A Multi-Model Machine Learning Approach for Monitoring Calories Being Burnt During Workouts Using Smart Calorie Tracer

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Abstract

INTRODUCTION: In today's health-conscious world, accurate calorie monitoring during exercise is crucial for achieving fitness goals and maintaining a healthy lifestyle. However, existing methods often lack precision, driving the need for more reliable tracking systems. This paper explores the use of a multi-model machine learning approach to predict calorie burn during workouts by utilizing a comprehensive dataset.
OBJECTIVES: The objective of this paper is to develop a user-friendly program capable of accurately predicting calorie expenditure during exercise, leveraging advanced machine learning techniques.
METHODS: Techniques from social network analysis were employed to analyze the dataset, which included information on age, gender, height, weight, workout intensity, and duration. Data preprocessing involved handling missing values, eliminating irrelevant columns, and preparing features for analysis. The dataset was then divided into training and testing sets for model development and evaluation. Machine learning models, including Neural Networks, AdaBoost, Random Forest, and Gradient Boosting, were chosen based on their performance in regression tasks.
RESULTS: The neural network model demonstrated superior performance in predicting calorie burn, outperforming other models in terms of MSE, RMSE, and an R2 score. Data visualization techniques aided in understanding the relationship between variables and calorie burn, highlighting the effectiveness of the neural network model.
CONCLUSION: The findings suggest that a multi-model machine learning approach offers a promising solution for accurate calorie tracking during exercise. The neural network model, in particular, shows potential for developing user-friendly calorie monitoring applications. While limitations exist, such as dataset scope and environmental factors, this study lays the groundwork for future advancements in calorie monitoring and contributes to the development of holistic fitness applications.

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1. Introduction

Tracking and keeping track of the calories you burn while exercising has grown in importance in today's health-conscious world. Calorie monitoring that is accurate and convenient can help people achieve their fitness objectives, live a healthy lifestyle, and optimize their workout routines. Calorie burn monitoring is a difficult undertaking since measuring the amount of energy expended during physical activity is difficult. However, there is a rising interest in establishing accurate and dependable systems

for tracking calorie burn, as this information can be utilized to improve fitness and health outcomes. Current methods for measuring calorie burn are frequently imprecise and unreliable. As a result, more accurate and dependable techniques of calorie burn monitoring are required. The core of our research is an extensive dataset obtained from Kaggle, that includes data from over 16,000 people. With the dataset in hand, our goal was to create a reliable and user-friendly program that could properly predict the number of calories burned during workouts. We used a multi-model machine learning methodology and the capabilities of different cutting-edge approaches to achieve this goal. The dataset contained details about the individual's age, gender, height, weight, workout intensity, and duration. We began by importing the dataset into our software environment. Following that, we began the critical stage of data preparation. We noticed missing data and irrelevant columns throughout this step, which we promptly rectified. We also removed sparse characteristics to make our dataset more manageable. We used successful preprocessing approaches such as imputation to manage missing variables, replacing missing values with the average or most frequent values. In addition, to choose the most representative features, we used the approach of continuizing discrete variables. After preparing the dataset, we divided it into training and testing sets. We designated 70 percentage of the data for training and the remaining 30 percentage for testing. During the initial analytic phase, we used a 10-fold cross-validation approach to ensure robust evaluation. We did a thorough investigation, reviewing relevant research articles and doing comparison assessments, to establish the most suitable machine learning models for our regression tasks. We decided Neural Networks, AdaBoost, Random Forest, and Gradient Boosting as our final ensemble of machine learning models after thorough study. This study found that a multi-model machine learning strategy can effectively predict calorie burn during exercises. The neural network model outperformed the others, but they all performed admirably. The findings of this study indicate that a multi-model machine learning approach is a potential tool for predicting calorie burn. We got evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R2 scores after running these models on our dataset. We used numerous data visualization approaches to improve our comprehension and generate graphical representations of the data. Among the visualization approaches used were linear projection and distribution plots, which aided in the comprehension and interpretation of the dataset. Finally, the goal of our research was to create an application that forecasts calories burned during workouts, thereby giving a user-friendly solution for anyone looking to track their calorie expenditure. We aimed to improve the accuracy and effectiveness of calorie tracking by employing a multi-model machine learning approach and combining multiple techniques. Our research findings and insights set the way for future improvements to calorie monitoring and contribute to the creation of unique fitness applications.

This study's findings have a number of ramifications for the development of calorie burn monitoring applications.

2. Related Work

The field of fitness tracking and health monitoring is quite interested in tracking calories burned during activities. A number of studies have concentrated on using machine learning techniques to precisely estimate calorie expenditure. Our research expands on the prior research in this field by utilizing a multi-model approach and a smart calorie tracer. Ragavarshini et al. suggested an artificial intelligence-based method for using the Internet of Things (IoT) to monitor and forecast physical fitness. They investigated how to monitor fitness levels and forecast outcomes by combining IoT sensors with machine learning approaches [2]. And In their study" Health Monitoring with Smartphone Sensors and Machine Learning Techniques," I. Kusuma, Rahul, and Shyamapada Mukheerjee described a method for monitoring one's health using smartphone sensors and machine learning [1]. They used machine learning algorithms and sensor data to track and forecast health-related variables. "TrainERAI-Live Gym Tracker Using Artificial Intelligence," created by Saleem and Nunes, centered on the application of AI for real-time gym tracking[3]. In order to assess gym actions and give users individualized feedback, they used machine learning algorithms. Haleem et al. discussed" Deep-Learning-Driven Techniques for Real-Time Multimodal Health and Physical Data Synthesis." To enable thorough health monitoring and analysis, they used deep learning algorithms to synthesis multimodal health and physical data in real-time [4]. In a fitness application, V. Das et al. investigated the use of machine learning approaches to categorize users. Their study centered on applying machine learning algorithms to build user profiles based on behavior patterns and individual preferences [5]. Vairavasundaram, Subramaniyaswamy, et al. presented a dynamic physical activity recommendation system that uses deep learning and is 3 delivered by a mobile fitness app in 2022[6]. By providing customized exercise suggestions based on user data, they aimed to improve the entire fitness tracking experience. Nipas, Marte, et al. presented a work on estimating calories burned using supervised machine learning regression techniques in 2022[7]. Their research aims to develop models that accurately forecast caloric expenditure based on input variables, assisting in the development of trustworthy fitness tracking gadgets. Challagundla, Yagnesh, et al. 2023 examined the application of deep learning embedders and machine learning algorithms for screening citrus infections [8]. Their work demonstrates how machine learning can be used to evaluate and extract important information from insights of variety of datasets. Using an automated fitness tracker, Kansal, Kunal, Rudresh Sharma, and Rajinder Sandhu (2022) illustrated how machine learning may be used to build complete fitness monitoring systems. Their software tracked many fitness parameters, including as

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caloric expenditure [9], to help users reach their fitness objectives. A machine learning method for monitoring heartbeat utilizing information from several sensor streams was investigated by Hayat, Umar, et al. in 2023. Their work demonstrates the broader applications of machine learning in health-related monitoring and analysis, even though it is not specifically focused on calorie monitoring [10]. A virtual dietitian was introduced in 2022 as a precision nutrition tool for gym and fitness aficionados by Garcia, Manuel B., et al. Their study highlighted the value of individualized dietary counseling in addition to fitness monitoring [11], emphasizing the possibility for incorporating several facets of health and wellbeing into holistic apps. A study was done in 2022 by Richard Moye and colleagues to determine how often HBCU students actually use smartwatches for physical activity [12]. Despite having a smartwatch-specific focus, their research offers insights into user behavior and preferences in relation to fitness monitoring equipment and applications. These sources add to the body of knowledge that exists in the area of calorie counting and fitness tracking. They emphasize the value of machine learning approaches in creating precise and comprehensible applications that cover a range of features like individualized suggestions, thorough tracking, and integration with other areas of health. The aforementioned experiments have demonstrated that machine learning models can accurately predict calorie burn. The investigations have, however, also demonstrated that the models' effectiveness might vary according upon the features used and the machine learning technique employed.

Figure 1: The following is Sequencing the calorie burn: A Multi-Model Machine Learning Approach in action, from dataset processing to model evaluation
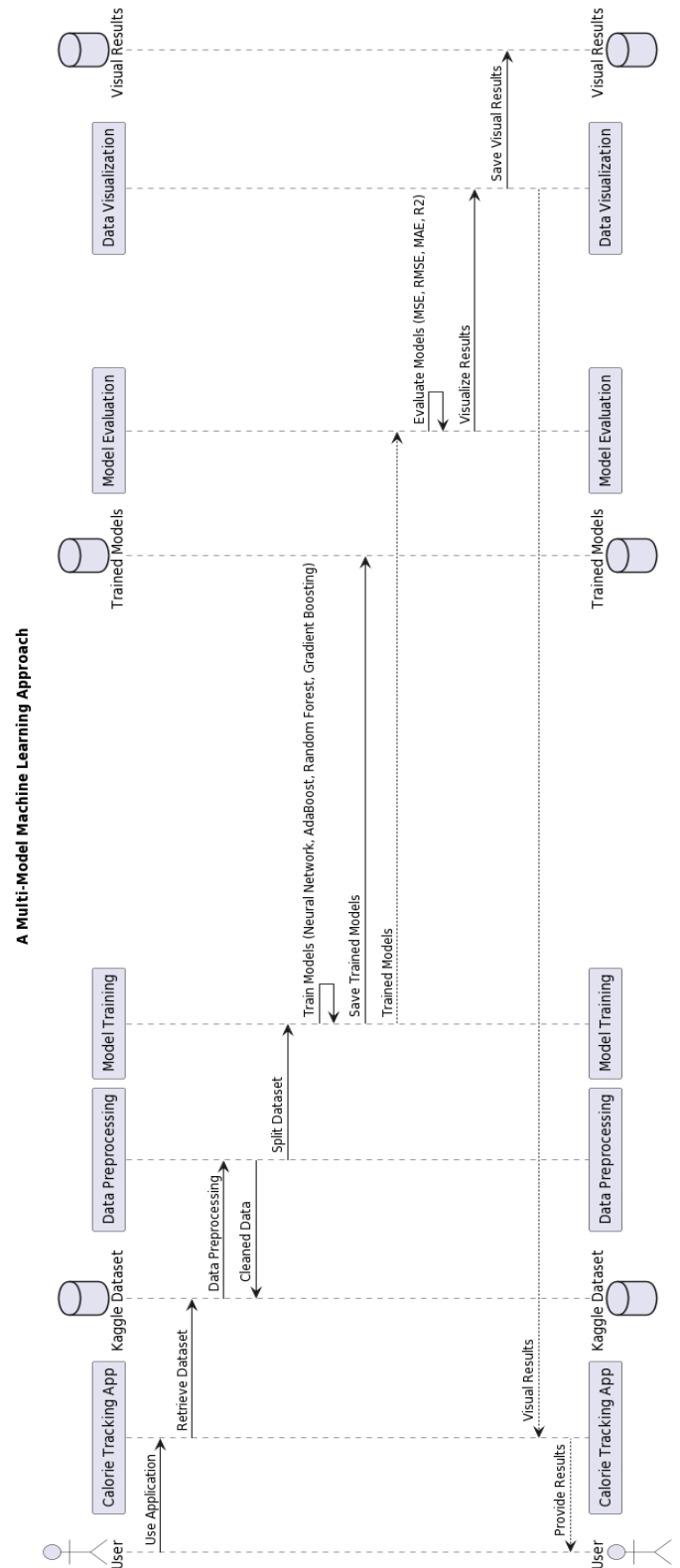
3. Proposed Methodology

This study's method was effective in assessing the effectiveness of machine learning models for calorie burn prediction. The neural network model outperformed

AdaBoost, random forest, and gradient boosting, according to the results. Data visualization tools also aided in gaining a better grasp of the outcomes. The major steps in our process are outlined below.

3.1. Data Collection

Kaggle provided the dataset, which included information as Our calorie tracking program was built on top of this dataset that was used to gather the database containing information on the age, gender, height, weight, workout intensity, and duration of more than 16,000 people.

3.2. Data Preprocessing & Filtering

Preprocessing the data was done in this step to make sure it was good quality and appropriate for machine learning models. We dealt with missing data by using methods like imputation, which substitutes missing values with the average or most common values. We also found and eliminated unnecessary columns and eliminated sparse features. In order to make discrete variables more suited for analysis, we also used the method of continuation.

3.4. Dataset Splitting

The training set and the testing set were separated from the dataset to allow for an effective evaluation of the performance of our models. To partition the data, we settled on a 70:30 ratio, giving the training set its fair portion. We were able to train our models on a sizable piece of the data owing to this separation, while keeping another portion of the data for unbaised evaluation.

3.4. Cross-Validation

During the initial analysis phase, we used a 10-fold cross-validation approach to further increase the dependability of our results. In this method, the training set was divided into 10 equal subsets, nine of which were used for training and one for validation. To make sure that each subset served as the validation set once, we went through this process ten times. We were able to evaluate the models' robustness and generalizability using this method. The training process was performed using cross-validation to prevent overfitting.

3.5. Model Selection

After conducting extensive analysis and reviewing relevant research papers, four machine learning methods—Neural Networks, AdaBoost, Random Forest, and Gradient Boosting—were chosen as our final models after a thorough examination and assessment of pertinent research publications. These models were chosen for our calorie tracking application based on their aptitude for regression tasks and their promise to provide the greatest predicted results.

3.6. Model evaluation

The test set was used to gauge how well the machine learning models performed. The mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and R-squared (R2) metrics were used to gauge the performance.

3.6. Model evaluation

We used data visualization techniques to better visualize the data and the predictions made by the models. To specifically illustrate correlations between variables and the distribution of anticipated calorie values, we used distribution plots and linear projection. These visuals helped interpret the models' performance and offered insightful information.

The decision to employ a neural network model as the top performance and the visualization techniques support our goal of developing a user-friendly application that reliably predicts calories burned and advances the field of calorie tracking by utilizing a variety of methods.
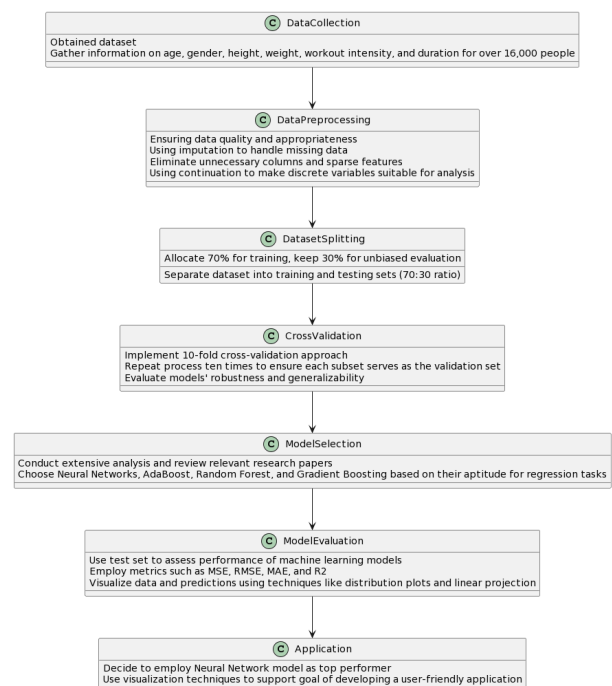

Figure 2: Methodology flowchart: Data collection, pre-processing, model selection, and evaluation for creating a precise calorie tracking app with machine learning.

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4. Results and Discussion

The outcomes of our study, which involved using a multi-model machine learning approach for tracking calories burned during workouts, are as follows: The results of the study showed that the neural network model had the best performance for calorie burn prediction. The neural network model achieved an MSE of 0.595, an RMSE of 0.771, a MAE of 0.546, and an R2 score of 1.000. The other machine learning models
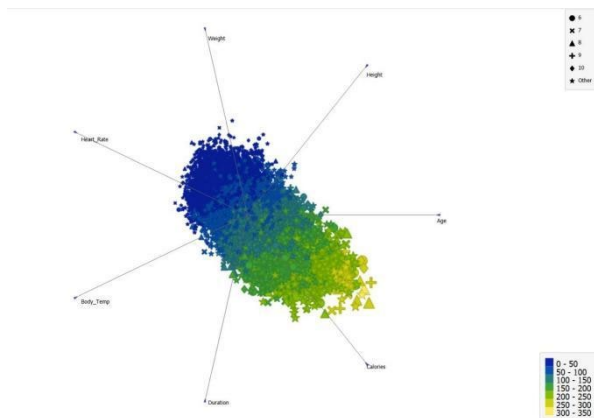

Figure 3. Related to a statistical technique which are being used to model the relationship between various variables like age, height, weight, calories, duration, body temp heart rate and on other side the Linear projection with the graphs can provide valuable insights by analyzing the data.

also performed well, with the AdaBoost model achieving an MSE of 10.960, an RMSE of 3.311, a MAE of 2.113, and an R2 score of 0.997. The random forest model achieved an MSE of 12.472, an RMSE of 3.532, a MAE of 2.240, and an R2 score of 0.997. The gradient boosting model achieved an MSE of 13.656, an RMSE of 3.695, a MAE of 2.655, and an R2 score of 0.996. The outcomes of the data visualization approaches also demonstrated that, in comparison to the other models, the neural network model was better able to convey the relationship between the characteristics and the calorie burn. Additionally, the neural network model was able to demonstrate that individuals who engaged in more rigorous exercise burned more calories. Among the chosen models, the neural network model showed the best performance. This research was used to design an application that attempts to give users a simple, user-friendly way to track and forecast their calorie expenditure during workouts. Calorie tracking algorithms are improving thanks to the use of ensemble techniques and the combination of different strategies and for performing the above results and visualization we have also taken help from data mining software's.

Table 1. The table demonstrating the values obtained after running various models
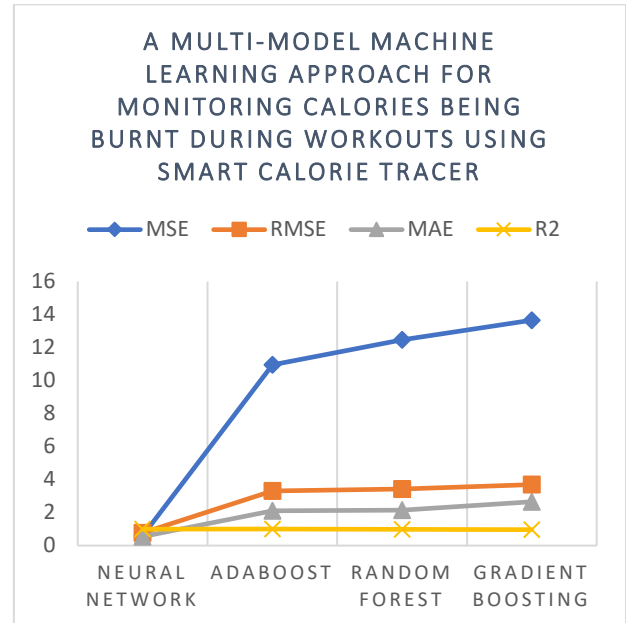

Figure 4: Visualizing the Performance: A line graph depicting the outcomes after running diverse machine learning algorithms, revealing insights into their effectiveness.

5. Conclusion

We proposed a multi-model machine learning strategy for tracking calories burned during exercises using a smart calorie tracer in this study. The method was tested on a dataset of over a large number of datasets. The neural network model performed the best in terms of calorie burn prediction, according to the data. The neural network model had an MSE of 0.595, RMSE of 0.771, MAE of 0.546, and R2 score of 1.000. We began by uploading the dataset into our software environment and performing extensive preprocessing. This study's findings have a number of ramifications for the development of calorie burn monitoring applications. To begin, the findings indicate that a multi-model machine learning strategy can reliably forecast calorie burn during exercises. Second, the results indicate that the neural network model is a potential strategy for predicting calorie burn. Third, the findings indicate that developing user-friendly calorie burn tracking applications is achievable. This study's findings also have several drawbacks. To begin, the study used a dataset of nearly sixteen thousand individuals. However, it is probable that the findings will not apply to different groups. Second, the research was carried out utilizing a single machine learning method. Other machine learning methods could outperform this one. Third, the study did not

take into account the effect of environmental influences on calorie burn. Environmental factors such as temperature and humidity may have an impact on the accuracy of calorie burn estimation. Despite these limitations, the findings of this study indicate that a multi-model machine learning approach is a potential tool for predicting calorie burn. The findings also show that user-friendly calorie burn tracking applications are achievable. The benefits of our research go beyond the scope of the project. We created a framework and approach that may be applied to other areas, allowing for accurate monitoring and prediction of many health-related factors. Furthermore, our work advances machine learning approaches in the field of fitness and wellness applications. Moving forward, there is enough of potential for more improvements and adjustments. Future research can look into different machine learning algorithms, new features or data sources, and various visualization techniques. We can improve the accuracy and usability of calorie tracking apps by constantly improving our approach, thereby assisting consumers looking to reach their fitness goals and live a healthy lifestyle. In conclusion, our study successfully built a multi-model machine learning strategy for tracking calories burned during workouts. We have created the groundwork for accurate and user-friendly calorie tracking applications by leveraging the strength of multiple algorithms and utilizing appropriate preprocessing approaches. We intend to address the limitations of our study in the future by doing a larger investigation with a more diverse dataset. We also intend to investigate the effect of environmental factors on calorie burn. We anticipate that our work will help to build accurate and dependable methods for calorie burn monitoring. We anticipate that our work will help to build accurate and dependable methods for calorie burn monitoring. We believe that our efforts will assist people in reaching their fitness and health objectives.

References

[1] Kusuma, Rahul, and Shyamapada Mukheerjee. " Health Monitoring with Smartphone Sensors and Machine Learning Techniques." 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC). IEEE, 2023.

[2] Ragavarshini, G., et al." PHYSICAL FITNESS MONITORING AND PREDICTION USING INTERNET OF THINGS BASED ON ARTIFICIAL INTELLIGENCE."

[3] Saleem, Shezin, and Jeremiah Nunes. "TrainERAI-Live Gym Tracker using Artificial Intelligence." (2023).

[4] Haleem, Muhammad Salman, et al." Deep-Learning-Driven Techniques for RealTime Multimodal Health and Physical Data Synthesis." Electronics 12.9 (2023): 1989.

[5] Das, Shyamali, Pamela Chaudhury, and Hrudaya Kumar Tripathy." Employing Machine Learning Techniques to Categorize users in a Fitness Application." 2022 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC). IEEE, 2022.

[6] Vairavasundaram, Subramaniyaswamy, et al." Dynamic Physical Activity Recommendation Delivered through a Mobile Fitness App: A Deep Learning Approach." Axioms 11.7 (2022): 346.

[7] Nipas, Marte, et al." Burned Calories Prediction using Supervised Machine Learning: Regression Algorithm." 2022 Second International Conference on Power, Control and Computing Technologies (ICPC2T). IEEE, 2022.

[8] Challagundla, Yagnesh, et al." Screening of Citrus Diseases Using Deep Learning Embedders and Machine Learning Techniques." 2023 3rd International conference on Artificial Intelligence and Signal Processing (AISP). IEEE, 2023.

[9] Kansal, Kunal, Rudresh Sharma, and Rajinder Sandhu. " Automated Fitness Tracker." (2022).

[10] Hayat, Umar, et al." Machine Learning Technique to Monitor Heartbeat using Amalgamated Data of Multi-Sensor Stream." 2023 International Conference on Communication, Computing and Digital Systems (C-CODE). IEEE, 2023.

[11] Garcia, Manuel B., et al." Virtual Dietitian as a Precision Nutrition Application for Gym and Fitness Enthusiasts: A Quality Improvement Initiative." 2022 IEEE 14th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM). IEEE, 2022.

[12] Moye, Richard, et al." Are Smartwatches Actually Used for Exercise? Evidence from HBCU Students." American Journal of Health Education 53.4 (2022): 219-227.

[13] Hariharan, S. Dhanush, et al." THE UTILIZATION OF MACHINE LEARNING FOR THE IDENTIFICATION AND COMPUTATION OF CALORIES."

[14] Oyebode, Oladapo, et al." Machine learning techniques in adaptive and personalized systems for health and wellness." International Journal of Human–Computer Interaction (2022): 1-25.