Mobile Application for Controlling a Healthy Diet in Peru Using Image Recognition

Leonardo Cornejo
Universidad Peruana de Ciencias Aplicadas (UPC)
Lima, Perú
u201510756@upc.edu.pe

Rosa Urbano
Universidad Peruana de Ciencias Aplicadas (UPC)
Lima, Perú
u201517763@upc.edu.pe

Willy Ugarte
Universidad Peruana de Ciencias Aplicadas (UPC)
Lima, Perú
willy.ugarte@upc.pe

***Abstract*—Overweight is one of the big ills that affects the world population, especially the Peruvian population, and this is caused mainly by people's ignorance of the amounts and nutritional values to consume according to their current condition. For this, there are various solutions focused on controlling a healthy diet for people, among the best known are the mobile food control applications. These apps are quite useful for monitoring people's food intake, as their databases have lots of food nutrition information. However, most of the information they have is focused on a foreign public, which may have different eating habits than Peruvians. That is why we present the application "NutriCÁM", which monitors the consumption of meals by users and provides the functionality of image recognition for meals, for the user to have a more friendly way to record and monitor its consumption, mainly focused on Peruvian gastronomy. The results are a Peruvian food recognition model based on the training of the pre-trained Convolutional Neural Network ResNet-50 and a dataset of 3600 food images, and a mobile application focused on the control of nutrition that caused 70% of improvement or maintenance in the current condition of 10 users.**

I. Introduction

Today, overweight is a serious problem worldwide, according to the World Health Organization (WHO), it has tripled since 1975. In 2016, more than 1.9 billion adults were overweight and approximately 650 million of them were obese [1]. In Peru, almost 70% of the adult population are overweight and/or obese [2].

One of the main reasons for being overweight is an unhealthy diet, which is defined as a diet based on many calories, a lot of fast food, high-calorie drinks and with excessively large portions, but with little or no consumption of fruits and vegetables, which contributes to weight gain [3].

Likewise, the National Institute of Health affirms that 29% of Peruvians consume junk food at least once a week and in the case of fried foods, 87.1% consume them with the same frequency [2]. In addition, 40% of the energy consumption or caloric intake of Peruvians comes from rice, potatoes, noodles, and refined grains [4] and these eating disorders are generated by the lack of food education (such as not knowing what to eat, overeat a food and stop consuming other essentials) [3].

Besides, people who are overweight are more prone to contracting diseases such as high blood pressure, diabetes, cardiovascular diseases, among others [5]. Likewise, in this time of pandemic, COVID-19 patients who are overweight are those at greatest risk of death, due to alterations in their immune systems and greater obstruction in their airways [6].

For this, various solutions have been created focused on the control of a healthy diet of people, among them are mobile applications such as MyFitnessPal, Fat Secret and MyNetDiary that allow the user to register the food they consume daily, in this way the user can control the nutritional values, mainly calories, that you consume. However, these applications are focused on a more foreign audience since the foods they have in their databases do not cover most of the dishes of Peruvian cuisine. Likewise, the National Institute of Health of Peru develops mobile applications to contribute to the nutritional knowledge of the public. One of them is the application called "Peruvian Food Composition Tables - TPCA", which offers the user the nutritional information (calories, proteins, fats, among others) of a great variety of Peruvian dishes, however, it does not offer the monitoring of user consumption [7]. Therefore, the National Institute of Health of Peru developed its application INS CENAN [8], which in addition to monitoring the meals consumed by the user, offers information on the user's current condition (such as Body Mass Index and Estimated Body Fat percentage) and useful tips for health care, however, currently there is no information about it nor is it available in any of the mobile app stores.

Faced with this problem, a technological solution is proposed focused on people who want to have better control of their weight according to their Body Mass Index. The solution is not restricted to a specific type of user, anyone who wants to have more information about the food they eat and wants to improve their eating habits can make use of it. For the monitoring of food consumption and the registration of users' meals, the solution was inspired by the most popular mobile applications and with the highest approval by users, and for the nutritional information offered, data from official papers and the National Institute of Health. In addition, with the use of Artificial Intelligence and Transfer Learning, the solution will offer the functionality of food image recognition, so that the user can have a more friendly way to record their daily consumption.

II. Theoretical Framework

A. Image Recognition

It consists of identifying and recognizing specific characteristics within images in order to apply it to a specific area. Image recognition can be applied in different fields, such as the classification of electrocardiograms of the human heart, detection of down cancer and even in the estimation of happiness [9]. As an example, we have one of the functionalities developed in this project, which is the recognition of food images, which consists of classifying what food is found in an input image by a user.

Fig. 1. Image recognition example used for food recogni-tion [10]

B. Body Mass Index

The Body Mass Index (BMI) is the parameter used to measure people's weight level. It is calculated with the weight in kilograms divided by the square of the height in meters (kg / m2). The BMI is considered an alternative method for the measurement of body fat, in addition to being inexpensive and easy to apply, in order to detect weight categories that can lead to health problems [11]. For example, a person with a height of 1.75m and a weight of 80kg has a BMI of 26.1, so it would be at the level of overweight, as can be seen in Table I.

TABLE I. BMI Classification [12]

BMI Classification	
Underweight	< 18.5
Normal range	$18.5 - 24.9$
Overweight	≥ 25.0
Pre-obesity	$25.0 - 29.9$
Obesity	≥ 30
Class I obesity	$30.0 - 34.9$
Class II obesity	$35.0 - 39.9$
Class III obesity	≥ 40.0

C. Healthy Diet

A healthy diet helps protect against malnutrition in all its forms, as well as prevent non-communicable diseases (NCDs) such as diabetes, cancer, heart disease, among others. A healthy diet varies according to individual characteristics of people, such as age, gender, lifestyle, and degree of physical activity. However, the basic principles that constitute a healthy diet are the same. In the case of adults, a healthy diet, according to the WHO, consists of at least 400g of fruits and vegetables per day, less than 5g of salt per day, less than 30% of the total caloric intake should be from fat and less than 10% of the total caloric intake must come from free sugars (equivalent to 50g) [3].

D. Transfer Learning

A large amount of data and training time required by deep learning algorithms allows greater precision, depending on the use to which it will be applied to the final model, be it prediction, decision making, classification of objects in images, among others. However, these two factors can take too long, due to the large amount of work required, both for data collection and for training. This effort is reduced thanks to transfer learning, which is a method of Artificial Intelligence, whose approach is to transfer knowledge from domains with information and skills already learned in previous tasks to new domains, which must share common ground. This approach is important, mainly in the context of deep convolutional neural networks, for classification using previously trained architectures [13].

III. System Design

This works consists of the implementation of a technological solution focused on people who want to have better control of their weight according to their Body Mass Index. The solution is not restricted to a specific type of user, anyone who wants to have more information about the food they eat and wants to improve their eating habits can make use of it. One of the functionalities provided by the solution is Recognition of food images, so that the user can know their nutritional values.

A. Main modules of the solution

1) Caloric plan assignment module: Module focused on assigning the caloric plan to users. The process of this module begins by requesting the user's data (Date of birth, height, sex, current weight and level of physical activity). From the weight and height of the user, the equation was applied to calculate his Body Mass Index, which is the weight in kilograms times the square of the height in meters ($\frac{kg}{m^2}$) [12], to be able to indicate your weight level and ideal weight range (Table II) and the possible diseases related to your weight level [15]. Subsequently, the solution tells the user his caloric plan calculated according to his entered data. For this, various equations were used to calculate the caloric expenditure at rest of people according to their height, sex, and age. For people with a low and normal weight level, the FAO/WHO/UNU formulas

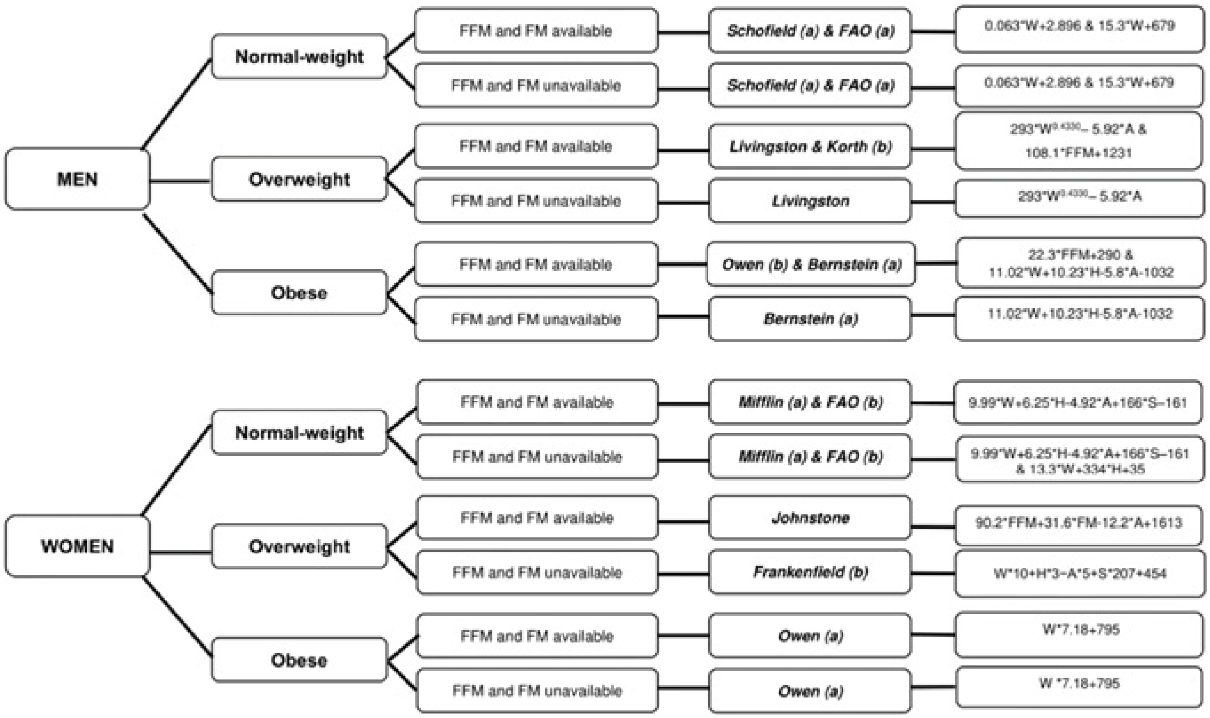


Fig. 2. Equations for calculating caloric expenditure at rest. Abbreviations: M: men; F: women; W: weight; H: height; A: age; S (men = 0; women = 1); FFM: fat free mass; FM: fat mass [14].

were used, both for men and women. For overweight people, 2 equations were used; for men the Livingston equation was used and for women the Frankfield equation was chosen. Finally, for people with obesity, 2 equations were applied; for men the Bernstein equation was used and for women the Owen equation was applied [14]. The equations can be seen in Fig. 2.

On the other hand, a factor that is not taken into account in the previous equations is the level of physical activity, which, if not taken into account, would impact on the allocation of the users' caloric plans. For this, the factors of physical activity levels offered by the FAO/WHO/UNU equation were applied, which can be seen in Table II.

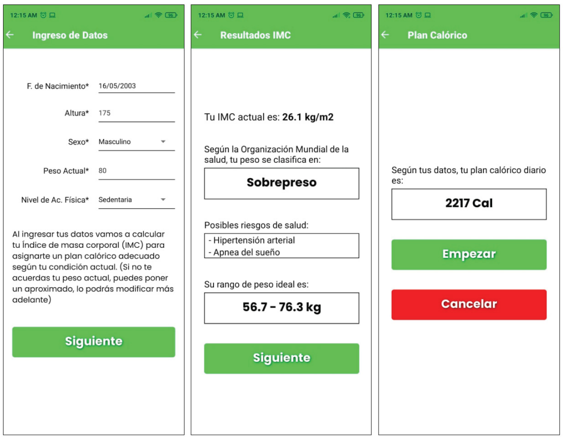
TABLE II. FACTORS ACCORDING TO THE LEVEL OF PHYSICAL ACTI-VITY [16]

Activity	Men	Women	Physical Activity
Sedentary	1,20	1,20	Without activity
Light	1,55	1,56	3 hours per week
Moderate	1,80	1,64	6 hours per week
Intense	2,10	1,82	4 or 5 hours daily

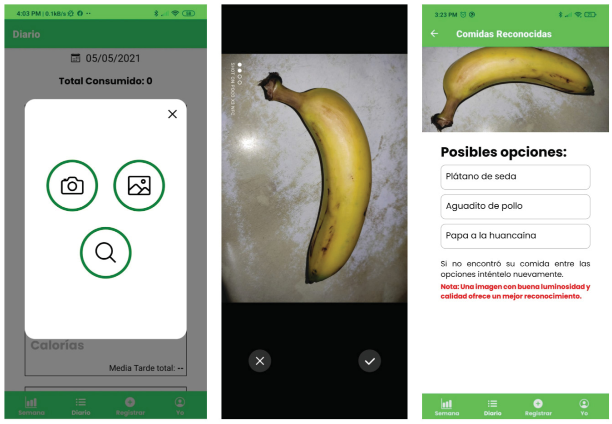
The caloric plan assigned to the user would be the result of their energy expenditure at rest according to the corresponding equation, multiplied by the factor corresponding to their level of physical activity. In Fig. 3a you can see the process of assigning the caloric plan.

2) Image Recognition Module: Module focused on the recognition of the foods that the user photographs. The process of this module starts when the user selects the camera option among the 3 registration options. Afterwards, the application will access the smartphone camera, so that the user can photograph their food. Once the photo is taken, the application will present to the user 3 possible options depending on the food recognized in the image. The user may choose one of these options, in order to record it in their daily record. In Fig. 3b you can see the food recognition process.

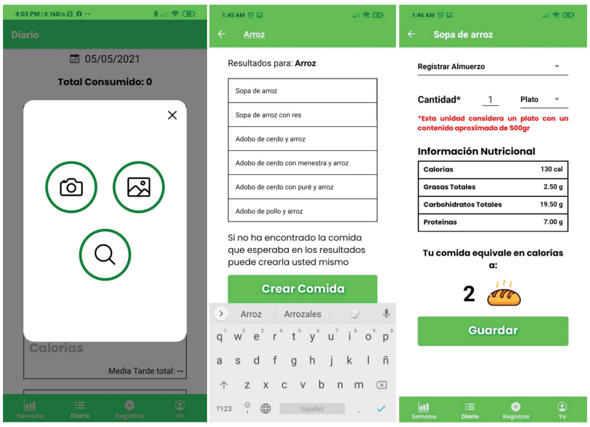
3) Meal registration module: Module focused on the registration of meals that the user consumes throughout the day. The process starts when the user selects one of the three registration options; Since the food recognition process was described in the previous module, the process that will be described is by text search. The user selects the magnifying glass icon and will be redirected to a screen where he must enter the food he wish to register, the application will present the list of meals according to the text he entered and the user must select the one he wishes to register. The user will be in the registration screen, where he must select the time of the meal (breakfast, mid-morning, lunch, mid-afternoon and dinner) and the number of portions according to the unit he choose (100 grams, unit, meal) , when he clicks to save the food it will have been registered in his daily register. Fig. 3c presents the interfaces of the process of this module.



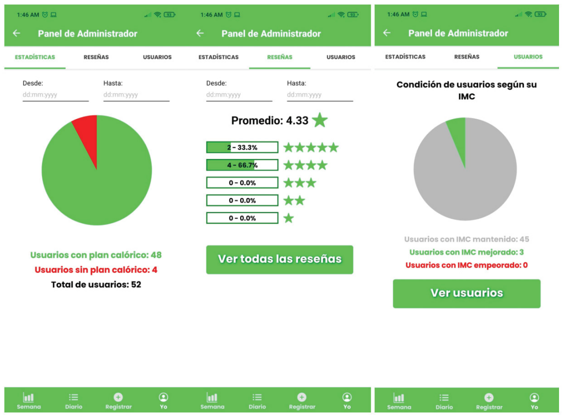
(a) Process of assign caloric plan.



(b) Food image recognition process.



(c) Food registration process via search.



(d) Administrator sections.

Fig. 3. Screen from the app

4) Administrator module: This module presents the sections that will be available to the user with the administrator role. The sections covered by the module are the statistics section, where the administrator can view in a graph the users who have or do not have caloric plans, the user reviews section, and the user condition section according to their BMI, where he can see a graph of users who have maintained, improved, or worsened their BMI. In Fig. 3d, the interfaces with the mentioned sections are presented.

B. Architecture

The architecture of the solution was modeled in such a way that it is scalable as shown in Fig. 4. Then, the components of the technology solution architecture will be described.

1) User: Person who interacts with the application to know the nutritional information of the meals he eats. Among the activities that he can perform are log in, create an account, register food in the daily register, create food, capture food image so that the application gives to the user its nutritional information, search for food, among others.

2) Administrator / nutritionist: He oversees monitoring the reports of the application (accounts created users with and without caloric plan, user reviews and scores, and users progress). The solution has been designed in such a way that a nutritionist can be the administrator since the functionality to monitor the progress of users' caloric plans was developed.

3) Smartphone: Device from where the mobile application will be accessed, both the user and the administrator. It can be a device with an iOS or Android operating system.

4) Internet: Medium to which the Smartphone must have access to carry out CRUD transactions in the application, such as logging in, registering food, looking for food, viewing nutritional information, among others, and sending images to the recognition model server. It is not necessary to have an internet connection to access the mobile application, since this, once downloaded to the Smartphone, can be accessed by the user or administrator at any time.

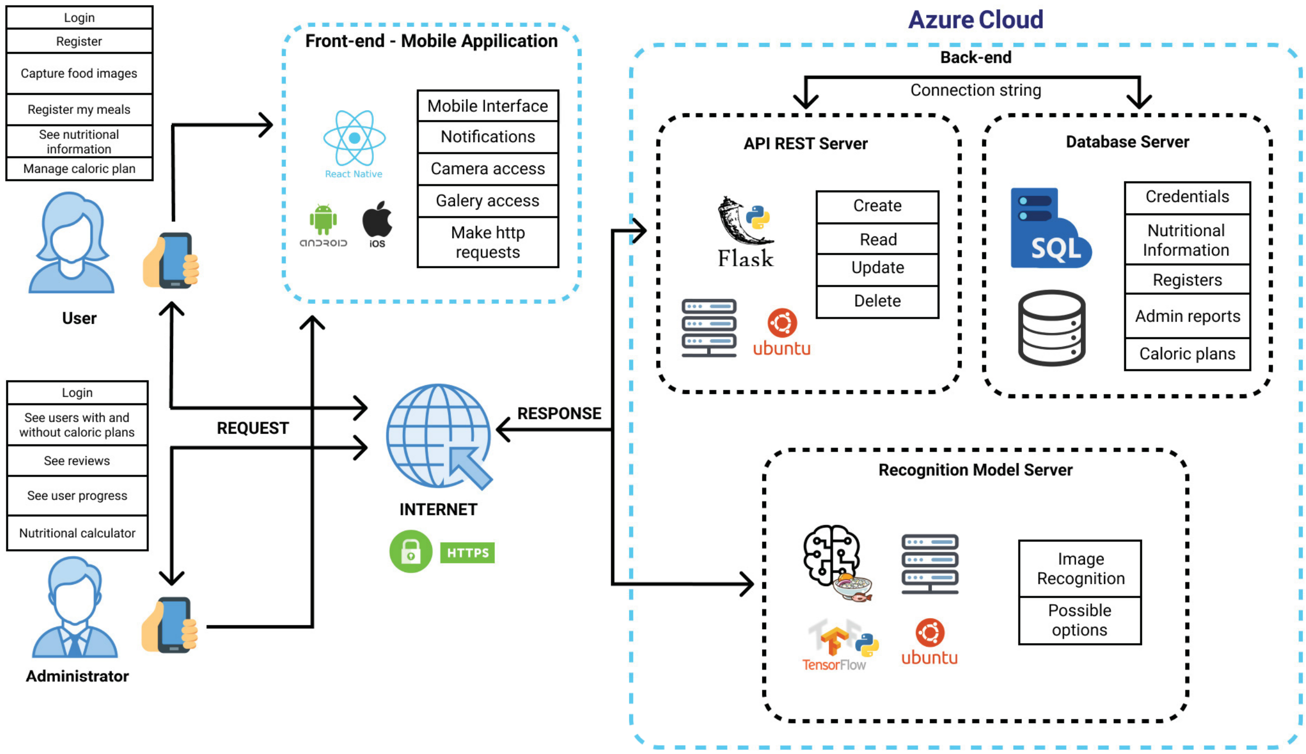


Fig. 4. Design of the architecture of the technological solution

5) Front-end Mobile application: Visual part of the mobile application, developed in React Native for availability on Android and iOS platforms. Provides the user with the mobile interface (from where the user can register, log in, register his meals, among other activities), application notifications (reminders and recommendations from experts), access to the device's camera and gallery, to capture images of meals or upload them and these are sent to the recognition model server, so that it returns the possible food options according to the image sent.

6) REST API server: Server which will host the REST API developed with Flask (Python micro-framework) that allows the mobile application to communicate with the database server, so that the user can perform CRUD transactions mentioned above. It has version 20.04 of the Ubuntu Server operating system and version 3.8 of Python as the runtime environment stack.

7) Database Server: Server, offered by the Azure SQL Database service, which will host the solution data, such as user credentials, nutritional information of the meals (which is mainly made up of the data from the Food Composition Tables offered by the National Institute of Health [17]), food records of users, administrator reports, users caloric plans, among others. It has a maximum data capacity of 20GB, for the data that is stored.

8) Recognition model server: Server which will host the Food Image Recognition Model developed with TensorFlow and Python, which will oversee recognizing the food images sent by the user through the application and must return three possible options about the food that it recognized. It has version 20.04 of the Ubuntu Server operating system and version 3.8 of Python as the runtime environment stack.

IV. Related Works

In [13], the authors question whether nutrition applications are viable, according to health professionals and their preferences regarding the characteristics that these applications may have based on reliability and functionality. Of the 1001 surveys used for the analysis, 45.4% indicated that they would recommend these applications to their customers. Also, the most important features for professionals are ease of use, whether it is free, and the validity of the information offered by the application. For our solution, an easy-to-use application inspired by the most popular nutritional applications was proposed, in addition, the nutritional information offered is mainly obtained from the Food Composition Table offered by the National Institute of Health of Peru.

The authors of [18] propose a food and drink recognition system, which can be used with uncontrolled images, for example, those taken by a person with their smartphone camera to their food. To do this, the authors developed a food and beverage image detection model called NutriNet, which is a modification of the AlexNet architecture, the winner of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012. Similarly, for our solution, we developed a food recognition model based on the RestNet-50 architecture, which is a convolutional neural network [19] that is 50 layers deep and is previously trained with more than a million images of the ImageNet database [20]. The RestNet architecture was selected, since it obtained a higher performance in the experiments that will be detailed in the next chapter. Also, thanks to its high degree of precision and low margin of error, RestNet won the 2015 ILSVRC competition [21].

The authors of [22] conducted research to evaluate the DietApp mobile app. For the development of this app on the Android platform, the Android Studio tool and the Android Software Development Kit were used. The app was also later developed for the iOS platform. According to the authors' research, the habit of a healthy life consists of a factor called the Recommended Daily Intake (RDI), which includes the necessary nutrients that a person must consume to maintain optimal health. On the other hand, for the development of our application the React Native library was used, which allows that, through a single code base, our application can be executed on Android and iOS devices, avoiding development for each platform independently which would lead to a greater consumption of time. Also, while it is true that calories are not the only nutrient in a healthy diet, it is one of the most important factors, since, as indicated by the WHO, the fundamental cause of overweight and obesity is an energy imbalance between calories consumed and expended [1]. That is why for our solution a caloric plan is assigned to the users, whose calculation is carried out using the equations mentioned in the previous section.

The contribution of the authors in [23] is a mobile application which seeks to support patients with diabetes to be able to carry out the process of monitoring their food so that they can photograph their food and the proposed solution must automatically recognize the food using Deep Learning techniques. This solution is aimed at the gastronomy of the Middle East, since the authors indicate that the prevalence of diabetes in that region is well above the world average. In this case, our solution is focused on a mobile application for monitoring the daily consumption of users, which seeks to support the Peruvian population, due to the high number of calories in their dishes [4] and the high rate of overweight [2].

V. Experiments

A. Experimental Protocol

1) Tecnologies used: The factors according to the level of physical activity [16]:

- Mobile App:
  - React Native 0.64.1
  - Expo Cli 4.1.0
- REST API:
  - Python 3.9.0
  - Flask 1.1.2
- Food Recognition Model:
  - Python 3.9.0
  - Tensorflow 2.5.0
- Database:
  - SQL Server 2019
- Deployment:
  - Azure SQL Database
  - Azure App Service
- Interviews:
  - Google Forms

2) Selection of pre-trained convolutional neural network: For the selection of the pre-trained convolutional neural network (CNN) to be used for our food recognition model, a comparison was made between the following: Inception v3 [24], Xception [25] y RestNet-50. In this training process, we defined to use 40 epochs, with a dataset that corresponds to 36 Peruvian meals with a total of 3,600 images, to corroborate the data and obtain the CNN that achieves the best performance of all epochs. The images used during the training were selected considering various attributes, such as good quality, with multiple meals, low lighting or cropped, to have greater precision, considering the photos of diverse conditions that users upload.

For the training of the 3 CNNs, a computer was used with the components listed in Table III.

TABLE III. Factors according to the level of physical activ-ity [16]

Item	Description
CPU	AMD Ryzen 5 3600 6-Core Processor @3.6Hz
GPU	Geforce GTX 1650
RAM	24GB DDR4 @1333MHz
OS	Windows 10 Pro-64-bit

The source code for the solution can be found at the following link: https://gitlab.com/Leonardo1609/nutricam

3) Test sample: For the test sample, the study "Habits and uses of mobile telephony" was analyzed [26] where they mention that there are 17.3 million mobile telephony users between 12 and 70 years of the ABCDE socio-economic levels. However, this project is aimed at people over 18 years of age, since a lower age implies a greater constancy in the variation of height [27], which can impact the accuracy of the caloric plans offered by the solution to users. That is why, for the calculation of the sample, the number of adolescents between the ages of 12 and 17 will be subtracted, which is 3 million 130 thousand [28]. To calculate the sample size, 14.17 million users are taken as the population size, a confidence level of 90% and a margin of error of 10%. Resulting in the sample size of 69 people.

4) Indicators: Three indicators are defined to assess the extent to which the overall objective is being achieved. These indicators will be measured through the survey carried out on the sample defined above. For the first 2 indicators, a survey was used, where the 69 participants were asked how likely it is that they recommend the application (Not at all likely 1- Very likely 5), how satisfied they are with the application (Very dissatisfied 1- Extremely satisfied 5) and how would you rate the accuracy of the recognition model (Not at all accurate 1 - Very accurate 5). On the other hand, for the third indicator, 10 of the 69 participants were asked to use the application for a period of 3 weeks, to know the impact of the application on their current physical condition.

TABLE IV. INDICATORS AND EXPECTED RESULTS

	Indicator	Variables	Number of Participants	Expected Result
IND01	% User satisfaction	User satisfaction	69	90% user satisfaction
IND02	% Accuracy in the use of the participants of the recognition model	Model accuracy	69	More than 85% model accuracy
IND03	% Of users with improvement in their current condition	Current BMI, Post BMI	10	60% of people improve or maintain their body mass index

B. Results

1) CNN selected: The results obtained (see Table V) are validated in 4 metrics: precision in training, precision in validation, loss function in training and loss function in validation.

TABLE V. RESULTS OBTAINED FROM TRAINING

	Accuracy		Loss Function	
	Training	Validation	Training	Validation
Inception v3	98.7%	77.3%	.9297	.8799
Xception	99.6%	85.0%	.0156	.7670
ResNet-50	99.9%	88.8%	.0012	.6585

From Fig. 5 to Fig. 8 can see the result in each epoch according to the validated metrics.

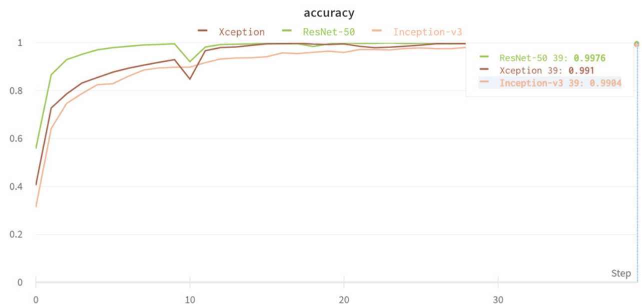


Fig. 5. Results of precision in training

In Fig. 5 we can see that ResNet-50 starts with greater precision in training, up to a point where there is no longer so much difference.

In Fig. 6 we see that ResNet-50 has a higher precision in validation in most epochs.

In Fig. 7 we see that ResNet-50 starts with a lower loss-in-training function and continues like this for most epochs.

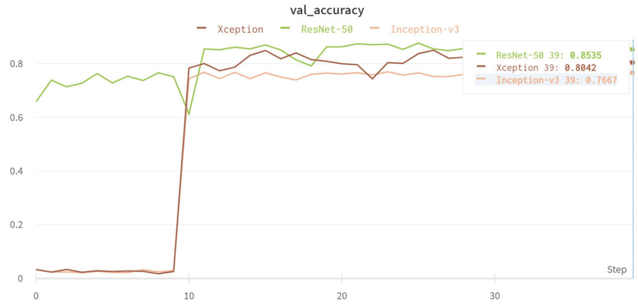


Fig. 6. Results of precision in validation

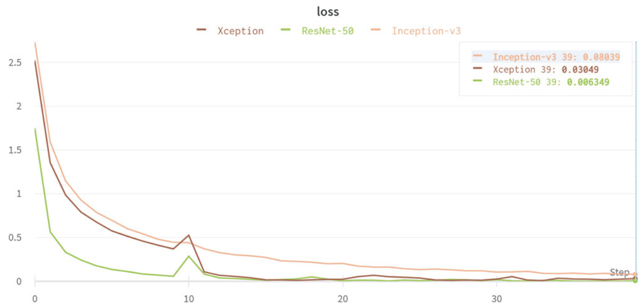


Fig. 7. Results of the loss-in-training function

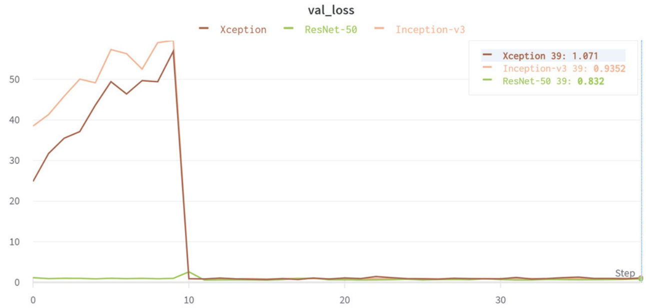


Fig. 8. Results of the loss-on-validation function

In Fig. 8 we see that ResNet-50 starts with a lower loss-on-validation function to a point where there is not much difference with the other 2 CNNs. From the previous results, the resulting model from the training of the pre-trained CNN ResNet-50 was selected as the recognition model.

2) Indicators:

- **IND01 (% User satisfaction)**: According to the survey carried out with the 69 participants, the results are as follows:
  - In Fig. 9, we see that 94.2% of respondents would recommend the application to their friends and family.
  - In Fig. 10, we see that 89.8% of respondents are satisfied with the application interface.
  - In Fig. 11, we see that 87.0% of respondents consider the application useful for nutritional control.

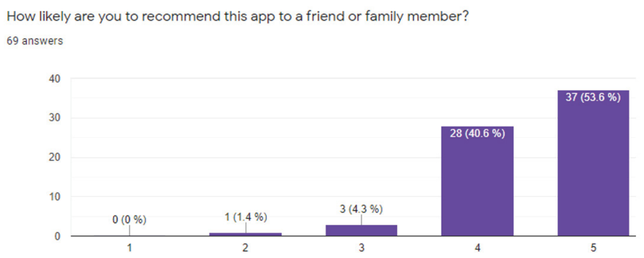


Fig. 9. Results of probability of recommendation of the application according to the respondents

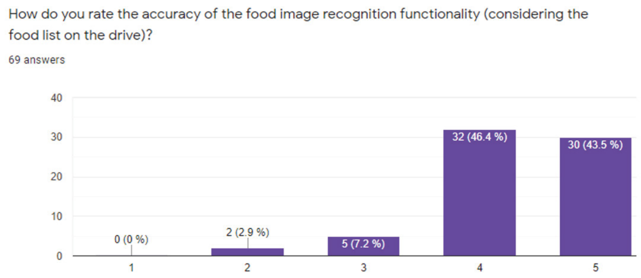


Fig. 12. Results of the precision of the recognition model according to the respondents

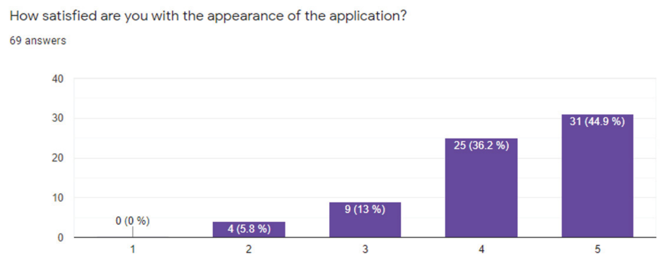


Fig. 10. User satisfaction results according to the respondents

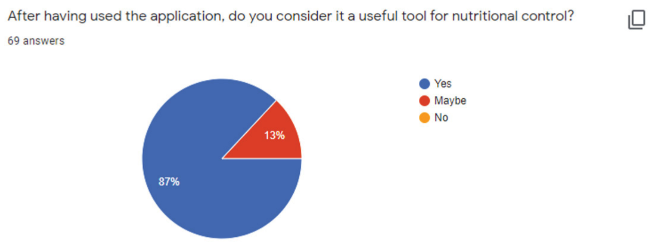


Fig. 11. Results of users who consider the application useful for nutritional control

As can be seen from the previous graphs, each one of them exceeded the expected acceptance percentage, which was 85%.

- **IND02 (% Accuracy of the recognition model according to the use of the participants**): According to the survey carried out, In Fig. 12, we see that 89.9% of respondents say that the food recognition functionality works accurately. As can be seen from the previous graph, the expected acceptance percentage was exceeded, which was 85% accuracy of the recognition model. In conclusion, the second indicator was fulfilled.
- **IND03 (% Of users with improvement in their current condition)**: For this indicator, a test was carried out on 10 of the 69 respondents, which consists of using the application for a period of 3 weeks, to know the impact, it has on their physical conditions. The participants are in an age range between 18 and 50 years. Participants were asked to record their new weight at the end of the time and the application would calculate their new Body Mass Index. To check if there was improvement in the condition of the users, the current BMI was compared with the previous BMI. If the patient's current BMI is closer to or within the range that is considered healthy, which is 18.5 to 24.9 kg/m2 [12] it is considered improvement, if the BMI did not change or both the current BMI and the previous BMI are within the healthy range it is considered maintained, and if the current BMI is further away from the healthy range, compared to the previous BMI it is considered a worsening.

TABLE VI. Results obtained from training

User	Previous BMI	Current BMI	Result
1	26.6	26.6	Mantained
2	24.7	25.4	Worsed
3	25.3	25.2	Improved
4	21.2	21.2	Maintained
5	23.1	22.3	Mantained
6	32.4	32.7	Worsed
7	17.3	18.3	Improved
8	23.5	23.5	Maintained
9	24.7	24.7	Maintained
10	26.1	-	-

As can be seen in Table VI, 70% of the users maintained or improved their BMI level, 20% of the users worsened their BMI level, and one user dropped out of the trial period. Therefore, it managed to meet the third indicator, since more than 60% of the users maintained or improved their current condition.

C. Discussion

According to the results obtained previously, it is shown that our solution becomes an effective tool for nutritional control in people, however, there are some factors that allowed us to achieve these results, which we will discuss below:

1) The CNN that performed the best based on the training results was ResNet-50; since between the specifications

of each CNN there was no great difference, both in the number of depth layers and in the input size of the images (even with Xception being the CNN with the greatest number of depth layers and the largest image input size), we speculate that this result was due to the ResNet-50 offering better performance in more complex visual patterns, which in this case are represented by food images.

2) The precision obtained, according to the responses of the respondents, of our food recognition functionality exceeded the expected result, due to the fact that the model resulting from the CNN training with the best performance was used, which was RestNet-50, however , there are respondents who claim that the functionality did not give them good results (9.9% - 5 respondents), we speculate that these cases were due to low lighting conditions, poor image quality or more complex visual patterns caused by the addition of ingredients or seasonings, which were not considered in the training dataset, so these are points to consider in the future.
3) The expected result for the third indicator was exceeded, since 70% of the participants met the objective of maintaining or improving their BMI, however, the case of the participants who did not achieve it was analyzed. User number 2, who has a light physical activity level and gained weight, indicated that he was trying to comply with the caloric plan, however, he considered it a high-calorie plan, which we speculate is due to the physical activity level factors, which may increase recommended calories somewhat, making it a factor to consider for future testing. On the other hand, user 6 told us that he used the application to record his meals, however, he did not follow his caloric plan, which influenced his weight gain.

VI. CONCLUSION

In one hand, we have demonstrated the effectiveness of our ”NutriCÁM” solution in the nutritional control of users. To achieve this, the use of reliable information has been vital, mainly conformed by the nutritional values of Peruvian dishes obtained from the National Institute of Health of Peru and the energy expenditure formulas obtained in [14].

On the other hand, pre-trained convolutional networks streamline the recognition model training process, resulting, in this case, in a highly accurate Peruvian food image recognition model.

For future experiments, the application of the object segmentation technique is proposed, in such a way that each food that makes up a dish can be recognized and obtain the corresponding proportion of each one, for greater precision, similiar studies have been proposed for other visualization task [29]–[31].

REFERENCES

[1] *Obesity and overweight*, World Health Organization, https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight.

[2] *Cerca del 70% de adultos peruanos padecen de obesidad y sobrepeso*, National Institute of Health of Peru, https://web.ins.gob.pe/index.php/es/prensa/noticia/cerca-del-70-de-adultos-peruanos-padecen-de-obesidad-y-sobrepeso.

[3] *Healthy diet*, World Health Organization, https://www.who.int/news-room/fact-sheets/detail/healthy-diet.

[4] I. Kovalskys, M. Fisberg, G. Gómez, R. G. Pareja, M. C. Yépez-García, L. Y. Cortés-Sanabria, M. Herrera-Cuenca, A. Rigotti, V. Guajardo, I. Zalcman-Zimberg, A. Nogueira-Previdelli, L. A. Moreno, and B. Koletzko, “Energy intake and food sources of eight latin american countries: results from the latin american study of nutrition and health (elans),” *Public Health Nutr.*, vol. 21, no. 14, 2018.

[5] *¿Por qué promover la alimentación saludable en el Perú?*, El Comercio, https://elcomercio.pe/especial/perusostenible/planeta/que-promover-alimentacion-saludable-peru-noticia-1994487.

[6] *The Health Effects of Overweight and Obesity*, Center for Disease Control and Prevention, https://www.cdc.gov/healthyweight/effects/index.html.

[7] *Más del 60% de peruanos mayores de 15 años sufre de sobrepeso u obesidad y podría hacer formas graves de COVID-19*, National Institute of Health of Peru, https://bit.ly/3F0iJnT.

[8] *Aplicaciones moviles*, National Institute of Health of Peru, https://web.ins.gob.pe/es/acerca-del-ins/aplicativos-moviles/apps.

[9] M. H. Modarres, R. Aversa, S. Cozzini, R. Ciancio, A. Leto, and G. P. Brandino, “Neural network for nanoscience scanning electron microscope image recognition,” *Nature Scientific Reports*, vol. 7, 2017.

[10] S. Mezgec, T. Eftimov, T. Bucher, and B. Seljak, “Mixed deep learning and natural language processing method for fake-food image recognition and standardization to help automated dietary assessment,” *Public Health Nutrition*, vol. 22, 2018.

[11] *About Adult BMI*, Centers for Disease Control and Prevention, https://www.cdc.gov/healthyweight/assessing/bmi/adult_bmi/index.html.

[12] *10 datos sobre la obesidad*, World Health Organization, https://www.who.int/features/factfiles/obesity/facts/es/.

[13] M. Vasiloglou, S. Christodoulidis, E. Reber Aubry, T. Stathopoulou, Y. Lu, Z. Stanga, and S. Mougiakakou, “What healthcare professionals think of “nutrition & diet” apps: An international survey,” *Nutrients*, vol. 12, no. 8, 2020.

[14] F. Amaro-Gahete, G. Sánchez-Delgado, J. Alcántara, B. Martínez-Téllez, V. Hernández, E. Merchán Ramírez, M. Löf, I. Labayen, and J. Ruiz, “Congruent validity of resting energy expenditure predictive equations in young adults,” *Nutrients*, vol. 11, 2019.

[15] *Consecuencias de la obesidad y el sobrepeso*, ObservaT Perú, https://observateperu.ins.gob.pe/noticias/209-consecuencias-de-la-obesidad-y-el-sobrepeso.

[16] G. Alfonzo-González, E. Doucet, N. Alméras, C. Bouchard, and A. Tremblay, “Estimation of daily energy needs with the fao/who/unu 1985 procedures in adults: comparison to whole-body indirect calorimetry measurements,” *European journal of clinical nutrition*, vol. 58, 2004.

[17] *Tablas peruanas de composición de alimentos*, National Institute of Health of Peru, https://tmh.short.gy/7MxYcY.

[18] S. Mezgec and B. K. Seljak, “Nutrinet: A deep learning food and drink image recognition system for dietary assessment,” *Nutrients*, vol. 9, 2017.

[19] K. O’Shea and R. Nash, “An introduction to convolutional neural networks,” *CoRR*, vol. abs/1511.08458, 2015.

[20] Y. You, Z. Zhang, C. Hsieh, J. Demmel, and K. Keutzer, “Imagenet training in minutes,” in *ICPP*. ACM, 2018.

[21] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *CVPR*. IEEE, 2016.

[22] I. de la Torre Díez, B. G. Zapirain, M. L. Coronado, J. J. P. C. Rodrigues, and C. del Pozo Vegas, “A new mhealth app for monitoring and awareness of healthy eating: Development and user evaluation by spanish users,” *J. Medical Syst.*, vol. 41, no. 7, 2017.

[23] M. Qaraqe, M. Usman, K. Ahmad, A. Sohail, and A. Boyaci, “Automatic food recognition system for middle-eastern cuisines,” *IET Image Process.*, vol. 14, no. 11, 2020.

[24] K. Ng, “Tuned inception V3 for recognizing states of cooking ingredients,” *CoRR*, vol. abs/1905.03715, 2019.

[25] F. Chollet, “Xception: Deep learning with depthwise separable convolutions,” in *CVPR*. IEEE, 2017.

[26] *Hábitos y usos de la telefonía móvil*, IPSOS Perú, https://www.ipsos.com/es-pe/habitos-y-usos-de-la-telefonia-movil.

[27] *Desarrollo del adolescente*, MedlinePlus, https://medlineplus.gov/spanish/ency/article/002003.html.

[28] *Perú tiene una población de 9 millones 652 mil niñas, niños y adolescentes al primer semestre del presente año*, INEI Peru, https://bit.ly/3ohUnQn.

[29] M. Rodríguez, F. Pastor, and W. Ugarte, "Classification of fruit ripeness grades using a convolutional neural network and data augmentation," in *FRUCT*. IEEE, 2021.

[30] D. J. Lozano-Mejía, E. P. Vega-Uribe, and W. Ugarte, "Content-based image classification for sheet music books recognition," in *EIRCON*. IEEE, 2020.

[31] C. Leon-Urbano and W. Ugarte, "End-to-end electroencephalogram (EEG) motor imagery classification with long short-term," in *SSCI*. IEEE, 2020.