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PAPER

Web Application Based on Artificial Intelligence for the Control of Healthy Habits in People with Unbalanced Diet in Lima

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ABSTRACT

This study presents the development of a web application designed to promote healthy habits using artificial intelligence, targeting people aged 18 to 50 years in Lima, Peru, who struggle with overweight or unbalanced diets. The application integrates personalized meal plans and exercise routines generated by machine learning algorithms based on users' health data. The system architecture includes a frontend built with Flutter and a backend using Spring Boot and Java, communicating with a Flask API that processes data with Random Forest models. Data from national health surveys and Kaggle nutrition and exercise databases were used to train the models. The usability of the application was validated through user satisfaction surveys and predictive model performance metrics. The results indicate that the app effectively helps users manage their eating and physical activity habits, with the meals model achieving an accuracy of 92.38%, recall of 93.47%, F1 score of 91.19%, and AUC-ROC of 91.41%, and the exercise model achieving an accuracy of 78.09%, recall of 76.28%, F1 score of 88.23%, and AUC-ROC of 94.90%, thus contributing to healthier lifestyles.

KEYWORDS

artificial intelligence, healthcare, web application, machine learning, weight control, food recommendation, exercise routine assistance

1 INTRODUCTION

Obesity and overweight have been the most common health problems in Peru in recent years. 41.4% of the population aged 15 years and older has one or more health-related risk factors, including high blood pressure, type 2 diabetes, or obesity. Namely, 36.9% of the population aged 15 years and older is overweight, 25.8% is obese, and 62.7% is overweight. When comparing this information with the results of the previous year, there was a significant increase of 1.2% in the case of obesity [1].

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In Peru, overweight and obesity in adults are increasing significantly. By 2022, obesity reached 27.8% in urban areas and 16.2% in rural areas; overweight was 38.5% and 32.8%, respectively. It is estimated that by 2035, 35% of Peruvian adults will be obese. This increase poses a considerable public health challenge, with impacts on cardiovascular diseases and diabetes, which demands effective policies and promotion of healthy habits to mitigate this problem [2].

Excessive fat diets, sedentary work, mobility, and reduced physical exercise due to urbanization are the main causes of obesity and overweight in people. In the same way, the lack of interest in agriculture, health, urban planning, transportation, and food distribution sectors generates an imbalance in the diet and in the daily routine. Consequently, the risk of musculoskeletal disorders, cardiovascular diseases, and some cancers increases their rate of occurrence. For example, childhood obesity is related to a higher risk of premature death and difficulties in adulthood. Also, children with this condition are more likely to suffer from breathing difficulties, more fragile bones, high blood pressure, insulin resistance, and psychological effects [3]. It is expected that by 2035, more than 50% of the world's population will be overweight and obese. It is imperative to implement comprehensive actions and evidence-based policies to promote healthier lifestyles and prevent diseases related to overweight and obesity [4].

Currently, there are several proposals aimed at improving the quality of life of people who are overweight or obese. These solutions employ different artificial intelligence approaches. In the field of supervised learning, classification [5, 6, 7, 8, 9] and regression [10, 11, 12] algorithms have been proposed. Furthermore, in the field of machine learning, applications of neural networks [13, 14, 15, 16] and deep learning [17, 18, 19, 20] stand out. Despite the novel techniques used to benefit health, it has been identified that most of these studies are more focused on the detection and control, but not on the prevention, of obesity.

We propose a web application capable of interacting with users who present nutritional difficulties and imbalances. After obtaining their health information to obtain their basal metabolic rate and assign the number of macronutrients to be ingested in daily meals, it also includes a daily exercise routine to achieve a goal in reducing weight healthily.

Thus, this study aims to explore whether an artificial intelligence-based application, which personalizes meal plans and exercise routines, can significantly improve users' eating habits and contribute to weight loss. The hypothesis driving this study is that personalized food and exercise recommendations based on artificial intelligence can lead to measurable improvements in users' health, specifically in reducing their body mass index (BMI) and improving overall well-being.

In this paper, Section 2 provides an analysis of the existing literature, Section 3 details the design of the proposal, Section 4 presents the results obtained, and Section 5 is dedicated to the discussion. Finally, Section 6 presents the conclusions of the study.

2 RELATED WORKS

Various systems have been proposed to assist individuals in managing their diet and exercise routines, incorporating artificial intelligence and machine learning techniques. For example, [5] describes a system using progressive web applications (PWA) and smart devices for meal plan management. The system allows users to visualize their meal plans, track their food and water consumption, and generate personalized meal plans using machine learning and IoT devices. However, while this approach reduces human-computer interaction, the system's high interaction cost, such as 8.66 seconds per food item addition, highlights a potential inefficiency in user experience. This presents an opportunity for improvement, which our application addresses by streamlining data input processes and providing more seamless interactions through a mobile interface.

On a different note, [15] focuses on the management of exercise plans for people with type 1 diabetes, incorporating decision trees to manage blood glucose during physical activity, recommending food supplements, and preventing hypoglycemia. While the system's focus on diabetes is critical, it underscores a limitation in current systems: most health applications, including this one, target specific conditions and may not offer comprehensive solutions for the general population. Our web application, by contrast, aims to provide an integrated approach to weight management, offering personalized meal and exercise recommendations for users with varying health conditions, including those with overweight or unbalanced diets.

In the realm of personalized recommendations, [14] proposes a lipid profile prediction model using non-invasive, cost-effective diagnostics, such as BMI and waist-to-height ratio (WHtR). While this approach offers a cost-effective solution for personalized health insights, it does not incorporate dynamic adjustments based on real-time user feedback. This is where our application provides an advantage: by continuously adapting meal and exercise plans based on user feedback, our system not only offers recommendations but also evolves with the user's progress, enabling more effective and sustainable health management.

Another innovative approach is presented by [6], where images of meals are captured to estimate nutritional content. The system uses computer vision to classify food types, calculate portion sizes, and determine macronutrient content. While this method is accurate, it relies heavily on image quality and user engagement in capturing the right angles. In contrast, our application focuses on simplicity by asking users to input basic health data, such as age and weight, to generate tailored recommendations, reducing the dependence on image-based input and enhancing user accessibility.

Furthermore, [17] and [12] present hybrid models that combine collaborative filtering and knowledge-based systems for food recommendations, adapting to users' preferences and health conditions. While these models emphasize customization, they still require substantial user input to fine-tune the recommendations. Our approach builds upon these models by incorporating continuous machine learning feedback loops, ensuring that the system becomes increasingly personalized over time, not only based on static preferences but also adapting to changes in users' health status.

Finally, while previous work, such as [9], has focused on exercise recommendations through specific modules like resting heart rate prediction, these systems often fail to integrate dietary and physical activity recommendations into one seamless platform. In contrast, our system combines both dietary and exercise recommendations in a unified application, offering a more comprehensive solution for users seeking to improve both their eating habits and physical activity levels.

3 OVERVIEW OF THE PROPOSED SYSTEM

The design of a web application using artificial intelligence to recommend healthy recipes and exercises is proposed. The design includes an artificial intelligence model, backend application architecture, and frontend application architecture. The model uses machine learning in its development and is divided into phases: i) User data processing at registration, ii) Generation of food plans for the user, iii) Generation of physical activity plans for the user, iv) User feedback on the generated plans, and v) Updating of the generated plans.

The first phase consists of storing the user's personal data, medical history, food and meal preferences, and goals. This information, apart from being recorded, will be analyzed by the model to identify previous profiles like the user's and the most efficient plans.

The second phase consists of generating a meal plan for the new user, considering the information entered in the registration and the most efficient meal plans of previous users with a similar profile.

The third phase consists of generating a physical activity plan for the new user, considering the information entered in the registry and the most efficient physical activity plans of previous users with a similar profile.

The fourth phase consists of analyzing the scores made by the user about the satisfaction of their eating and physical activity plans from the oldest to the most recent plan.

The last phase consists of updating the current food and physical activity plans considering the previous feedback phase. The backend application uses REST architecture in its development, having as a focus Domain Driven Design, a distributed software design approach in bounded contexts, controllers, services, repositories, and entities, among other elements that allow distributing the core and secondary content of the project. The frontend application uses Node.js in its development.

The content will be distributed in pages and components according to the number of windows, widgets, and user roles for the project. The windows are Login, Registration, Set preferences and goals, Welcome window, Meal plan management, and Physical activity plan management. The login window prompts for the username and password fields to authenticate. The registration window asks for the fields related to the user's personal data and medical history. It also allows the user to select the preferred foods and meals and the goals he/she wishes to achieve with respect to his/her health.

The welcome window displays the user's general information and list of daily activities in a general way of his plans. The meal plan management window displays the user's meal plan, the list of activities to be performed and performed filtered by day/week/month, and the user's progress at the dietary level. The physical activity plan management window displays the user's exercise plan, the list of activities to be performed and performed filtered by day/week/month, and the user's progress at the physical level. In the plan management windows, periodically, the user will be asked to rate the efficiency of the generated plan; the rating consists of answering questions with answers to mark and write.

3.1 Architecture

Physical architecture. Users interact with the frontend application (Flutter and Dart). It sends requests to an API (Spring Boot and Java) that manages the system logic. The API accesses a file system and a PostgreSQL database. In addition, it communicates with an AI model that analyzes data and returns recommendations (see Figure 1).

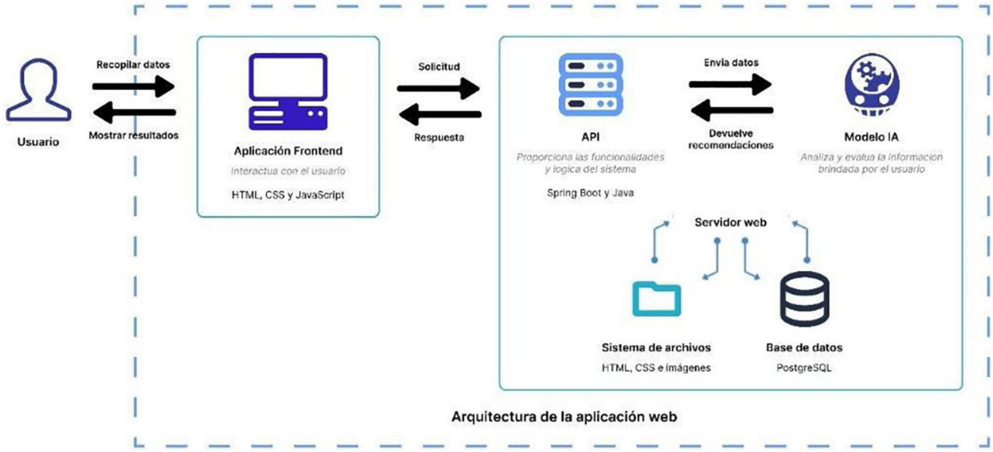

Fig. 1. Diagram of the proposed solution

Logical architecture. This type of diagram is used to represent the architecture of applications and systems running in the Amazon Web Services (AWS) cloud. Users access the application through Amazon CloudFront, which distributes the content. Amazon EC2 manages the application logic, and Amazon RDS stores the data. Amazon S3 is used for data storage, while Amazon SageMaker and SageMaker Studio Notebook facilitate model development and deployment. The entire solution is contained in a VPC to ensure security and isolation (see Figure 2).

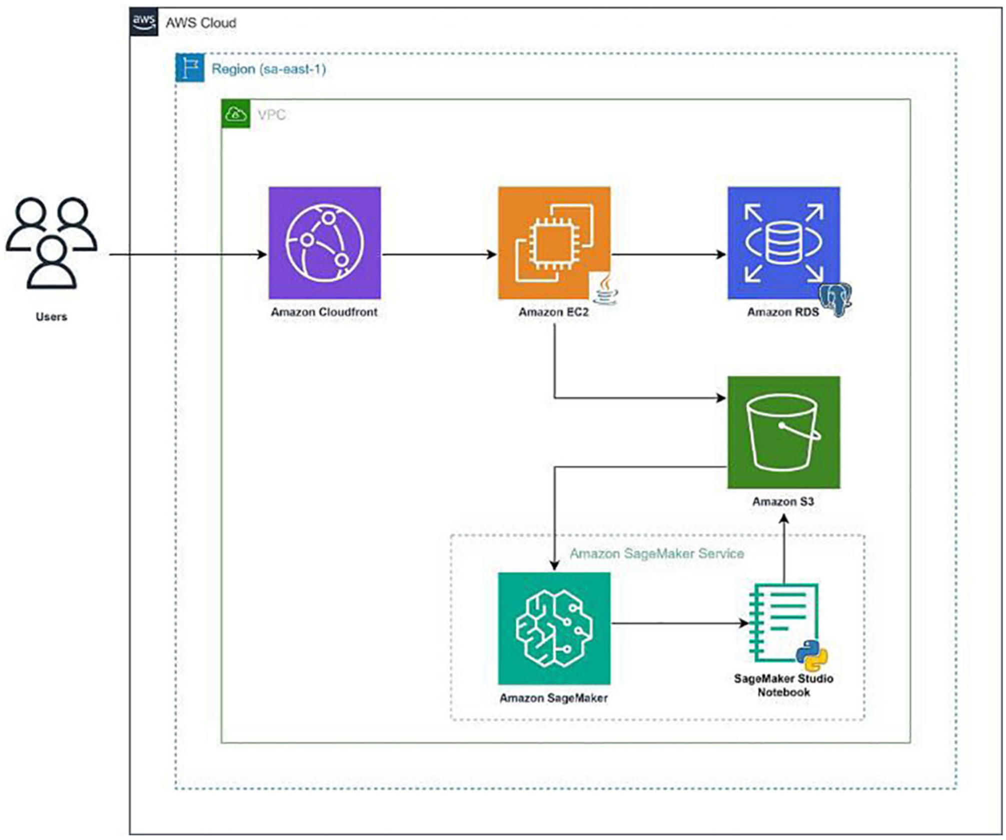

Fig. 2. Diagram of the architecture using instances in AWS

3.2 Model

This project focuses on the creation of predictive models to recommend exercises and daily meals based on various physical and nutritional parameters of the users. Machine learning techniques have been used to train models capable of providing personalized recommendations.

Methodology. The methodology followed in this project includes several key steps:

- Data Collection: A data set was collected that included information on abdominal circumference, physical activity, macronutrient intake and types of meals, as well as recommended exercises.
- Data preprocessing: Data were cleaned and transformed, including conversion of categorical variables to numerical values using factoring techniques.
- Feature Selection: Relevant features were selected for the exercise and meal prediction models. For exercises, columns such as "AbdominalCircumference" and "PhysicalActivity" were selected. For meals, columns related to caloric deficit and macronutrients for each meal were selected.
- Division of the Dataset: The data set was divided into training (80%) and test (20%) subsets to validate the performance of the models.

Machine learning algorithm. The Random Forest algorithm was selected for exercise and meal prediction because of its robustness and ability to handle data sets with multiple features. Random Forest is a set of decision trees that works as follows:

- Training: Independent models were trained for each of the target columns (exercise and meals) using a set of decision trees (see Figure 3).
- Prediction: Each model generates predictions for the target columns based on the input features provided.
- Assembly: The predictions from the different trees are combined to produce a final prediction that is more accurate and less prone to overfitting the training data.

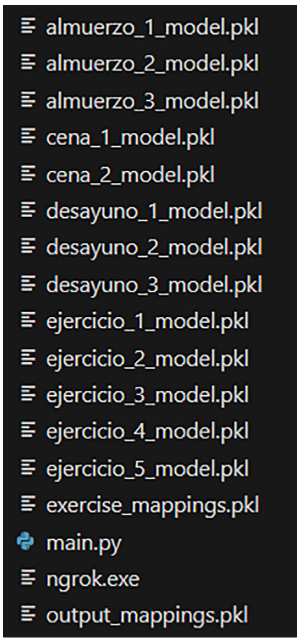

Fig. 3. Models created for the prediction of each meal and exercise

API flask. To integrate these models with the main backend, an API was developed in Flask. The API allows the backend, which is developed in SpringBoot, to communicate with the models created in Python to receive the meal and exercise recommendations. In Figure 4, the API receives JSON requests, processes the data, and returns the predictions in a format accessible to the main system. This implementation ensures a smooth and efficient integration for the generation of meal and exercise recommendations.

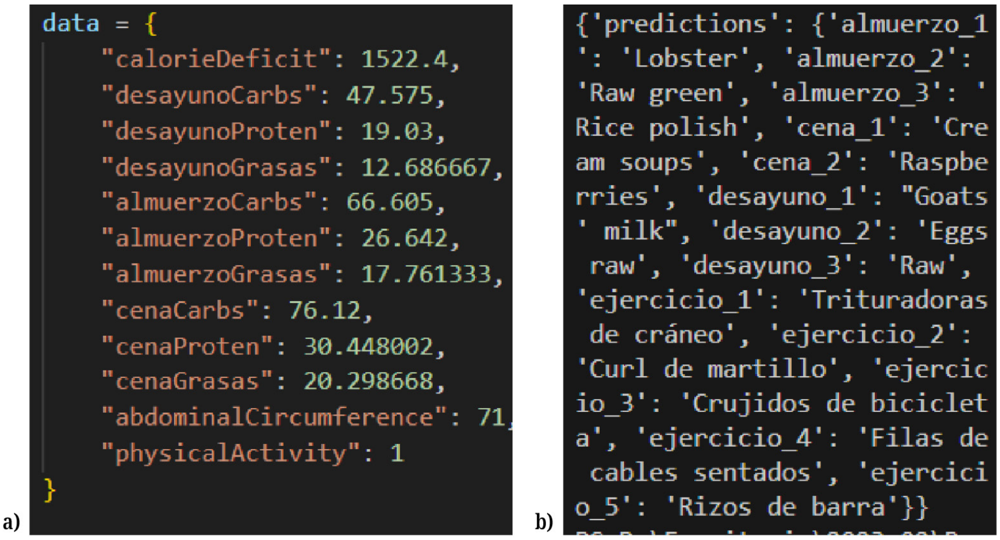

Fig. 4. Model: (a) Input data (b) Predictions

3.3 Datasets

Three databases have been used for this work:

i) *Demographic and Family Health Survey (ENDES).* The first database was obtained from the ENDES, elaborated by the National Institute of Statistics and Informatics (INEI) in 2022. This survey provides a rich source of data on the Peruvian population, including detailed information on the health of individuals. Data were filtered from people over 18 years old who filled in their personal health-related information, such as gender, age, weight, height, abdominal perimeter, and chronic diseases such as diabetes.

ii) *Kaggle (Food).* The second database was obtained from Kaggle, an online platform that hosts a wide variety of datasets from different domains. This specific database provides nutritional information on various foods, including categories such as dairy, fruits, fats, and oils, among others. Relevant data were selected that would allow the creation of personalized nutritional recommendations.

iii) *Kaggle (Exercises).* The third database, also obtained from Kaggle, contains detailed information on physical exercises. This database includes data on the type of exercise, the recommended number of repetitions, the intensity, and the areas of the body worked in each exercise. This data is essential for generating recommendations of suitable exercise routines for users.

Data preparation and data cleaning. Data preparation and cleaning are critical steps to ensure the quality and accuracy of machine learning models. The initial dataset from the DHS survey contained more than 80 columns, many of which were not relevant to our model. A manual removal of attributes was performed, keeping only those necessary for the nutrition and exercise calculations.

To process the data, the following steps were followed:

- *Data Type Conversion*: Weight and height columns were converted to numerical values, handling errors and missing values. Age was converted to integers, and gender and physical activity columns were treated as text strings.
- *Calculation of Basal Metabolic Rate (BMR)*: Different BMR formulas (Mifflin, FAO/OMS, and Harris-Benedict) were calculated based on weight, height, age, gender, and level of physical activity. Weight in kg and height in cm were considered as units for weight and height in cm (refer to Table 1).

Table 1. Formula to find the BMR

Formula	Calculation
Mifflin-St Jeor	Males: BMR = (10 × Weight) + (6.25 × Height) – (5 × Age) + 5 Women: BMR = (10 × Weight) + (6.25 × Height) – (5 × Age) – 161 Little or no exercise = BMR × 1.2. Light exercise (1–3 days per week) = BMR × 1,375. Moderate exercise (3–5 days per week) = BMR × 1.55. Heavy exercise (6–7 days per week) = BMR × 1,725. Very heavy exercise (twice a day, very hard workouts) = BMR × 1.9.
FAO/OMS	• 0–3 years Males: BMR = (60.9 × Weight) – 54 Women: BMR = (61.0 × Weight) – 51 • 3–10 years Males: BMR = (22.7 × Weight) + 495 Women: BMR = (22.5 × Weight) + 499
	• 10–18 years Males: BMR = (17.5 × Weight) + 651 Women: BMR = (12.2 × Weight) + 746 • 18–30 years Males: BMR = (15.3 × Weight) + 679 Women: BMR = (14.7 × Weight) + 496 • 30–60 years Males: BMR = (11.6 × Weight) + 879 Women: BMR = (8.7 × Weight) + 829 • Over 60 years old Males: BMR = (13.5 × Weight) + 487 Women: BMR = (10.5 × Weight) + 596

(Continued)

Table 1. Formula to find the BMR *(Continued)*

Formula	Calculation
Harris-Benedict	Males: BMR = 66.5 + (13.75 × Weight) + (5.003 × Height) – (6.78 × Age) Women: BMR = 655 + (9.56 × Weight) + (1.85 × Height) – (4.68 × Age) Little or no exercise = BMR × 1.2. Light exercise (1–3 days per week) = BMR × 1,375. Moderate exercise (3–5 days per week) = BMR × 1.55. Heavy exercise (6–7 days per week) = BMR × 1,725. Very heavy exercise (twice a day, very hard workouts) = BMR × 1.9.

The selection of the appropriate formula was made according to BMI classification and physical activity level (refer to Table 2).

Table 2. Choice of formula to find BMR based on patient's BMI

Body Mass Index	$BMI = \frac{Weight}{\left(\left(\frac{Height}{100}\right)^2\right)}$ • Insufficient Weight $BMI \leq 18.5$ • Normal Weight $18.6 \leq BMI \leq 24.9$ • Overweight $25.0 \leq BMI \leq 29.9$ • Obesity Type 1 $30.0 \leq BMI \leq 34.9$ • Obesity Type 2 $35.0 \leq BMI \leq 39.9$ • Obesity Type 3 $BMI \geq 40.0$

Based on the patient's personal information, the most appropriate formula is assigned to calculate BMI (see Figure 5).

```
def calcular_TMB(Weight, Height, Age, Gender, PhysicalActivity):
  classificationIMC = calcular_clasificacion_IMC(Weight, Height)

  if classificationIMC in ['Obesity_Type_II', 'Obesity_Type_III']:
       return calcular_TMB_MIFFLIN(Weight, Height, Age, Gender, PhysicalActivity)
  else:
     if PhysicalActivity == 'No':
         return calcular_TMB_FAO_ONU(Weight, Age, Gender)
     else:
         return calcular_TMB_harris_benedict_simplificada(Weight, Height, Age, Gender, PhysicalActivity)
```

Fig. 5. Function to assign appropriate formula

- *Macronutrient calculation*: The daily requirement of macronutrients (carbohydrates, proteins, and fats) was calculated according to the individual caloric deficit, which is the reduction of calories from those that should be consumed per day. In this way a healthy weight can be maintained.

$$Deficit = \text{BMR} \times (\text{BMR} \times 0.20)$$

Macronutrient ratios were adjusted according to whether the individual had diabetes (see Figure 6).

```
def calcular_macronutrientes(deficit, Diabetes):
    c_carbohidratos = deficit * 0.50
    c_grasas = deficit * 0.30

    # Para diabetes, ajustamos la cantidad de proteína según el total calórico
    if Diabetes == 'YES':
        # Ajustamos directamente los gramos de proteínas basándonos en el total calórico
        g_proteinas = deficit * 0.2 / 4 / 0.8
    else:
        c_proteinas = deficit * 0.20
        g_proteinas = c_proteinas / 4

    g_carbohidratos = c_carbohidratos / 4
    g_grasas = c_grasas / 9

    return {
        "Carbohidratos_G": round(g_carbohidratos, 2),
        "Proteinas_G": round(g_proteinas, 2),
        "Grasas_G": round(g_grasas, 2)
    }
```

Fig. 6. Function for macronutrients

- *Distribution of Macronutrients in Meals*: Macronutrients were distributed in specific proportions for breakfast, lunch, and dinner (refer to Table 3).

Table 3. Distribution of macronutrients per meal

Meal of the Day	Formula
Breakfast (25%)	breakfast_carbs = carbohydrates * 0.25 breakfast_prot = protein * 0.25 breakfast_fat = fats * 0.25
Lunch (35%)	lunch_carbs = carbohydrates * 0.35 lunch_prot = protein * 0.35 lunch_fat = fats * 0.35
Dinner (40%)	cena_carbs = carbohydrates * 0.40 cena_prot = protein * 0.40 cena_gras = fats * 0.40

- *Food Data Integration*: Foods were selected from the relevant categories and assigned to meals based on nutritional requirements. That is, without exceeding the limit of consumption for the day and meal. Three meals are generated for breakfast, lunch, and dinner, which are two meals.
- *Exercise Assignment*: Exercises were assigned to ensure that there was no repetition of exercise types within the same session. Five exercises were assigned per user to work the whole body and obtain optimal results.

As seen in Figure 7, the three datasets have been unified for training and creating the predictive model for food and exercise.

	Gender	Age	Diabetes	Weight	Height	AbdominalCircumference	PhysicalActivity	TMB	ClassificationIMC	Deficit	...	almuerzo_1	almuerzo_2	almuerzo_3	cena_1	cena_2	ejercicio_5	ejercicio_1	ejercicio_2	ejercicio_3	ejercicio_4
0	1	39	2.0	75.0	171.0	95.6	1	1749.00	3	1399.20	...	51.0	82.0	201.0	236.0	183.0	32	43	14	20	34
1	2	22	2.0	65.9	158.1	89.5	2	2027.48	3	1621.98	...	65.0	133.0	221.0	238.0	149.0	40	35	26	25	50
2	2	20	2.0	58.3	161.5	82.9	2	1949.09	2	1559.27	...	75.0	129.0	216.0	239.0	192.0	45	6	26	37	20
3	1	33	2.0	73.8	170.7	93.7	1	1735.08	3	1388.06	...	36.0	101.0	214.0	241.0	163.0	15	34	11	32	25
4	2	38	2.0	53.9	151.5	74.9	1	1297.93	2	1038.34	...	40.0	107.0	212.0	241.0	193.0	51	22	34	12	16

Fig. 7. Finished dataset with the union of the other datasets consulted

3.4 User interface

The frontend solution uses the Dart programming language and the Flutter framework. It follows an architecture based on the MVC (Model-View-Controller) design pattern and uses the GetX package for state management and navigation. This approach allows us to organize in an efficient and modular way the different parts of the project. Below are some views of our solution:

i) *Login and password recovery*. In Figure 8, the first page of a form, the patient's credentials (username and password) are requested. If the patient wants to recover a password, he/she will be asked to enter an e-mail address.

Fig. 8. Screenshots of the application: (a) Login view (b) Password recovery view

ii) *Patient initiation and plan*. The first page shows the main banner and redirection button to the current plan view (see Figure 9). If the user has an active plan, he/she will get the daily dietary and exercise recommendations.

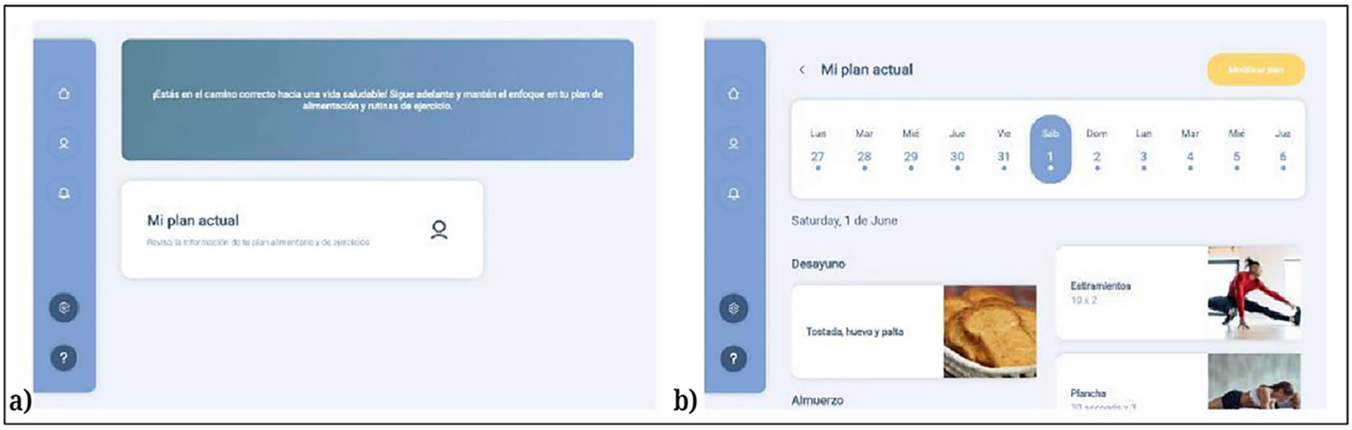

Fig. 9. Application screens: (a) Patient home view (b) Patient plan view

iii) *Food visualization*. The user can select a meal, and the application will display a new page with the list of ingredients of the meal, the nutritional information of the food, and action buttons such as "change meal" or "mark meal as completed" (see Figure 10).

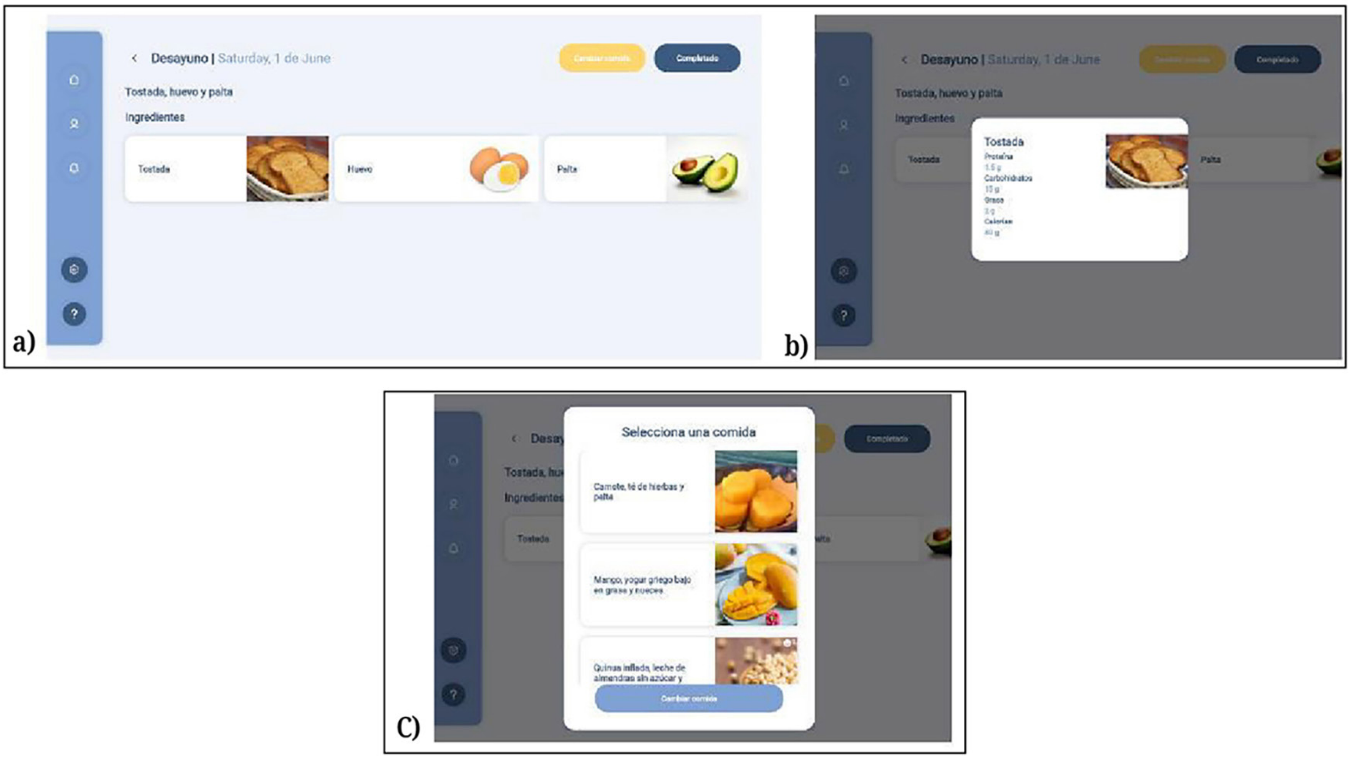

Fig. 10. Screens of the application (a) View of a meal (b) View of the nutritional information of a food (c) View of meal change

- **iv)** *Routine display*. The user can select the title of the routine, and the application will display a new page with the list of exercises for a day, the number of sets and reps, and action buttons such as "change exercise" or "mark routine as completed" (see Figure 11).

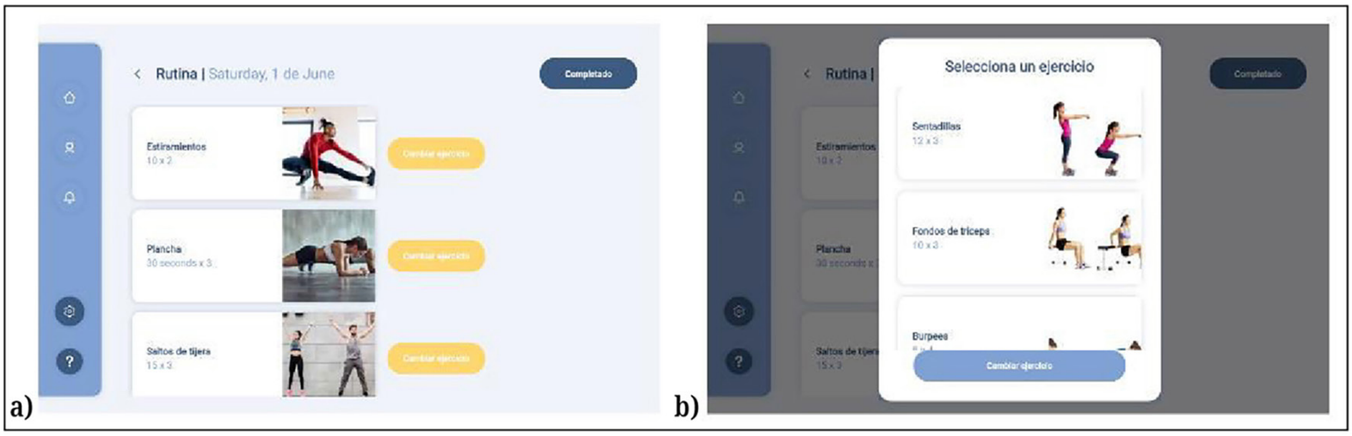

Fig. 11. Screens of the application (a) Routine view (b) Exercise change view

- **v)** *Patient profile display*. In Figure 12, the page displays a patient's personal information, as well as their dietary conditions and health conditions.

Fig. 12. Patient profile view

vi) *Nutritionist home*. Figure 13 shows the main banner and redirection buttons to the patient view and to the register a patient view. The nutritionist, to see his list of patients, must click on the second button on the first page. It will show personal data of their patients and data on their respective plans.

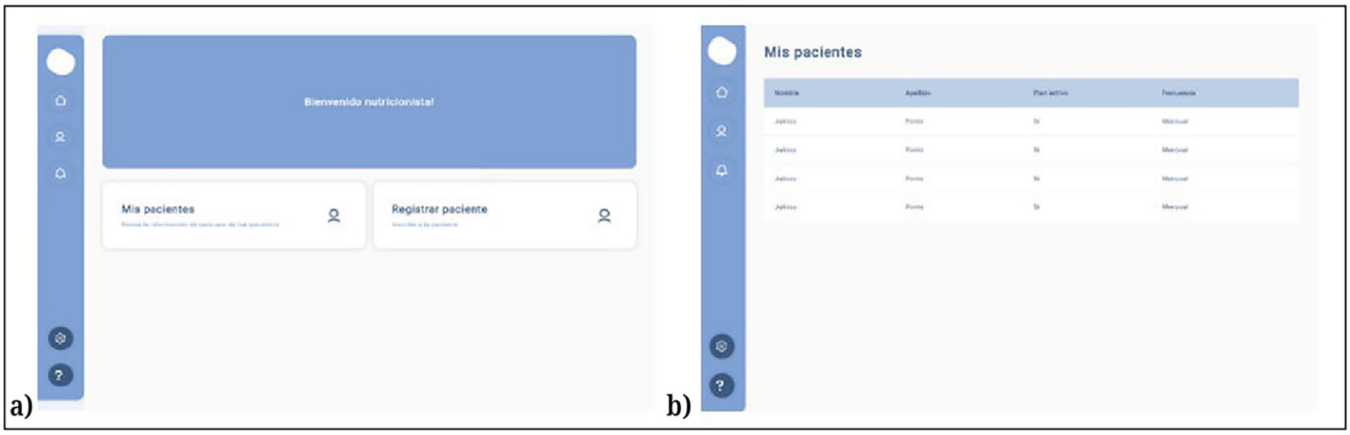

Fig. 13. Screenshots of the application: (a) Nutritionist home view (b) Nutritionist patient view

vii) *Patient registration*. On the first page, through a form, you are asked to register a patient's personal information, dietary conditions, and health conditions. The last page is the patient registration approval page (see Figure 14).

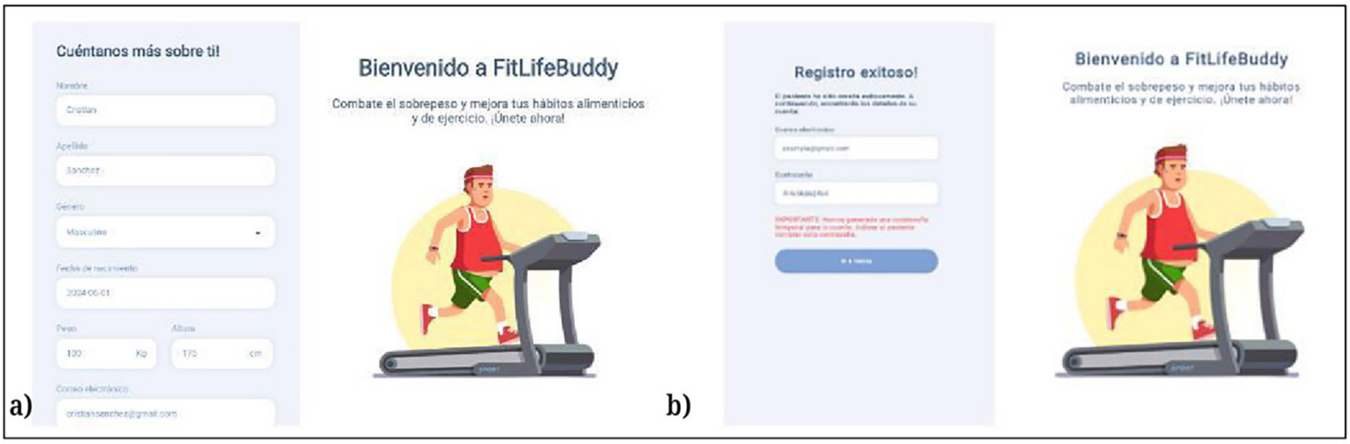

Fig. 14. Application screens: (a) Patient registration view (b) Registration approval view

3.5 Measurement indicators

In this section, we describe the measurement indicators selected to evaluate both user satisfaction and the quality of the artificial intelligence model used in the recommendation of diets and exercises for overweight people.

- *User Satisfaction Indicators*: User satisfaction is crucial to the success of the application, as a positive experience promotes active participation and compliance with daily recommendations. Key indicators include ease of use, content and functionality, personalization, overall app performance, motivation and engagement, and overall satisfaction. Each question is scored from 1 to 5, where 1 means "strongly disagree" and 5 means "strongly agree" (refer to Table 4).

Table 4. Questions for patients

ID	Ask
Q1	How easy was it for you to navigate the application?
Q2	Do you consider the user interface to be intuitive?
Q3	Were you able to quickly find what you were looking for?
Q4	How useful do you find the recipes provided?
Q5	Are the exercise options adapted to your needs and physical conditions?
Q6	Is there enough variety in the recipes and exercises offered?
Q7	Do you find the instructions provided clear and accurate?
Q8	Do you feel that the application understands and adapts to your personal needs?
Q9	How would you rate personalized recommendations?
Q10	Does the application work without technical errors?
Q11	Are page load times acceptable?
Q12	Does the application motivate you to follow a healthier lifestyle?
Q13	How often do you plan to use this application?
Q14	Overall, are you satisfied with the application?
Q15	Would you recommend this application to others with similar needs?

- *Model Quality Indicators*: To ensure that the Random Forest model provides accurate and effective recommendations, the following quality indicators will be used to validate its optimal performance (refer to Table 5).

Table 5. Model quality indicators

Evaluation	Description	Formula
Accuracy	Evaluates the proportion of correct recommendations made by the model. It will be calculated as the number of correct recommendations divided by the total number of recommendations.	$Accuracy = \frac{TP}{TP + FP}$ *TP* (True Positives): Number of true positives. *FP* (False Positives): Number of false negatives.
Recall	Measures the model's ability to correctly identify all relevant instances.	$Recall = \frac{TP}{TP + FN}$ *TP* (True Positives): Number of true positives. *FN* (False Negatives): Number of false negatives.
F1 Score	It provides a balanced measure between accuracy and recall. These metrics will be calculated using standard formulas to evaluate the overall performance of the model.	$F1\,Score = 2 \times \frac{Precisión \times Recall}{Precisión + Recall}$
AUC-ROC (Area Under the Operating Characteristic Curve)	Evaluates the model's ability to differentiate between classes of interest (e.g., effective versus ineffective recommendations). An AUC closer to 1 indicates high performance.	True Positive Rate (TPR) $TPR = \frac{TP}{TP + FN}$ False Positive Rate (FPR) $FPR = \frac{FP}{FP + TN}$

4 EXPERIMENTATION

4.1 Evaluation of the application

To validate the application, the nutrition experts provided the contact number of their patients who were recently seen. The interviews began on May 13 and will end on May 26, 2024, after consultation of their availability and if the user could support the review. A total of 33 people were interviewed, ranging from overweight to type 2 obesity. Figure 15 shows that the application has received a mostly positive response in terms of usability, intuitiveness, and usefulness of the functionalities provided. However, there are areas for improvement, especially in the organization of information and technical stability, which could be optimized to further improve the user experience. Overall, satisfaction is high, and many users are willing to recommend the application, indicating a solid foundation for its future success.

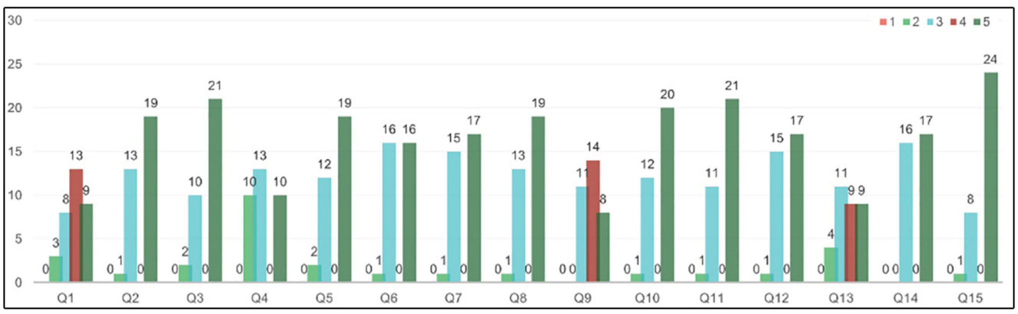

Fig. 15. Usability survey results

4.2 Evaluation of the models

The results of the evaluation metrics for each model are detailed below. Based on the above metrics, they are essential to understand the performance of each model in terms of ranking. An interpretation for each result obtained is presented below. Table 6 shows solid performance in the models with acceptable scores on all metrics. The breakfast and exercise models tend to perform particularly well compared to the lunch and dinner models. The metrics indicate that the models are effective in predicting and discriminating their respective classes, with areas for improvement in accuracy and recall in some specific cases.

Table 6. Interpretation of model results

Model	Scoring by Metrics	Interpretation
lunch_1	Accuracy: 85.89%. Recall: 83.87%. F1 Score: 79.68% AUC-ROC: 77.18%.	This model has high precision and recall, indicating that it is effective in correctly predicting lunch items. However, the F1 score and AUC-ROC suggest that there is still room for improvement in terms of balancing accuracy and recall and in the ability to discriminate between classes.
lunch_2	Accuracy: 79.13%. Recall: 78.63%. F1 Score: 78.61% AUC-ROC: 84.70%.	The model has good overall performance with a reasonable ability to distinguish between classes (high AUC-ROC).
lunch_3	Accuracy: 77.99%. Recall: 88.70%. F1 Score: 88.06%. AUC-ROC: 91.62%.	The extremely high F1 score suggests a good balance between precision and recall, although individual accuracy could be improved.
cena_1	Accuracy: 76.27%. Recall: 78.29%. F1 Score: 93.30% AUC-ROC: 89.89%.	The extremely high F1 score suggests a good balance between precision and recall, although individual accuracy could be improved.
cena_2	Accuracy: 84.73%. Recall: 92.81%. F1 Score: 75.20%. AUC-ROC: 79.20%.	The model has a very high recall, indicating that almost all real positives are captured, but the F1 score suggests that the accuracy needs improvement.
breakfast_1	Accuracy: 92.38%. Recall: 93.47%. F1 Score: 91.19% AUC-ROC: 91.41%.	This model performs excellently on all metrics, suggesting a high predictive and discriminatory capability.
breakfast_2	Accuracy: 79.34%. Recall: 76.42%. F1 Score: 85.60%. AUC-ROC: 92.62%.	Good overall balance with a high F1 score and an excellent AUC-ROC, indicating a strong discrimination capability.
breakfast_3	Accuracy: 93.06%. Recall: 84.61%. F1 Score: 76.38% AUC-ROC: 89.80%.	High accuracy and AUC-ROC, but the F1 scores, suggests that detection of true positives could be improved.
exercise_1	Accuracy: 78.09%. Recall: 76.28%. F1 Score: 88.23% AUC-ROC: 94.90%.	Excellent AUC-ROC and F1 Score, indicating strong balanced predictive and discriminatory ability.

(Continued)

Table 6. Interpretation of model results *(Continued)*

Model	Scoring by Metrics	Interpretation
exercise_2	Accuracy: 92.79%. Recall: 82.41%. F1 Score: 83.40% AUC-ROC: 76.54%.	High accuracy, but the lower AUC-ROC suggests that the model could be improved in discrimination ability.
exercise_3	Accuracy: 88.94%. Recall: 89.16%. F1 Score: 83.42% AUC-ROC: 76.48%.	Good overall performance with high precision and recall.
exercise_4	Accuracy: 80.31%. Recall: 82.34%. F1 Score: 76.76% AUC-ROC: 87.54%.	Good balance between precision and recall, and high discrimination capability.
exercise_5	Accuracy: 94.59%. Recall: 93.64%. F1 Score: 88.66% AUC-ROC: 81.59%.	Excellent overall metrics, suggesting strong predictive and discriminatory capabilities.

Figure 16 presents an evaluation of various models used in the project, comparing four key metrics: Accuracy, Recall, F1 Score and AUC-ROC. The breakfast and exercise models show outstanding performance. For example, the breakfast_1 model achieves high values on all metrics, with accuracy and recall above 90%, as well as F1 Score and AUC-ROC also above 90%. In contrast, the lunch and dinner models present higher variability, although they still show robust values. The exercise models, especially exercise_5, achieve a remarkably high AUC-ROC of approximately 95%, indicating excellent discriminative ability. Overall, the models evaluated demonstrate robust performance on most metrics, highlighting the effectiveness of the approach taken in this project for personalized diet and exercise recommendations.

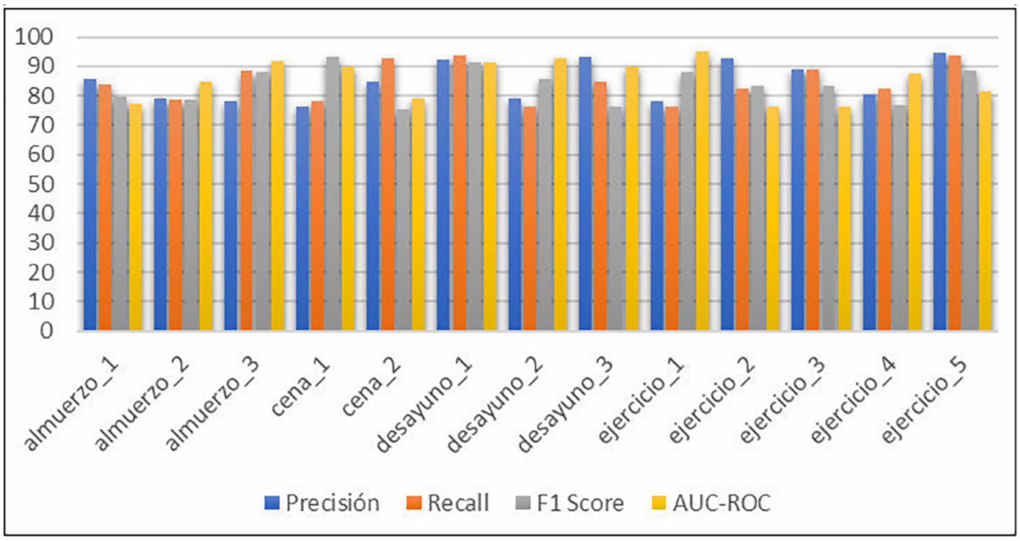

Fig. 16. Model evaluation

5 DISCUSSION

When comparing the performance of our model with previous studies, we see that the breakfast model in our system achieves a precision of 92.38% and an AUC-ROC of 91.41%, which are comparable to the 92.3% precision and 0.95 AUC-ROC reported in study [6]. However, the differences in the approaches used are notable. While study [6] utilizes CNNs and 3D algorithms for segmentation and image recognition, our model employs Random Forest, a simpler approach that, while more accessible, has the advantage of being less dependent on input data quality (such as food images) and adapts better to users' demographic data. This approach enables more effective personalization of food and exercise recommendations, with superior performance in terms of precision and recall.

In terms of exercise recommendations, our system's model stands out with an AUC-ROC of 94.90%, significantly higher than those of the compared models. For example, in study [15], applications based on LSTM achieve a precision of 97.74% but with a lower recall (89%), indicating that while these models have high precision, their ability to correctly identify all relevant cases is limited. In contrast, ours offers balanced performance across precision, recall, and AUC-ROC metrics, suggesting it is more capable of discriminating between different classes, especially in the context of personalized recommendations.

Additionally, although the LSTM-based model in [10] achieves slightly higher accuracy (97.74%), its focus is solely on food recommendations. In contrast, our system offers a holistic solution that integrates both nutrition and physical exercise, addressing health in a more comprehensive manner. This not only enhances the effectiveness of the recommendations but also contributes to a more sustainable habit change in the long term.

The fuzzy reasoning-based model presented in [17] achieves a precision of 92.3% and an F1 score of 92.1%, which is comparable to our results. However, the key difference lies in that fuzzy reasoning does not offer the same real-time personalization capability. Our model, on the other hand, adapts the recommendations based on user feedback, allowing for greater accuracy and relevance as users' habits change. This feedback-based approach provides dynamic recommendations, which is not common in existing systems.

In summary, while existing models have achieved satisfactory results in specific areas such as food or exercise recommendations, our system stands out by integrating both areas and offering dynamic personalization, making it a more complete and effective solution for improving users' lifestyle habits. This integration of nutrition and exercise, along with the use of Random Forest to personalize recommendations, provides a significant advantage over existing approaches that focus on one area only.

The age of the database, whose records correspond to the period 2022, constitutes a limitation of this study, as significant changes may have occurred in the variables analyzed since their collection. It is recommended that future research use more recent datasets to validate and update the results presented here.

6 CONCLUSION

The implementation of the web application for the promotion of healthy habits proved to be an effective tool for people with overweight or unbalanced diets.

The results obtained indicate high satisfaction among users, who reported significant improvements in their health indicators thanks to the personalized meal and exercise recommendations provided by the application. The predictive models based on Random Forest demonstrated remarkable accuracy and adaptability, allowing customized adjustments according to the individual needs of each user. This adaptability is crucial to ensure that diet and exercise recommendations are relevant and effective in improving users' health.

In addition, the system architecture, which integrates a frontend developed in Flutter, a backend in Spring Boot, and models in Flask, guarantees robust performance and easy scalability. This efficient integration facilitates not only the current use of the application but also its future expansion, allowing the incorporation of new functionalities and adaptation to a larger number of users. The use of reliable and diverse data sources, such as the Demographic and ENDES and Kaggle datasets, brought great value to the project, ensuring that the data used to train the models were accurate and relevant. This not only improves the quality of the recommendations but also strengthens users' confidence in the application.

The app not only addresses the immediate need to control weight and improve diet but also has the potential to significantly impact public health. By offering an accessible and personalized tool, the app can help mitigate the growing problem of obesity and overweight in urban areas, particularly in Lima, where rates of these conditions are alarming. In summary, this technological solution represents an important advance in the use of artificial intelligence for health management, providing an innovative and effective approach to the promotion of healthy lifestyle habits.

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