Development and Preliminary Evaluation of a Machine Learning Based System for Personalized Workout Recommendations at Gyms

Jordi Krisber Flores-Sosa*, Ernesto Bolaños-Rodríguez, Juan Carlos Gonzalez-Islas, Gaby Yolanda Vega-Cano, Omar Arturo Domínguez-Ramírez and Genaro Moreno-Beltrán

Universidad Autónoma del Estado de Hidalgo, Hidalgo, Mexico

Abstract

The objective of this project is to apply machine learning (ML) algorithms to design a mobile app (EvoAI) that provides personalized fitness routines for young people aged 15 to 29 who frequent gyms in Tizayuca, Hidalgo, Mexico. By analyzing users' physical, dietary, and motivational data, the ML algorithms generate personalized recommendations that help them more easily achieve their fitness goals. To validate the feasibility of the system, five multiclass classification algorithms were evaluated, and the one with the best performance was selected. For the evaluation, the 5-fold stratified cross-validation method is applied. The main conclusions drawn from the performance analysis show that the Naive Bayes classifier achieves the best predictive balance in the face of class imbalance, obtaining the highest macro F1-score in the comparison at 56.50%. This demonstrates the superiority of probabilistic statistical models over models based on distance metrics such as k-NN, which suffer a severe drop in performance when working with few samples. The system was evaluated on a representative sample of 81 users using a usability questionnaire that achieved a Cronbach's alpha reliability coefficient of 0.95, indicating that the results are accurate and contain minimal errors. This research is a preliminary development because the following requirements must be addressed for its consolidation: the need for cross-platform expansion, demographic scaling to increase the amount of data, and the incorporation of a smart nutrition module.

Keywords

Machine Learning, Usability, Personalized Workouts, Mobile App, Gyms

1. Introduction

Physical activity is of utmost importance for the prevention of noncommunicable diseases and the promotion of physical and mental health among the population. According to the World Health Organization (WHO), it is estimated that one in four adults and more than 80% of adolescents do not meet the recommended minimum levels of physical activity, which increases the risk of cardiovascular disease, type 2 diabetes, obesity, certain types of cancer, and mental disorders [1]. In this context, digital technologies have taken on an increasingly important role in promoting healthy lifestyles through tools that facilitate the monitoring of physical activity, tracking of progress, and the generation of personalized recommendations.

In this regard, machine learning has enabled the development of data analysis systems related to physiological, anthropometric, and behavioral variables to generate training programs tailored to each user's specific needs [2, 3]. At the same time, the growing availability of smartphones and wearable devices has driven the development of smart mobile apps for planning and tracking physical exercise [4, 5, 6]. Consequently, the combination of mobile apps, machine learning, and smart devices represents one of the major trends in the field of sports and digital health, making it possible to offer training programs that are increasingly precise, adaptive, and user-centered [3, 7].

IWSAI 2026: 1st International Workshop on Systems, Applications, Artificial Intelligence and Innovation, September 16–18, 2026, Piura, Peru

*Corresponding author.
fl377704@uaeh.edu.mx (J. K. Flores-Sosa)
0009-0007-7707-7080 (J. K. Flores-Sosa); 0000-0002-1432-7720 (E. Bolaños-Rodríguez); 0000-0002-2190-0660 (J. C. Gonzalez-Islas); 0000-0003-1440-1617 (G. Y. Vega-Cano); 0000-0002-9663-8089 (O. A. Domínguez-Ramírez); 0009-0009-0519-2332 (G. Moreno-Beltrán)

In Mexico, promoting physical activity is a priority for reducing the incidence of diseases associated with a sedentary lifestyle and obesity. According to the Sports and Physical Exercise Module (MOPRADEF) published by the National Institute of Statistics and Geography (INEGI), approximately four out of every ten people over the age of 18 engage in sufficient physical activity during their free time, while a considerable proportion remains inactive or drops out of training programs before reaching their goals [8].

Among the main reasons for dropping out are lack of time, lack of motivation, a lack of knowledge about how to plan appropriate routines, and limited access to personalized guidance. This situation is particularly relevant among young people, as adopting healthy habits during this stage influences the prevention of chronic diseases and quality of life in adulthood [1, 8, 9]. Although the number of gyms and mobile apps focused on physical training has increased in recent years, most of these tools offer programs that do not take into account individual differences in users' physical condition, body composition, personal goals, athletic experience, diet, or level of motivation [6].

The scientific community's interest in using machine learning to design personalized training programs has grown significantly in recent years. Various studies have shown that algorithms such as decision trees, support vector machines, artificial neural networks, and deep learning models can classify users, predict their physical progress, and generate recommendations tailored to their individual characteristics [2, 5]. Likewise, recent studies have proposed deep learning models to dynamically recommend physical activity plans via mobile apps [10], while systematic reviews highlight the potential of machine learning to optimize personalized exercise prescriptions and monitoring using smart devices [11]. Similarly, evidence suggests that mobile apps with personalization strategies improve exercise adherence and the user experience, although challenges remain regarding adaptation to different population profiles and the clinical validation of these systems [12]. Overall, several systematic reviews conclude that the incorporation of artificial intelligence into mobile health apps increases adherence to exercise programs, improves the accuracy of recommendations, and promotes greater user engagement through continuous personalization strategies [3, 7, 9].

However, most of these developments have taken place in countries with demographic and socioeconomic characteristics different from those of Mexico, and they have focused primarily on monitoring physical activity using wearable devices. There is a limited amount of research aimed at developing mobile applications that integrate anthropometric variables, dietary habits, personal goals, and user preferences to recommend personalized training routines using machine learning algorithms. This issue is also present in Tizayuca, Hidalgo, where there is a lack of personalized fitness training programs for young people who go to gyms. Of the 40,865 residents aged 15 to 29, an estimated 4,000 frequent these facilities, and approximately 63% do not follow a personalized routine [13]. As a result, generic training programs that do not take into account users' individual characteristics or goals are prevalent, limiting the effectiveness of exercise and adherence to physical activity. In this context, the development of a machine-learning-based mobile app is justified by its ability to analyze multiple user variables and generate personalized training recommendations, helping to optimize exercise planning, complement the work of trainers, and promote healthy lifestyle habits through the use of smart technologies.

In response to this issue, the objective of this research is to apply machine learning to develop a mobile app capable of recommending personalized fitness routines for young people between the ages of 15 and 29 who attend gyms in the municipality of Tizayuca, Hidalgo. To this end, we first identify the reasons why users consider personalized training programs important, as well as the variables that influence their needs and preferences. Next, a comparative analysis of the mobile apps available on the market is conducted to identify their features and establish the functional elements required for the design of the proposed solution. Finally, a mobile app based on machine learning algorithms is implemented to analyze variables such as age, gender, body mass index, athletic experience, eating habits, training goals, and frequency of gym visits in order to recommend personalized routines that improve upon existing apps. This work contributes to improving the structure of training programs, thereby encouraging users to continue engaging in physical exercise.

2. Methodology

The general methodology proposed for modeling, training, and evaluating the multiclass classification system for routines (beginner, intermediate, and advanced) is illustrated in the framework shown in Figure 1.

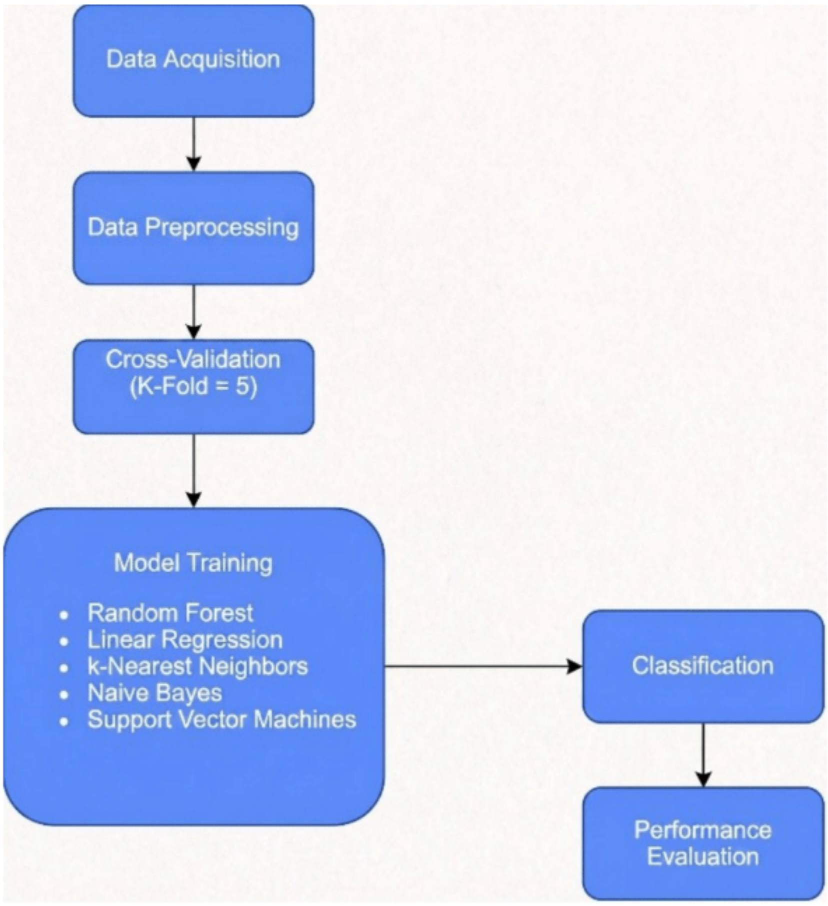

Figure 1: Workflow for evaluating machine learning models for a gym workout classification system.

2.1. Data Acquisition

Data were collected through the design and administration of a structured questionnaire aimed at young people between the ages of 15 and 29 who attend gyms in the municipality of Tizayuca, Hidalgo. This instrument enabled the collection of the independent variables used to train the machine learning algorithms, including personal information (age, weight, height, presence of chronic conditions such as hypertension or diabetes, and history of injuries), dietary habits (calorie control, type of diet), and training characteristics (weekly frequency, experience, and body composition goals).

The study population consisted of young people aged 15 to 29 who frequent gyms in Tizayuca, Hidalgo, with an estimated population of N = 4,000 users (Planning, Tizayuca Planning and Foresight Unit, 2025) [13]. To obtain a statistically representative sample, the formula for finite and known populations was used, with a 95% confidence level and a 10% margin of error, as shown in Equation 1.

$$n = \frac{z_{\alpha}^{2} N.p.q}{e^{2}(N-1) + z_{\alpha}^{2}.p.q} \tag{1}$$

Where: **n:** Sample size, **N:** Population size or sample frame: 4,000 users [13], **i:** Unforeseen or uncontrolled error, 10% = 0.1, **p:** Probability of Success = 0.5, **q:** robability of failure = 0.5, **Z:** Statistic for the Gaussian Normal Curve, at a 95% confidence level and a 5% margin of error: Z = 1.96 [14].

Substituting the values into the equation yields a sample size of 81 users, a number considered sufficient to represent the study population, and the questionnaire was administered to this group.

Participants were selected using proportional stratified probability sampling [15] to ensure representation of different levels of experience in physical training. It is worth noting that informed consent, signed by each participant, was obtained to confirm their agreement to participate in this study. The strata were defined according to the participants' length of time exercising at the gym:

- *Beginners:* Less than one year of training.
- *Intermediate:* Between one and three years of training.
- *Advanced:* More than three years of training.

The proportional allocation of the sample resulted in the questionnaire being administered to 43 beginner users, 23 intermediate users, and 15 advanced users. This database constitutes the set of information used for training and evaluating the machine learning algorithms responsible for generating personalized exercise programs.

Subsequently, to evaluate the acceptance and ease of use of the EvoAI mobile app, a usability questionnaire was administered to the same participants, using the same proportional stratified probabilistic sampling scheme. Thus, the usability evaluation included 43 beginner users, 23 intermediate users, and 15 advanced users, allowing us to analyze perceptions of the app across different user profiles and compare its performance across different levels of experience.

The result was a database consisting of 81 records and a total of 19 attributes. The 18 variables are divided into two types based on their mathematical nature:

- *Continuous variables:* Age, weight, and height.
- *Discrete and categorical variables:* 15 attributes derived from the closed-ended questions in the questionnaire (such as the presence of medical conditions, level of motivation, and use of mobile apps).

The variable Time Training represents the user's level of experience with physical training. This variable is divided into three categorical classes to be predicted: beginner (class 1), intermediate (class 2), and advanced (class 3). Table 1 presents the operationalization of the key variables used to train the algorithm.

2.2. Preprocessing

Preprocessing focused on adapting the input variables for the computational algorithms. The 15 discrete variables were categorized. This parameterization is essential for preventing anomalies during training, ensuring that the classifiers correctly interpret the survey options rather than processing them as numerical values.

Second, for the three continuous variables (age, weight, and height), a standardization process was implemented during the training phase. This was done to prevent distance-based models from developing an algorithmic bias toward features with values such as weight, compared to those with smaller ranges, such as height.

2.3. Stratified cross-validation

For the evaluation, the 5-fold stratified cross-validation method was applied. Since the database contains 81 unbalanced records—43 beginners, 23 intermediate, and 15 advanced—the stratification ensured that this same proportion of classes remained constant in each partition. Under this scheme, 80% of the data was allocated to the model training phase, and the remaining 20% was reserved for performance evaluation. This division ensures that the evaluation utilizes all available information [16].

Table 1
Table of Variable Rationale.

Categories	Dimension	Indicator	Items
Personal Date	General Age	Age	Age
		Sex	Male/Female
		Height	Height
		Weight	Weight
		Injuries	Yes/No
		Diseases	Diabetes / High Blood Pressure / Bulimia, Anorexia / Depression, Anxiety / Other
Workouts	Training Data	Objective	Build muscle mass / Tone your body / Lose weight / Gain strength / Other
		Exercises He Does	Weights / Cardio / Both
		Meal Management	Yes/No
		Time spent training	Beginner/ Intermediate/ Advanced
		Training Time	Less than 30 min / 30 min to 1 hour / 1 to 2 hours / More than 2 hours
		Frequency	1 day / 2 days / 3 days / 4 days / 5 days 6 days / 7 days s
Potential Applications	Application Data	Interest	Yes/No
		Implementation of the Application	Workout Recommendations / Nutrition Recommendations / Workout Tracking / Other

2.4. Model Training

To ensure complete reproducibility of the experiments, the random number generator seed was set using the rng (“default”) command. During this phase, five multiclass classification algorithms were implemented and evaluated. With the exception of the k-NN model, all algorithms were trained using strictly the default hyperparameters set in the software (MATLAB). The configuration and functions applied to each model were as follows:

- k-Nearest Neighbors (k-NN): Implemented using the ‘fitcknn‘ function, this was the only model with a manually tuned hyperparameter, setting the number of neighbors to evaluate to 5 (‘NumNeighbors = 5‘).
- Support Vector Machines (SVM): Trained using the ‘fitcecoc‘ function with its default hyperparameters for solving multiclass problems.
- Random Forest: Implemented using its standard default configuration as an ensemble of classification trees using the ‘fitcensemble‘ function.
- Naive Bayes (NB): Run using the ‘fitcnb‘ function with its default hyperparameters, configured solely to process qualitative variables using discrete distributions.
- Linear Discriminant Analysis (LDA): Implemented using the ‘fitcdiscr‘ function as a linear classifier, run with its default algorithmic settings.

2.5. Performance Rating and Evaluation

Once the models were trained, the classification phase was carried out using 20% of the data corresponding to the test folds. Using MATLAB’s ‘predict‘ function, the algorithms evaluated previously unseen users and assigned them a skill level (beginner, intermediate, or advanced). Next, we evaluated the performance of each model by comparing its predictions with the actual user levels. To do this, we constructed a confusion matrix, which is a summary of the results obtained across the five test folds.

Since the dataset is imbalanced, simply measuring the overall accuracy percentage is not sufficient. Therefore, model performance was evaluated using the Macro Average metrics, which are the average of the performance across the three classes, to obtain a more accurate result [17]:

- Overall Accuracy: Represents the total percentage of correct predictions for the 81 users evaluated.Precision: Measures the proportion of correct predictions when the model assigns a user to a specific level.
- Recall: Measures the model's ability to correctly identify all users who actually belong to a class.
- Specificity: Evaluates the model's ability to correctly identify negative cases; that is, to avoid assigning a user to a difficulty level that does not apply to them.
- F1-Score: This is the harmonic mean of Precision and Recall. This metric is particularly useful and important for confirming that the model performs well despite data imbalance.

2.6. Development Methodology for the Mobile App

The waterfall model has been selected for the development of this project. This methodology is characterized by its sequential and structured approach; this model was chosen because it allows for detailed planning and better control of the process, which is ideal for ensuring that the project has well-defined objectives and requirements from the outset [18]. Development is divided into the following phases:

- Requirements analysis and definition: Functional and non-functional requirements of the application.
- System and software design: Design of the application architecture, user interface (UI), and user experience (UX).
- Implementation: Coding the application and training the ML algorithms.2.6.1 Software Architecture.

2.6.1. Architecture is based on a client-server model

- Client: This is the interface through which the user interacts with the system; it is responsible for collecting and displaying data.
- Server: The backend hosts the database and the ML algorithms. Here, user information is processed using the ML algorithms, which generate the personalized routine and send it to the client.2.6.2

2.6.2. User Interface (UI) Design and User Experience

Following a user-centered design (UCD) approach, the visual identity is designed to be motivating, clear, and energizing. The choice of colors is based on color psychology to enhance the user experience [19].

Primary Color (Green): This is the app's primary color. Green is described as the color of life and health and is associated with energy, well-being, and progress. Its use aims to inspire users to adopt a healthy lifestyle and feel a positive connection to their physical progress.

Background (White and Light Gray): These colors are used primarily for backgrounds, as they create a sense of cleanliness and simplicity. They help the content and important elements stand out, allowing users to focus on their routines.

Text and Elements (Black and Dark Gray): These shades are used for text and crucial interface elements. These colors provide contrast against light backgrounds, thereby enhancing the readability and clarity of visual elements. Black is associated with power, strength, and discipline, while dark gray is associated with balance and consistency.

According to Eva Heller [19] in her book:The Psychology of Color: How Colors Affect Feelings and Reason, the combination of green, white, and dark gray is associated with sports. This color choice reinforces the app's identity, conveying professionalism, energy, progress, and motivation in physical performance.

3. Analysis and Discussion of Results

3.1. Previewing Prototypes and Application Views

This is the first screen the user sees; it features a clean, minimalist design. The user is given the option to log in or create a new account. The main goal is to ensure quick and optimized access; see Figure 2.

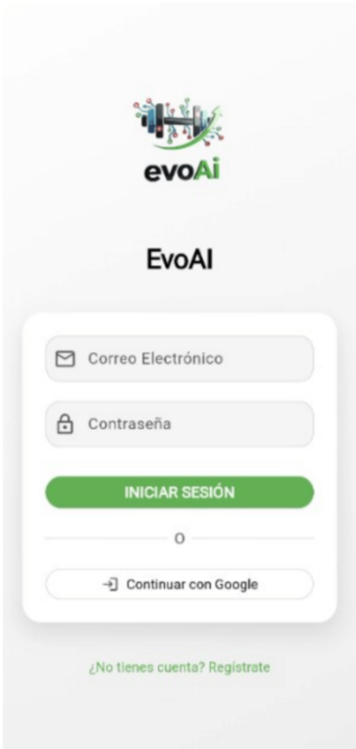

Figure 2: Login and Registration Interface.

The main panel, which serves as the user's command center, prominently displays the training routine assigned for the day, along with a summary of the user's weekly progress. This interface is designed to show only the most relevant information so that the user knows exactly what to do; see Figure 3.

On the following screen, the user can view detailed information about each exercise in their personalized routine, including the exercise name, the number of sets, and the number of repetitions. Each exercise can be selected to display a brief animation or description of the correct technique, thereby reducing the risk of injury; see Figure 4.

The following interface is designed to provide visual feedback on your consistency. Using graphs and a calendar that tracks your daily gym attendance, this system compares the training sessions you've completed against the weekly frequency suggested by the routine assigned by the ML algorithms; see Figure 5.

The following interface displays nutritional recommendations that are aligned with the user's primary goal. Its purpose is to maximize the effectiveness of the physical stimulus generated by the workout by providing a solution for calorie expenditure and muscle recovery; see Figure 6.

The following screen provides a structured view of the physical data entered during registration. In

Figure 3: Main Panel of the application.

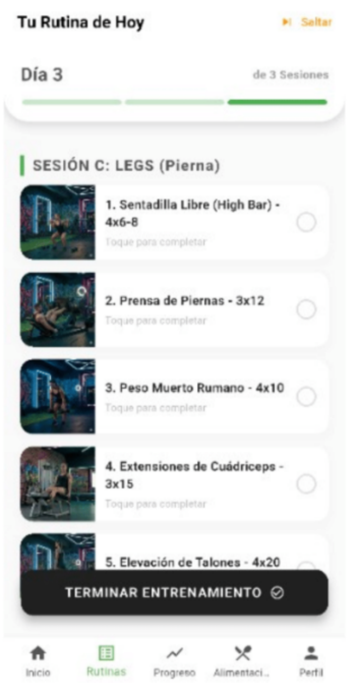

Figure 4: Routines Module.

addition, this interface allows users to update their personal information and view the plan assigned to them by the ML algorithm. This screen also allows users to log out. The interface manages the user's connection status, integrating Firebase Authentication security protocols to ensure the protection of personal data and enable a secure and efficient logout process; see Figure 7.

Figure 5: Progress Module.

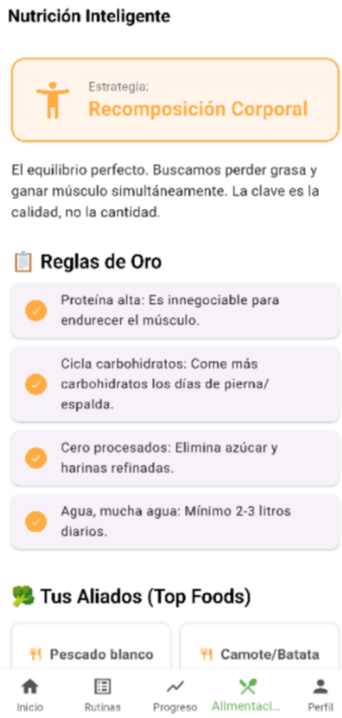

Figure 6: Smart Nutrition Module.

3.2. Analysis of Metrics and Predictive Results

To evaluate the performance of the classifiers, the confusion matrix was used as a tool. Based on the accumulation of the predictions made in each iteration of the cross-validation, these matrices were constructed to extract the performance metrics presented in Table 2.

To quantify predictive performance, five metrics are evaluated: Accuracy, Precision, Sensitivity, and

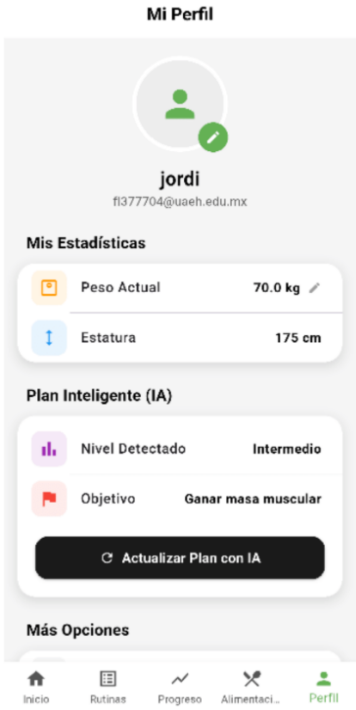

Figure 7: My Statistics Module.

F1-Score. The consolidated results are presented in Table 2.

Table 2
Quantitative Results of the Evaluation Metrics.

Model	Accuracy	Precision	Sensitivity	F1-Score	AUC-ROC
Random Forest	0.5926	0.5231	0.4974	0.7715	0.5020
KNN	0.5556	0.5046	0.4384	0.7401	0.4338
NB	0.5926	0.5920	0.5485	0.7671	0.5650
LR	0.5309	0.5134	0.5040	0.7367	0.5084
SVM	0.5679	0.5326	0.5176	0.7637	0.5223

Source: Compiled by the author.

The analysis shows that the class imbalance—43 beginners, 23 intermediate learners, and 15 advanced learners—affects the models' performance, making macro metrics particularly important for evaluating their ability to recognize all categories. Among the models evaluated, Naive Bayes achieved the best overall performance, with an Accuracy of 0.5926, a Macro Precision of 0.5921, a Macro Recall of 0.5485, and an F1-Score of 0.5650, demonstrating the best balance across the three classes. Random Forest achieved the same accuracy of 0.5926 and had the highest specificity at 0.7715, but its lower recall and F1-score indicate a reduced ability to correctly identify minority categories. On the other hand, k-NN had the lowest performance, with an accuracy of 0.5556 and an F1-score of 0.4338, possibly due to the small number of samples. SVM and LR showed intermediate performance, without outperforming Naive Bayes.

Naive Bayes was the most balanced and appropriate model for this dataset, while Random Forest stood out primarily for its ability to avoid misclassifications.

Figure 8 shows the resulting confusion matrix for the Random Forest algorithm.

This graph shows the distribution of the classifications generated by the model, highlighting the

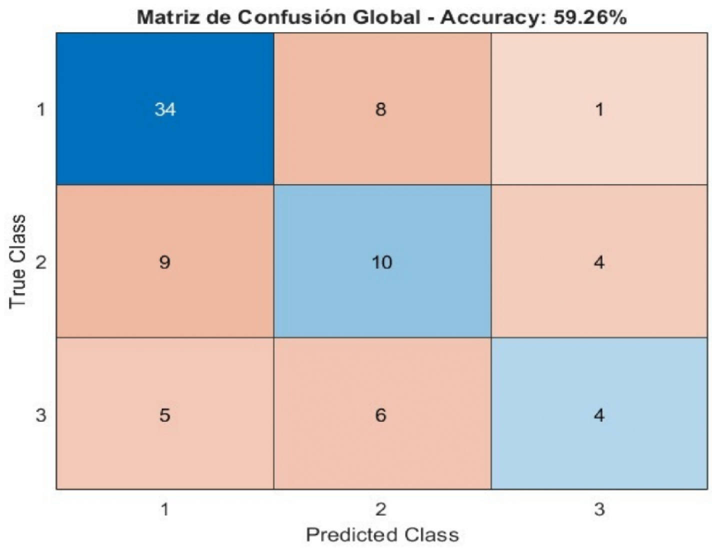

Figure 8: Confusion matrix for the Random Forests model.

trend in the predictions compared to the actual user categories (beginners, intermediate, and advanced) and illustrating how the model performs in the face of the database's inherent imbalance.

3.3. Usability Validation

After integrating the SVM model into the application's back end, EvoAI underwent rigorous usability testing in a real-world environment with the sample population (81 users). A standardized 19-item questionnaire (Likert scale) designed to assess the dimensions of efficiency, effectiveness, and satisfaction was administered [12].

Statistical analysis of the instrument yielded a Cronbach's alpha coefficient of 0.95, calculated using SPSS for Windows version 26.0, which attests to outstanding reliability and internal consistency; this confirms that the collected data are stable, accurate, and have a minimal margin of error. Figure 9 presents the responses given regarding the efficiency category in usability.

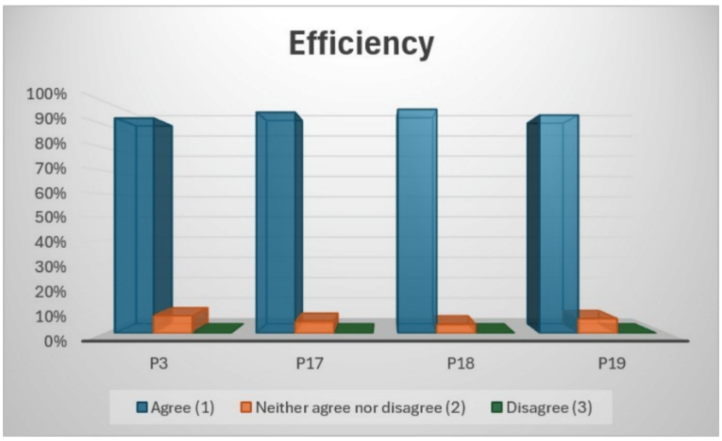

Figure 9: Results of the responses to the question regarding the efficiency of the designed mobile app (EvoAI). (Created by the author).

Efficiency: The results have been satisfactory in the efficiency category, meaning that the vast majority of participants perceive that EvoAI allows them to perform tasks quickly and with minimal effort.

Furthermore, regarding the results of the question in the usability questionnaire about the effectiveness of the designed mobile app, Figure 10 shows its performance.

Figure 10: Results of the responses to the question regarding the effectiveness of the designed mobile app (EvoAI). (Created by the author).

Effectiveness: An analysis of the effectiveness based on the results obtained shows that nearly all participants believe that EvoAI allows them to successfully complete tasks and achieve the proposed objectives.

Finally, Figure 11 shows the trend in responses to the question regarding user satisfaction with the designed mobile application.

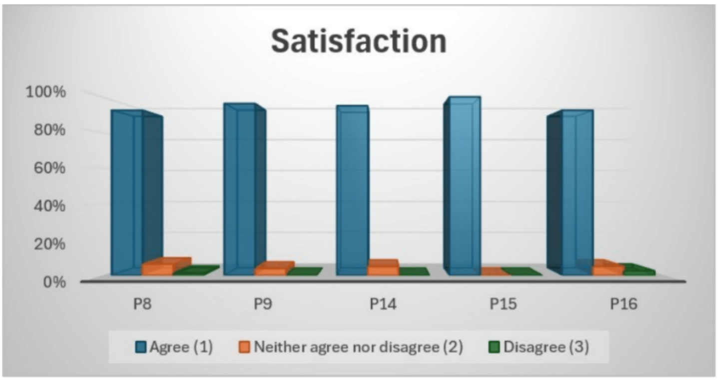

Figure 11: Results of the responses to the question regarding user satisfaction with the designed mobile app (EvoAI). (Created by the author).

Satisfaction: Users report an extremely positive overall experience. They say they feel motivated, in control of their actions within the software, and highly likely to continue using it.

4. Conclusion

The development and implementation of the EvoAI system successfully fulfill the overall objective of applying artificial intelligence to the automated generation of fitness routines, demonstrating technical superiority over the generic alternatives currently available. The main conclusions of the research are:

- Performance analysis shows that the Naive Bayes classifier achieves the best predictive balance in the face of class imbalance, obtaining the highest macro F1-score in the comparison at 56.50%. This demonstrates the superiority of probabilistic statistical models over models based on distance metrics such as k-NN, which suffer a severe drop in performance when working with few samples.
- Democratization of physical health: By integrating biometric, nutritional, and motivational parameters, EvoAI breaks down the economic barrier that limits access to personal training

services. Its use reduces the risk of injuries resulting from inexperience and promotes consistent adherence to physical activity among young people.
- Excellence in Usability (DCU): Achieving a Cronbach's alpha of 0.95 in the usability validation confirms that the complex calculations of machine learning are successfully translated into an intuitive, efficient, and highly satisfying graphical interface.

It is worth noting that this study is preliminary, as the intention is to take into account the following limitations for future research:

- Cross-platform expansion into iOS ecosystems.
- Implement a feedback system in which the model reassesses the user each month based on their compliance rate and progress, dynamically adjusting the routine.
- Demographic scaling: The models were trained, calibrated, and validated using a population sample limited to residents of the municipality of Tizayuca, Hidalgo State, Mexico. We propose expanding data collection to the state and national levels.
- Incorporate a smart nutrition module: Using the same anthropometric data and the user's goal, the module can calculate macronutrient requirements (proteins, carbohydrates, and fats) and suggest meal plans that complement the assigned routine.

Declaration on Generative AI

During the preparation of this paper, the authors used DeepL to assist with the translation of the manuscript from Spanish into English and ChatGPT to support language revision and improve the clarity of the text. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the final content of the paper.

References

[1] W. H. Organization, WHO guidelines on physical activity and sedentary behaviour, World Health Organization, 2020.
[2] C. C. Aggarwal, et al., Neural networks and deep learning, volume 10, springer Cham, 2018.
[3] E. Yang, Y. Hwang, J. Kim, Artificial intelligence-based personalized healthcare and fitness systems: A systematic review, 2023.
[4] D. Riebe, J. K. Ehrman, G. Liguori, M. Magal, ACSM's guidelines for exercise testing and prescription, American College of Sports Medicine, 2018.
[5] I. Goodfellow, Y. Bengio, A. Courville, Y. Bengio, Deep learning, volume 1, MIT press Cambridge, 2016.
[6] J. M. Peake, G. Kerr, J. P. Sullivan, A critical review of consumer wearables, mobile applications, and equipment for providing biofeedback, monitoring stress, and sleep in physically active populations, Frontiers in physiology 9 (2018) 743.
[7] S. Intille, M. Dunton, Just-in-time adaptive interventions for physical activity, 2021.
[8] National Institute of Statistics and Geography (INEGI), Survey on sports participation and physical activity (mopradef) 2024, 2024.
[9] H. Kamel Boulos, A. Zhang, Digital health technologies and artificial intelligence for personalized physical activity interventions: A review, 2021.
[10] S. Vairavasundaram, V. Varadarajan, D. Srinivasan, V. Balaganesh, S. B. Damerla, B. Swaminathan, L. Ravi, Dynamic physical activity recommendation delivered through a mobile fitness app: A deep learning approach, Axioms 11 (2022) 346.
[11] H. Jubair, M. Mehenaz, Utilizing machine learning algorithms for personalized workout recommendations and monitoring: A systematic review on smartwatch-assisted exercise prescription, Digital health 11 (2025) 20552076251355365.

[12] T. Davergne, P. Meidinger, A. Dechartres, L. Gossec, The effectiveness of digital apps providing personalized exercise videos: systematic review with meta-analysis, Journal of medical Internet research 25 (2023) e45207.
[13] Tizayuca Planning and Foresight Unit, Demographic data for the municipality, 2025.
[14] D. Lind, W. Marchal, S. Wathen, Applied Statistics for Business and Economics, McGraw-Hill Interamericana, 2019.
[15] R. Hernández-Sampieri, C. Mendoza, Research methodology: quantitative, qualitative, and mixed routes, Mexico City: McGraw-Hill (2018).
[16] F. Mohr, J. N. van Rijn, Fast and informative model selection using learning curve cross-validation, IEEE Transactions on Pattern Analysis and Machine Intelligence 45 (2023) 9669–9680.
[17] A. Ahmadzadeh, D. J. Kempton, P. C. Martens, R. A. Angryk, Contingency space: a semimetric space for classification evaluation, IEEE Transactions on Pattern Analysis and Machine Intelligence 45 (2022) 1501–1513.
[18] Z. A. Yenioğlu, Integrating waterfall methodology and object oriented approach within a decision support system development life cycle design, Erciyes Üniversitesi Fen Bilimleri Enstitüsü Fen Bilimleri Dergisi 38 (2022) 446–457.
[19] E. Heller, The psychology of colour: How colours affect feelings and reasoning, Barcelona: Editorial Gustavo Gili (2004).