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Original Article

Personalized Gym Recommendation System Using Machine Learning

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Abstract - *The Personalized Gym Recommendation System (PGRS) is a digital platform designed to provide tailored fitness and health advice to gym-goers, particularly beginners and intermediates. This study introduces an innovative approach to simplify workout routines by leveraging machine learning algorithms to analyze user data and generate personalized recommendations. The dataset, obtained from Kaggle, originally contained 14589 records with 15 columns, and three additional columns were added, resulting in 18 columns. Eight machine learning models were trained for both classification and regression. The Decision Tree regression model worked wonders; the accuracy was 100% against the training set and 99.95% against the test set. Next in line were the results of the Decision Tree classification model, which turned out very good; training accuracy equaled 99.33%, while test accuracy equaled 92.22%. The main challenge in our study was joining regression and classifier classes into a single model. The main difference between these two classes is that regression predicts continuous values, whereas classification does the opposite by grouping data into specific categories.*

Keywords - *Blockchain technology, Civic engagement, Decentralized systems, Online petitions, Policy-making.*

1. Introduction

Gyms are essential facilities for individuals seeking to improve their physical fitness and overall health. Despite the growing popularity of gyms, many users struggle with inefficient workout routines due to a lack of personalized guidance. Existing gym recommendation systems often fail to account for individual preferences, fitness levels, or health conditions, leading to suboptimal outcomes. For example, users aiming to lose weight may inadvertently engage in exercises better suited for muscle gain, increasing the risk of injury and delaying progress. [1]. The study used machine learning to give health advice based on personal information like weight and height. This was significant since maintaining good health had become increasingly critical, particularly as more individuals became overweight. The software estimated body fat using regression analysis and offered dietary and exercise advice. It also provided individualized plans based on fitness level, including diet recommendations and exercise advice. Users could even consult a doctor online. This strategy is intended to improve people's health management using technology [2]. The study created a system for predicting physical fitness based on variables such as calorie burn, ethnicity, gender, preferences, and health conditions. The recommendation system attempted to forecast client interests and deliver personalized workout suggestions, taking into account comorbidities, geographical location, physical activity and eating trends [3]. Authors [4] proposed a physical fitness Recommender framework for thyroid patients using restricted Boltzmann machines. They aimed to improve fitness guidance systems by considering previously disregarded aspects such as thyroid health, activity preferences, and calorie intake. It created individualized exercise programs for thyroid patients, customizing workouts based on information about the influence of exercise on thyroid function. The system used hybrid models to create individualized routines considering user-specific factors such as calorie consumption, gender, age, and exercise intensity. The technology customized workouts based on user feedback and physiological data to ensure individualized training routines. In the fitness domain, personalization has gained traction through technologies such as DNA-based insights, wearable trackers, and contextual multi-arm bandit architectures. These systems leverage user-specific data such as heart rate profiles and activity logs to optimize recommendations. However, existing systems often lack transparency in goal-setting algorithms or fail to comprehensively address comorbidities and physiological variations. The current generation is increasingly concerned about their health and fitness. However, gym-goers often do not clearly know their fitness goals, what exercises they should do, and what equipment to use, leading to inefficient workout routines and delayed progress. For example, someone aiming to lose weight might engage in exercises that are better suited for gaining weight, risking serious injury. Many individuals struggle to achieve their fitness goals due to the limitations of existing personalized fitness recommendations. The main problem is that everyone wants the coach to track their progress or provide recommendations, which is a significant burden for gym coaches. This study addresses these limitations by developing a Personalized Gym Recommendation System (PGRS) that uses machine learning algorithms to provide tailored fitness recommendations based on user-specific data such as age, weight, height, and health conditions. By filling this research gap, the PGRS aims to revolutionize fitness management through individualized workout strategies that enhance adherence and efficiency.

2. Literature Review

Recent advancements in machine learning have enabled personalized health recommendation systems to be developed. For instance, a diet recommendation system was proposed using classifiers like KNN, SVM, and Decision Tree to tailor diets based on individual health goals. Similarly, integrated IoMT-assisted patient diet recommendation systems with deep learning techniques to provide customized dietary advice. According to [5], a diet recommendation system was developed using several machine learning classifiers to tailor diets to individual health goals. It assessed diet programs' precision, recall, accuracy, and F1-score for weight gain, weight loss, and healthy living by comparing classifiers such as KNN, SVM, Decision Tree, Random Forest, Naive Bayes, and Extra Tree.

Integrating a machine learning model, we created an efficient IoMT-assisted patient diet recommendation system, focusing on integrating deep learning and machine learning to generate appropriate diet guidance. To recommend meals, the algorithm reviewed health databases and took into account parameters such as age, gender, sickness, and nutritional content. The recommendation process was improved using algorithms such as logistic regression, Naive Bayes, RNN, LSTM, GRU, and MLP [6].

The fitness industry has made a huge turn toward customization, acknowledging each individual's unique physiological and psychological characteristics. This trend is seen using genetic insights from DNA testing, personalized fitness technologies, and AI's transformative role in producing bespoke fitness programs. Fitness personalization is creating individualized workout regimens, food plans, and lifestyle changes depending on factors such as body composition, metabolic rate, chosen activities, and pre-existing medical conditions. This strategy improves health and well-being goals while increasing fitness outcomes [7]. The study investigates the evolution of modern gym and fitness culture, exposing how it has grown into a global billion-dollar industry. It investigates transitioning from a male-dominated, national muscular culture to a multinational, commercialized industry promoting varied fitness and lifestyle concepts. The study identifies three important globalization eras that influenced this transition. It also tracks the growth of bodybuilding ideas, linking early physical culture to current ones. This analysis sheds light on the sociological and economic reasons fueling the emergence of fitness culture [8]. The study examined algorithms for recommending fitness tracker goals to increase user engagement. It consisted of three sequential investigations that assessed transparency, trust, and goal commitment using qualitative and quantitative methods. A specialized algorithm generated step data and goal suggestions for participants. The findings revealed that transparency in goal ideas improved goal commitment. However, participant recruitment and cultural variables posed challenges. The study stressed the significance of transparent goal-setting algorithms in fitness trackers and proposed areas for future investigation [9].

The study aims to create a tailored exercise recommendation system based on wearable trackers and mobile health technology. It presents a novel method for personalized workout suggestions based on a contextual multi-arm bandit architecture that collects and analyzes users' physiological data and everyday activities. Twenty female college students tried the system and reported a considerable increase in daily exercise time. Furthermore, the walking and recommendation system components earned high satisfaction ratings, confirming the efficiency of the mHealth training program [10]. The study proposes a novel way to make individualized workout suggestions by modeling heart rate and activity data with FitRec, an LSTM-based model. FitRec incorporates context from a user's previous actions to more accurately record individualized variations in heart rate profiles during exercise. The algorithm was tested using a dataset containing workout logs and sensor data, outperforming baseline methods in tasks such as personalized recommendations [11].

According to [12], a developed drug recommendation system utilizing machine learning to analyze sentiment in drug reviews was created. The method improves prescription accuracy by analyzing patient feedback and personalizing suggestions based on individual preferences. It uses vectorization and classification algorithms, with the LinearSVC classifier attaining 93% accuracy using TF-IDF vectorization. The study offers a data-driven approach to tailored treatment that prioritizes patient sentiment.

Recommendations for improvements, such as data balancing and hyperparameter optimization, aim to improve the system's performance in real-world situations. On the other hand, [13] developed a multi-threaded collaborative filtering recommendation system to enhance scalability and efficiency. By dividing users into parallel threads, the system achieves faster computation and improved performance without compromising data security. This study builds upon these advancements by introducing a novel gym recommendation system that combines regression and classification models to address gaps in current approaches. Unlike previous works focusing solely on diet or activity tracking, this system integrates diverse parameters such as user preferences, health conditions, and progress tracking for holistic fitness management.

3. Methodology

3.1. System Description

The Personalized Gym Recommendation System provides tailored exercise routines based on user-specific traits such as age, gender, weight, height, preferences, and health conditions. The system ensures sustained effectiveness while minimising injury risks by incorporating adaptive algorithms that evolve with users' fitness levels.

The tailored approach, along with technology and support elements, results in a holistic and fun training experience, leading to greater outcomes and overall well-being. The system also fosters a comprehensive fitness experience, including personalized guidance for warm-ups, cooldowns, and recovery strategies, ensuring a holistic approach that supports not only exercise but overall well-being.

Combining data-driven insights with a user-centric approach, the Personalized Gym Recommendation System offers a safe, effective, and enjoyable path to fitness success, empowering users to achieve their health goals confidently and easily.

3.2. System Architecture

Our system architecture diagram depicts the steps involved in creating a machine learning model. The architecture consists of several stages:

- Data Collection: Data from Kaggle containing 14,589 records was used.
- Data Preparation: Preprocessing included handling missing values and feature engineering.
- Model Training: Eight machine learning models were trained for classification (e.g., Decision Tree) and regression tasks (e.g., Linear Regression).
- Model Selection: Performance metrics such as accuracy and RMSE were used for evaluation.
- Recommendation Generation: The final model generates personalized recommendations based on user input.

Data collection is the first step, followed by data preparation. The dataset includes demographic information (age, gender), workout history (calories burned), preferences (exercise type), and health conditions (diabetes).

Moreover, columns were added during preprocessing to enhance feature representation which involves extracting and preparing the dataset for training. The information is then separated into training and testing sets. The data trains multiple models, including linear regression, decision trees, random forests, and K-nearest neighbor. Following testing, the model is selected, and additional feature testing is performed to enhance the model and assure peak performance.

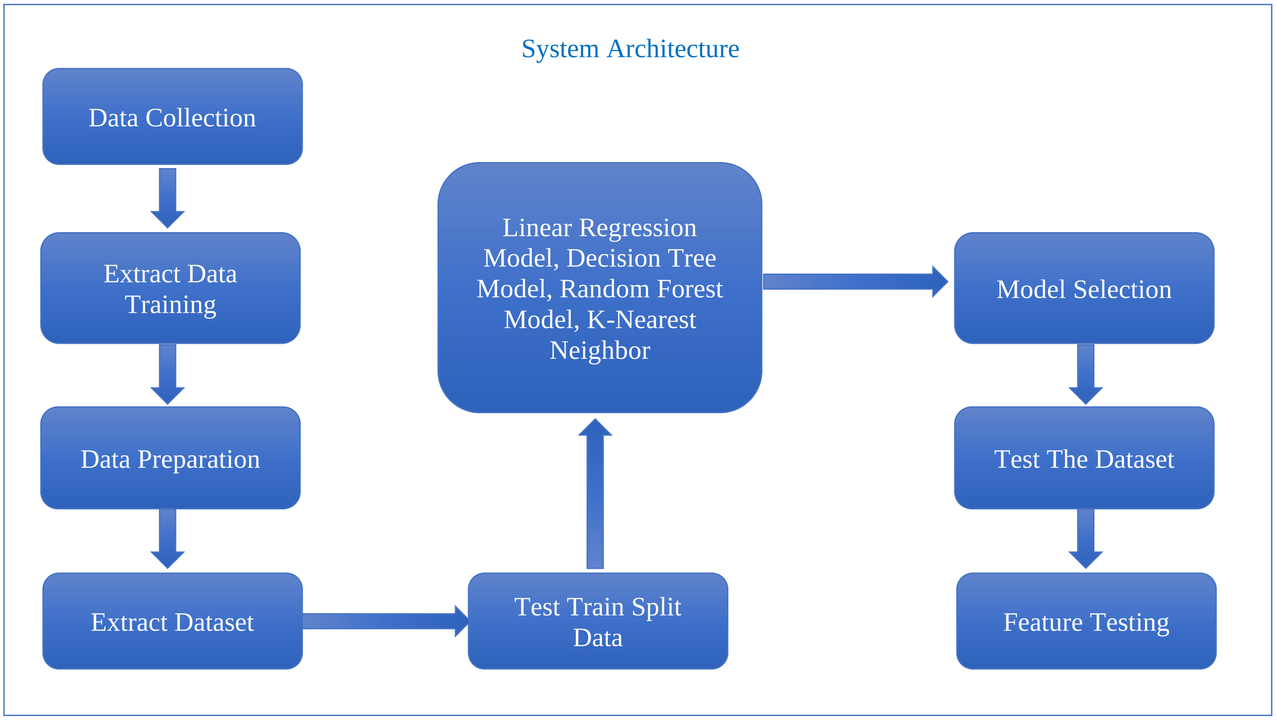


Fig. 1 System architecture

3.3. Data Collection

The gym suggestion program is intended to assist consumers in finding the finest fitness routines for their specific needs. It makes use of data from a Kaggle dataset, including 14589 records and 15 columns, including information about gym-goers' preferences, workout history, and demographics.

3.4. System Methodology

We developed a personalized gym recommendation system using eight machine learning models: decision tree regression, random forest, KNN, gradient boosting, AdaBoost, SVM, logistic regression, and linear regression.

The decision tree regression model performed best with 100% training accuracy and 99.94% testing accuracy for regression, 99.33% training accuracy and 92.22% testing accuracy for classification. Random forest and gradient boosting also showed high accuracy, particularly in regression tasks, with nearly perfect results.

3.5. System Development Environment

The Personalized Gym Recommendation System was developed using a combination of front-end and back-end technologies. The system was developed using:

- Flask (Python) for back-end development.
- HTML/CSS/Bootstrap for front-end design.
- MySQL for database management.

3.6. Existing System

Existing gym recommendation systems focus heavily on simple parameters like location, pricing, and available facilities. These algorithms frequently neglect users' tastes and fitness goals, resulting in generic and ineffective recommendations. Furthermore, many of these systems do not use advanced algorithms to evaluate user data and provide more personalized recommendations.

3.7. Current System

This technology revolutionizes gym choices using data analytics to deliver personalized suggestions based on user preferences (sex, age, height, weight) and health information (hypertension, diabetes). It provides personalized training regimens, equipment recommendations, nutritional advice, and membership alternatives. Over time, the algorithm learns from user interactions and continuously refines its recommendations to ensure they remain relevant. Its user-friendly design streamlines decision-making and increases user engagement, eliminating the shortcomings of existing gym systems.

4. Implementation and Testing

The main objective of this study is to build a system that helps gym-goers get a recommendation system to make their exercises easy. Our system for implementing machine learning and webserver. The graphical user interface software component is the Python flask at the front end. We also use Python so that the Models of Data Collection program must implement the dataset as the back-end. Figure 2 shows a histogram and a boxplot of age. The histogram shows how often each age group appears, and the boxplot shows the spread and middle range of ages. Both charts help us see how the ages are distributed.

Figure 3 shows a histogram and a boxplot of height. The histogram illustrates how often each height range occurs, with most people clustered around a specific height. The boxplot summarizes the heights' overall spread and middle range, showing no extreme values or outliers.

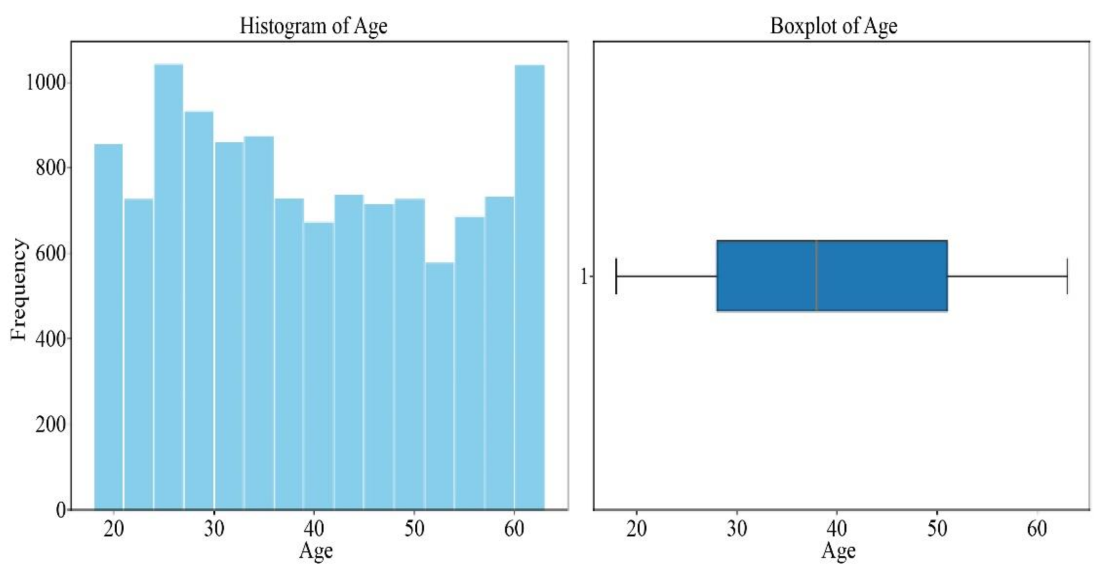


Fig. 2 Age distribution analysis

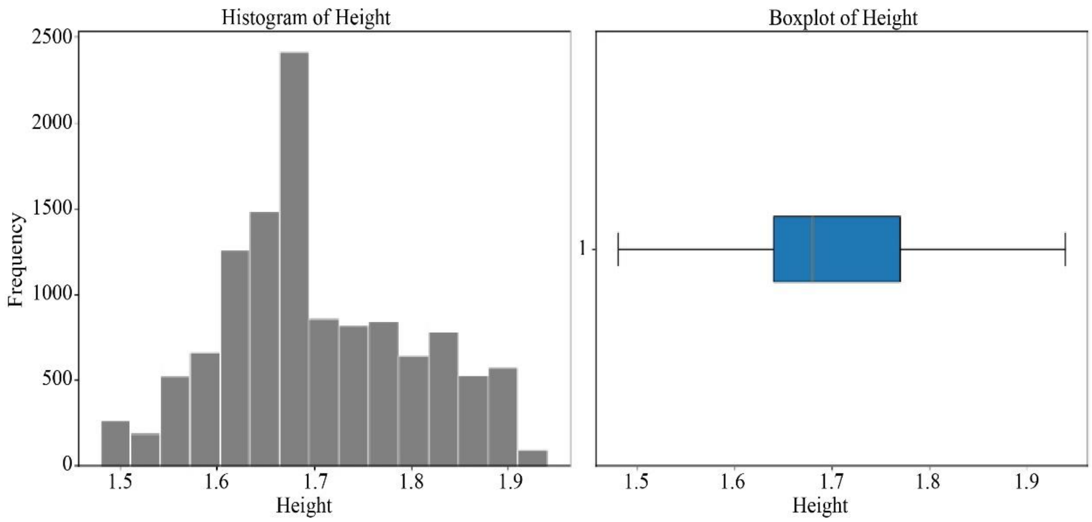


Fig. 3 Height distribution analysis

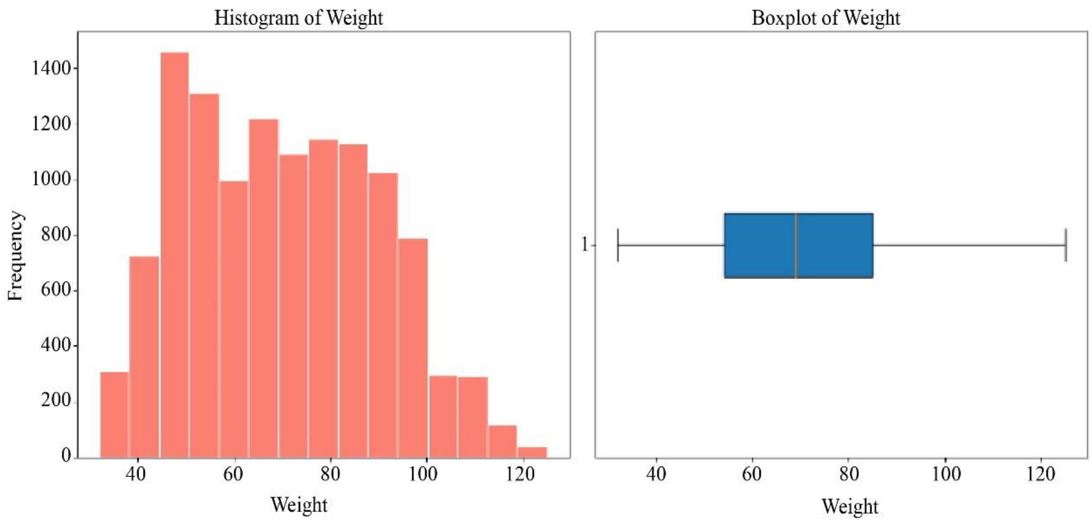


Fig. 4 Weight distribution analysis

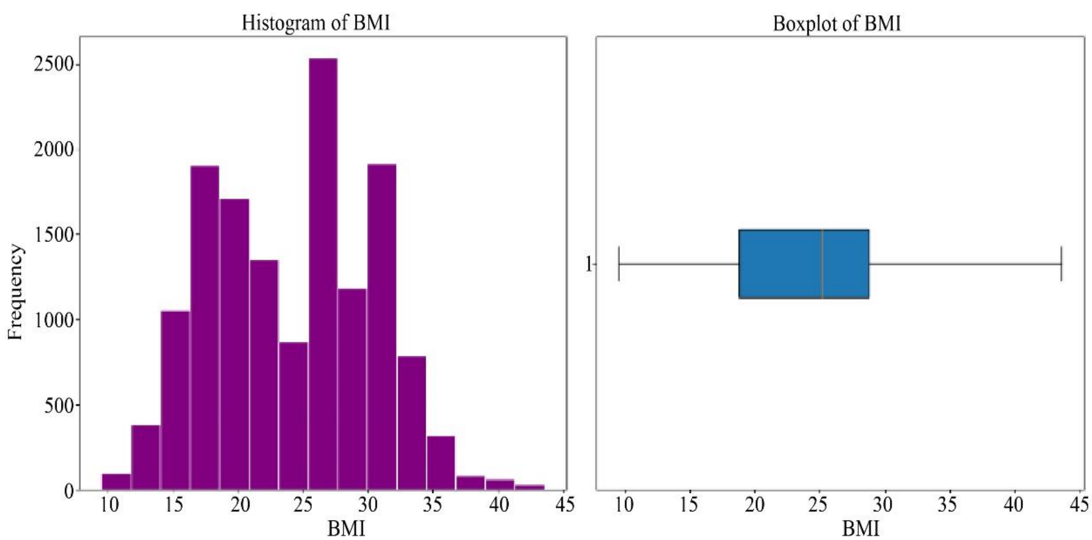


Fig. 5 BMI distribution analysis

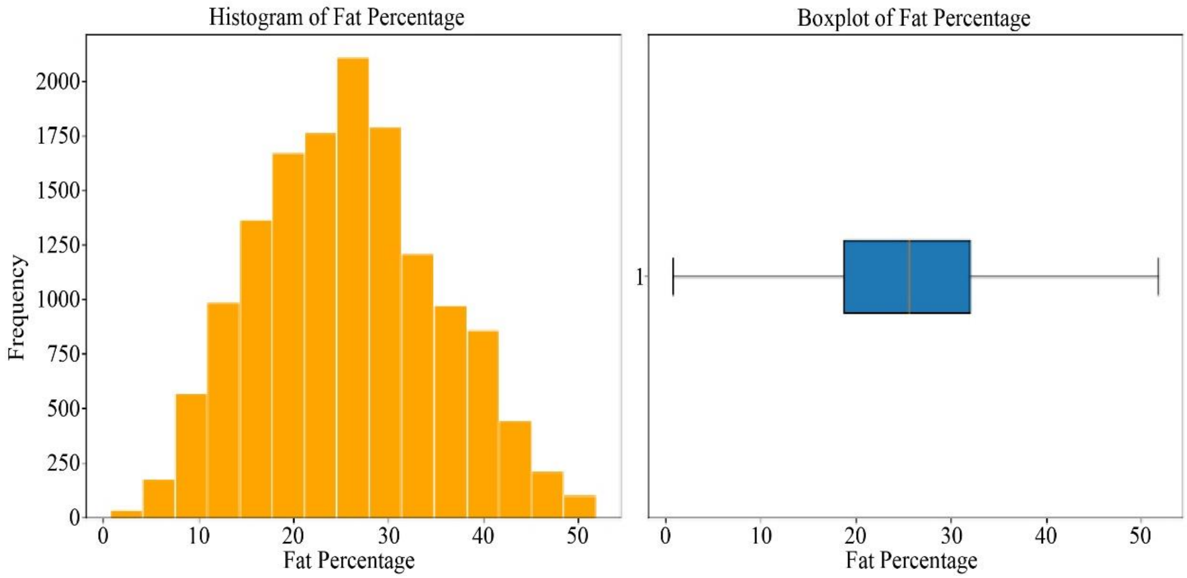


Fig. 6 Bodyfat distribution analysis

Figure 4 shows a histogram and a boxplot of weight. The histogram displays the frequency of different weight ranges, with most weights concentrated in the middle range. The boxplot provides a summary of the weight distribution, showing the spread and central range with no outliers present. Figure 5 shows a histogram and a boxplot of BMI. The histogram illustrates the frequency of different BMI ranges, with a noticeable concentration around the middle values. Figure 6 shows a histogram and a boxplot of fat percentage. The histogram reveals the distribution of fat percentages, with most values clustered around the middle. Figure 7 shows the sex distribution in a dataset, with 60.1% of the individuals being male and 39.9% being female. The chart visually highlights the larger proportion of males compared to females. Figure 8 shows the distribution of fitness levels, with the highest count in the overweight category. Normal and underweight categories have similar counts, while the obese category has the lowest count. The chart provides a clear comparison of how individuals are distributed across different fitness levels. Figure 9 shows a nearly equal distribution between individuals with weight gain and weight loss fitness goals. Figure 10 shows a fitness report with a BMI of 16.44, focusing on weight gain and muscular fitness. It recommends exercises like squats and a diet rich in vegetables and proteins. The report also advises consulting a professional before making significant changes.

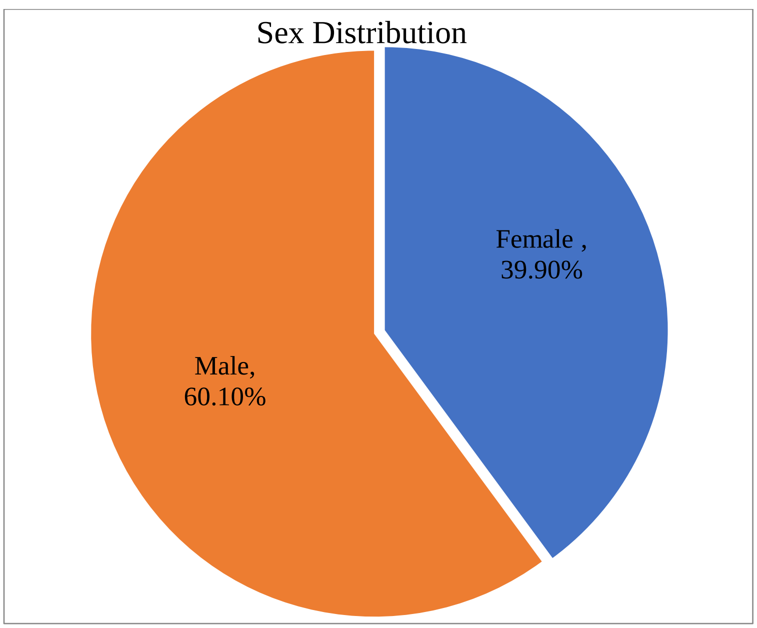


Fig. 7 Sex distribution analysis

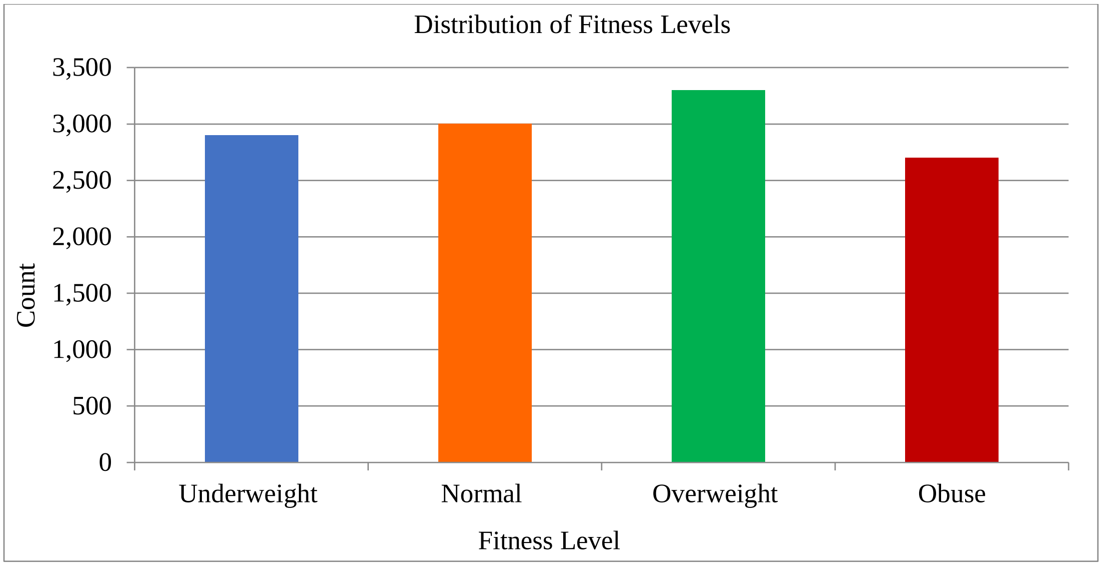


Fig. 8 Fitness level

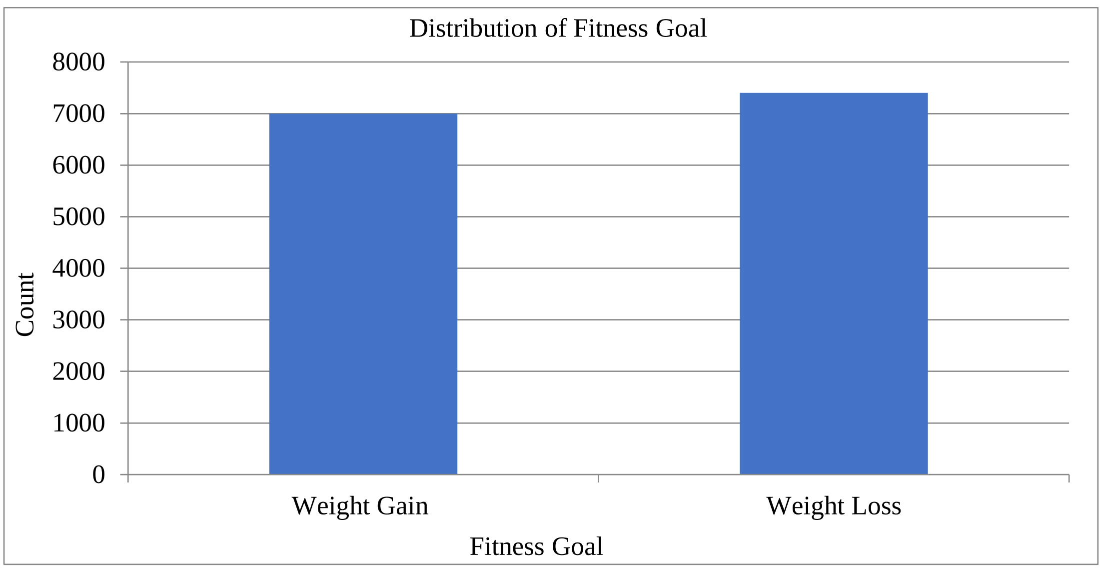
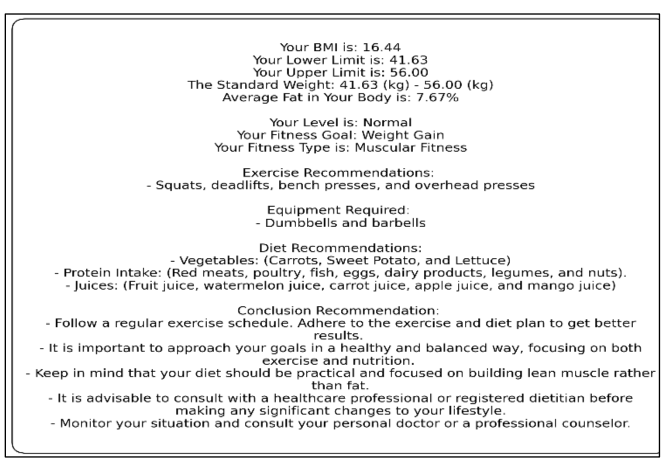


Fig. 9 Fitness goal


Your BMI is: 16.44
Your Lower Limit is: 41.63
Your Upper Limit is: 56.00
The Standard Weight: 41.63 (kg) - 56.00 (kg)
Average Fat in Your Body is: 7.67%

Your Level is: Normal
Your Fitness Goal: Weight Gain
Your Fitness Type is: Muscular Fitness

Exercise Recommendations:
- Squats, deadlifts, bench presses, and overhead presses

Equipment Required:
- Dumbbells and barbells

Diet Recommendations:
- Vegetables: (Carrots, Sweet Potato, and Lettuce)
- Protein Intake: (Red meats, poultry, fish, eggs, dairy products, legumes, and nuts).
- Juices: (Fruit juice, watermelon juice, carrot juice, apple juice, and mango juice)

Conclusion Recommendation:
- Follow a regular exercise schedule. Adhere to the exercise and diet plan to get better results.
- It is important to approach your goals in a healthy and balanced way, focusing on both exercise and nutrition.
- Keep in mind that your diet should be practical and focused on building lean muscle rather than fat.
- It is advisable to consult with a healthcare professional or registered dietitian before making any significant changes to your lifestyle.
- Monitor your situation and consult your personal doctor or a professional counselor.

Fig. 10 Feature testing

Figure 11 displays the system's home page, showcasing the main interface and navigation options. Figure 12 shows a calculator interface where the user needs to input their age, height, weight, sex, and whether they have hypertension or diabetes. Figure 13 shows a personalized health report based on user input detailing BMI, fitness goals, and recommendations.

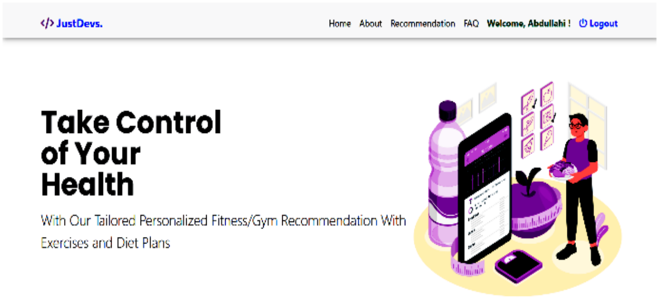


Fig. 11 Home page

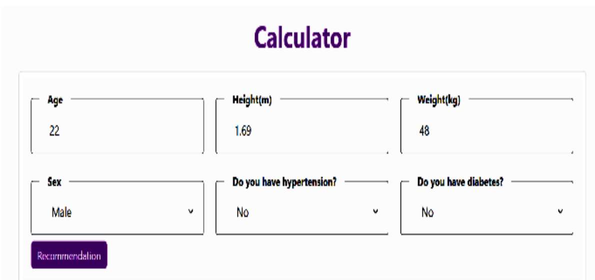


Fig. 12 User input

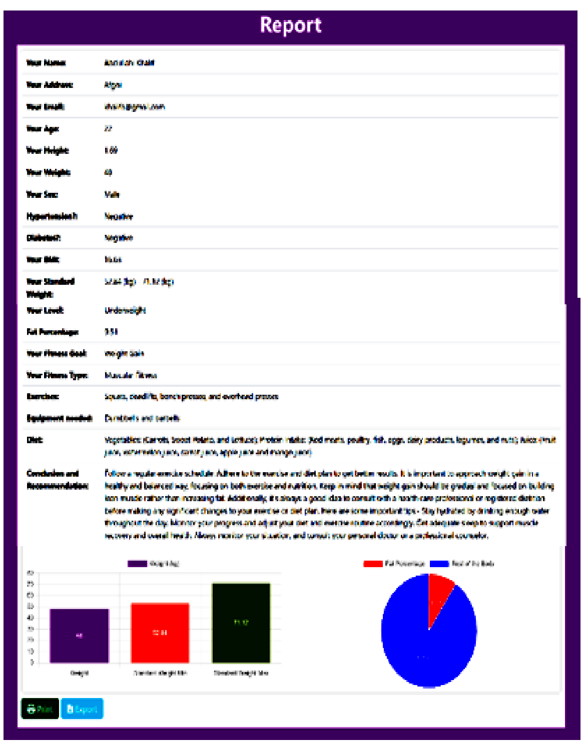


Fig. 13 Recommendation report

This section highlights petitions that have successfully influenced change or achieved their objectives. It provides inspiration and encouragement to other users by showcasing the impact that their participation can obtain.

5. Discussion and Results

Our research's key issue was merging regression and classifier classes into a single model. These two classifications are distinct: regression predicts continuous values, whereas classification categorizes data into particular groups. It was challenging to combine them into a single model because each required specific handling and optimization.

We had to carefully develop the model to balance these requirements without sacrificing accuracy. This was a difficult process that necessitated extensive work to guarantee that the model performed effectively for both types of predictions. Finally, one of the most difficult components of our research was its integration.

This study compares eight models and finds substantial variances in their performance. The Decision Tree regression model is exceptionally accurate, scoring 100% on the training set and 99.95% on the testing set.

The Decision Tree model likewise performs well in classification, with 99.33% training and 92.22% testing accuracy, respectively. Similarly, the Random Forest regression model shows outstanding accuracy, with 99.99% on training and 99.96% on testing, as well as 99.21% and 91.85% on classification tasks.

Table 1. Model accuracy model

No	Model	Type	Training Accuracy	Testing Accuracy
1.	Decision Tree Model	Regression	100%	99.95%
		Classification	99.33%	92.22%
2.	Random Forest Model	Regression	99.99%	99.96%
		Classification	99.21%	91.85%
3.	K-Nearest Neighbors	Regression	92.27%	88.40%
		Classification	21.18%	17.43%
4.	Gradient Boosting Model	Regression	99.85%	99.84%
		Classification	89.15%	88.27%
5.	Ada Boost Model	Regression	96.41%	96.26%
		Classification	5.24%	4.65%
6.	Support vector ML	Regression	48.17%	49.49%
		Classification	3.10%	3.14%
7.	Linear Regression	Regression	99.38%	99.36%
8.	Logistic Regression	Classification	85.09%	85.54%

6. Conclusion and Future Work

6.1. Conclusion

This study presents a novel Personalized Gym Recommendation System that leverages machine learning algorithms to provide tailored fitness advice based on user-specific data. By addressing limitations in existing systems, this research contributes significantly to individualized fitness management strategies that enhance adherence and efficiency.

6.2. Future Work

Future work will focus on expanding datasets and incorporating wearable device data for real-time recommendations. We recommend this work as a starting point for future research in this area. As researchers shift to this new focus, we recommend that they examine two essential points:

- Future researchers should improve the machine learning methods employed in this study.
- Researchers should develop a mechanism for tracking gym clients and collecting fitness statistics.

Acknowledgments

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References

[1] Bo Zhou et al., "Measuring Muscle Activities During Gym Exercises with Textile Pressure Mapping Sensors," *Pervasive and Mobile Computing*, vol. 38, pp. 331-345, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[2] J. Jeyaranjani and Utkash Kapoor, "Machine Learning Based Fitness Application Using BMI Value," *Journal of Physics: Conference Series, International Conference on Recent Trends in Computing 20-22*, Maharashtra, India, vol. 1979, no. 1, pp. 1-8, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Anganabha Baruah et al., "Machine Learning Based Yoga Recommendation System for the Physical Fitness," *8th International Conference on Science Technology Engineering and Mathematics*, Chennai, India, pp. 1-7, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Vaishali S. Vairale, and Samiksha Shukla, "Physical Fitness Recommender Framework for Thyroid Patients using Restricted Boltzmann Machines," *International Journal of Intelligent Engineering & Systems*, vol. 13, no. 5, pp. 247-256, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] Megh Shah, Sheshang Degadwala, and Dhairya Vyas, "Diet Recommendation System based on Different Machine Learners: A Review," *2nd International Conference on Artificial Intelligence and Smart Energy*, Coimbatore, India, pp. 290-295, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[6] Celestine Iwendi et al., "Realizing an Efficient Iomt-Assisted Patient Diet Recommendation System Through Machine Learning Model," *IEEE access*, vol. 8, pp. 28462-28474, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[7] Jennifer Smith Maguire, "The Culture of Fitness: Opportunities and Challenges for Health," *Marketing Sport and Physical Activity: Impacts on Health and Leisure: International Sports Marketing Conference*, Hong Kong Baptist University, pp. 1-11, 2006. [Google Scholar] [Publisher Link]

[8] Jesper Andreasson, and Thomas Johansson, "The Fitness Revolution: Historical Transformations in the Global Gym and Fitness Culture," *Sport Science Review*, vol. 23, no. 3-4, pp. 91-112, 2014. [Google Scholar] [Publisher Link]

[9] Paweł W. Woźniak et al., "Exploring Understandable Algorithms to Suggest Fitness Tracker Goals That Foster Commitment," *Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society*, Tallinn, Estonia, pp. 1-12, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[10] Milad Asgari Mehrabadi et al., "PERFECT: Personalized Exercise Recommendation Framework and architECTure," *ACM Transactions on Computing for Healthcare*, vol. 5, no. 4, pp. 1-25, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Jianmo Ni, Larry Muhlstein, and Julian McAuley, "Modeling Heart Rate and Activity Data for Personalized Fitness Recommendation," *The World Wide Web Conference*, San Francisco, USA, pp. 1343-1353, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[12] Satvik Garg, "Drug Recommendation System Based on Sentiment Analysis of Drug Reviews Using Machine Learning," *11th International Conference on Cloud Computing, Data Science & Engineering*, Noida, India, pp. 175-181, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[13] Xueli Xing, and Qiushi Wen, "A Human Resource Evaluation and Recommendation System based on Big Data Mining," *Scalable Computing: Practice and Experience*, vol. 25, no. 6, pp. 5539-5549, 2024. [CrossRef] [Google Scholar] [Publisher Link]