity, accuracy, Negative Predictive Value (NPV), and Positive Predictive Value (PPV). The results showed that the mobile application significantly reduced the evaluation time per student while maintaining a CR of 100% and a high PPV, confirming its efficiency and reliability as a support tool for early ADHD screening in educational environments.

The main novelty of this work lies in translating an ADHD detection model based on school-observable behavioral variables into a mobile application that can be used directly in a real educational context in Peru. Unlike previous studies that rely on specialized modalities such as Electroencephalography (EEG), functional Near Infrared Spectroscopy (fNIRS), functional Magnetic Resonance Imaging (fMRI), retinal imaging, or eye-tracking, this study contributes a low-cost and operational alternative oriented toward routine school screening. From a knowledge contribution perspective, the study adds evidence that Machine Learning (ML) models can be embedded into practical digital tools for educational environments, enabling faster first-level screening, systematic recording of student history, and immediate support for referral decisions without replacing clinical diagnosis.

As future work, it is proposed to extend the research with a larger and more diverse sample to improve generalizability and increase sensitivity. Additionally, new sources of information such as longitudinal behavioral records, neuropsychological measures, or assisted observational data could be incorporated. Future work should also evaluate cost-sensitive learning approaches, implement probability calibration techniques, and adjust the classification threshold to prioritize recall in screening scenarios. These improvements could contribute to a more robust system capable of supporting large-scale early detection initiatives in educational contexts.

DECLARATION OF COMPETING INTERESTS

Not applicable to this work.

ACKNOWLEDGMENT

We would like to thank the participating families and educational institutions for their collaboration in data collection, and the Research Department of the Universidad Peruana de Ciencias Aplicadas for supporting this study through the UPC-Expost-2026-1 incentive.

ETHICAL CONSIDERATIONS

This study was conducted in accordance with ethical standards for research involving minors in educational settings. Prior to data collection, formal authorization was obtained from the participating educational institution. Written informed consent was obtained from the legal guardians of all participating students. In addition, age-appropriate verbal assent was requested from the students before administering the questionnaires. Participation was voluntary, and families were informed of their right to withdraw at any time without academic or personal consequences. All collected data were anonymized prior to analysis. Personally identifiable information was separated from analytical datasets and stored using encrypted mechanisms. Data handling procedures complied with institutional guidelines and applicable data protection regulations concerning research involving minors.

DATA AVAILABILITY

The dataset used in this study contains sensitive information from minors and is therefore not publicly available. De-identified data may be made available upon reasonable request to the corresponding author, subject to institutional authorization and compliance with applicable data protection regulations.

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