International Journal Of Advance Research, Ideas And Innovations In Technology

ISSN: 2454-132X
Impact Factor: 6.078
(Volume 11, Issue 2 - V11I2-1281)
Available online at: https://www.ijariit.com

To Predict Calories Burnt During Various Physical Activities Like Walking, Running, Cycling, & Swimming

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ABSTRACT

This study aimed to create a new model to compute the number of calories expended during activities like swimming, cycling, running, and walking. We used vast data based on various criteria, including Vigor, activity duration, body heat, and heart rate. Our model estimates calorie burns accurately by using machine learning. Our model can be used for tracking personal exercise, controlling obesity, and improving sports performance by estimating calorie burn across different physical activities using the Mifflin St. Jeor equation. I am building a Kaggle dataset with crucial variables like heart rate, body temperature, and activity duration.

Keywords: *Calorie Burn Prediction, Physical Activity, Machine Learning, Health & Fitness, Personalized Recommendations, Data Collection, Energy Expenditure, Fitness Tracking, Wearable Devices, Activity Monitoring, Resting Metabolic Rate (RMR), Activity Intensity, Calories Burned*

INTRODUCTION

Calorie expenditure has an impact on general fitness and health. Weight control, personal training regimens, and general health optimization can all benefit from knowing how many calories are burned during exercise. The popular techniques for estimating caloric expenditure, such as heart rate monitoring or metabolic carts, are costly and intrusive. Thus, there is a clear need for inexpensive gadgets that can precisely calculate caloric expenditure. We intend to help people make the best choices regarding their physical activity and improve their well-being by developing an efficient model to forecast calorie burn.

THE KEY GOAL OF THIS STUDY

This study's main objective is

This work aimed to derive a strong and accurate model for prediction of calorie expenditure. The model will let one estimate calorie consumption for several kinds of physical activity including swimming, cycling, running, and walking. Our approach consists in:

Rich information gathering: We will compile a varied data set comprising many individual traits (e.g., age, gender, weight, and height), environmental factors (e.g., temperature and humidity), and activity data (e.g., exercise length, intensity, and heart rate).

Feature engineering is the extraction of pertinent data features. These are characteristics including type of activity, length, pace, distance, and heart rate variance.

Model training and selection: Various machine learning techniques (e.g., linear regression, decision trees, random forests) will be tried to ascertain the best approach for estimating calories.
Model performance evaluation: The selected model will be assessed on appropriate criteria. We shall apply performance measures including mean absolute error (MAE), root mean squared error (RMSE), and mean squared error (MSE).
Model deployment: design a basic app or API whereby users may enter exercise data and obtain exact calorie burned computation.

LITERARY REVIEW

We first looked at several regression models to project calories burned. Definition of Linear Regression:

statistical method displaying as a linear equation the link between a dependent variable (calories burned) and one or several independent variables (e.g., weight, duration, and intensity). How it functions: Based on independent variables, linear regression finds the line most likely to pass through the points to project the dependent variable. The Linear Regression had a 90.62% accuracy. With 8.39 mean absolute error. Supervised machine learning algorithm that discovers a hyperplane best discriminates the data points as much as possible in such a way that the margin between the closest data points and the hyperplane is maximized is the definition of Support Vector Regressor (SVR).

SVR operates by using kernels to translate the data into higher space, so enabling an easy linear separability of the data. The same as non-linear decision boundary in lower space is hyperplane in higher space. With a mean absolute error of 10.62 the support vector regulator accuracy was 88.11%.

DefiningRandom Forest:
It is a kind of ensemble learning in which a random sample of data and attributes trains every decision tree in an ensemble.
Random Forest generates the last prediction using all the decision trees by means of random voting. Random Forest lowers overfitting and improves generalizing ability. With a mean absolute error of 1.71 the random forest method was 98.09 accurate.

In machine learning, a decision tree regressor is a model that generates a tree-model to forecast a continuous outcome variable, say calories intake. Decision trees divide data along feature values into subsets creating branches and leaves. From the leaf node where the input data point resides, prediction is at last produced. Decision Tree accuracy is thus 96.23% and mean absolute error is 3.37 calories. XG Boost Regressor Definition: Combining several weak models—in this case, decision trees—gradually boosting creates a strong predictive model using an ensemble learning method. XG Boost sequentially adds decision trees to the collection, and every tree fixes the errors of the past trees.

It also applies regularization methods to prevent overfitting. Accuracy for XG Boost Regressor is 98.43% with the minimum error being 1.48 calories.

METHODOLOGY

Data Collection

Wearable Device Information: This includes data from purchases made on wearable devices, like fitness smartwatches and trackers, which monitor various metrics such as eye order, GPS data, accelerometer readings, and other relevant indicators.

Operator-Reported Information: This involves recording personal characteristics (like angle, height, sex, and age), the actions taken, duration of activities, and environmental factors.

Information Pre-Processing

Data Cleaning: This step involves removing outliers, handling missing values, and correcting inconsistencies within the dataset.

Feature Engineering: Here, we extract useful features from the raw data, such as:

Time-Based Features: Duration, pace, cadence

Heart Rate-Based Features: Average heart rate, heart rate variability

GPS-Based Features: Distance travelled, terrain type

Accelerometer-Based Features: Activity intensity, step count

Model Selection and Training

Exploratory Data Analysis (EDA): We analyze the data to uncover patterns, trends, and relationships, such as calorie expenditure.

Feature Selection: We identify significant features using methods like correlation coefficients and hypothesis testing.

Model Training: We employ various models, including:

Linear Regression: To establish baseline predictions

Decision Trees: To capture complex relationships

Random Forests: To improve accuracy by combining multiple decision trees

Neural Networks: To model intricate patterns from the integrated datasets

Model Evaluation

Evaluation Metrics: We utilize metrics like MSE, RMSE, and MAE to assess the effectiveness of the models.

Hyperparameter Tuning: We fine-tune the model's hyperparameters to enhance performance.

Check • Web Use: Collaborate on an innovative web project that allows operators to energize their action data and obtain precise estimates of kilocalorie intake. • Mobile App: Develop a flexible app that syncs with wearable devices for real-time tracking of kilocalorie expenditure. • API: Create an API to integrate the Check with other fitness and health applications. This methodological study aims to establish a highly accurate kilocalorie estimation Check, empowering individuals to make informed decisions regarding their health and fitness goals.

Methodology:

Create a Calories Calculator using the Mifflin St. Jeor Formula to determine the number of calories burned during activities like walking, running, cycling, and swimming.

For walking, running, and cycling, parameters include: slow, moderate, fast, very fast, and hiking. For swimming, options are moderate, laps, and vigorous.

The calculation will depend on factors such as duration and body weight. Users will select their activity and calculate how many calories they have burned.

The Mifflin-St Jeor formula is a widely used method for calculating the resting metabolic rate (RMR), which is the energy expended while at rest. RMR is also known as resting energy expenditure (REE). The formula, developed by MD Mifflin and ST Jeor, is as follows:

Formula:

For Women: (10 * weight [kg]) + (6.25 * height [cm]) – (5 * age [years]) – 161

For Men: (10 * weight [kg]) + (6.25 * height [cm]) – (5 * age [years]) + 5

Activity Level Factors:

Sedentary: *1.2

Lightly active: *1.375

Moderately active: *1.55

Active: *1.725

Very active: *1.9

Limitations

Here are the main limitations to consider:

Individual Variation: Everyone has a unique metabolic rate influenced by genetics, hormones, and other factors. The Mifflin St. Jeor equation may not accurately reflect these individual differences.

Body Composition: The ratio of muscle to fat in a person's body significantly impacts calorie expenditure during exercise. Unfortunately, this formula does not consider the variations in body composition.

Activity Intensity and Duration: Accurately estimating the intensity of activities (like light jogging versus vigorous running) can be challenging. Subjective measures, such as how hard someone feels they are working, can lead to inaccuracies.

Duration Monitoring: Tracking the exact duration of exercises, especially for activities like walking or cycling, can be tricky without specialized equipment.

Environmental Conditions: Factors like temperature and humidity can affect how the body regulates heat and burns calories. The Mifflin St. Jeor equation does not factor in these variables.

Altitude: Exercising at higher altitudes can influence metabolic rates, but this equation does not account for that either.

Dietary Elements: The thermic effect of food (TEF) refers to the calories burned during the digestion and absorption of food. While the Mifflin St. Jeor equation does not calculate TEF, it is still an important aspect of overall calorie expenditure.

Breaking Barriers: To enhance the accuracy of a calorie calculator, keep these points in mind:

Operator Input: Activity Level: Give users the chance to specify their intensity level (light, moderate, vigorous) using a standard scale like the Rating of Perceived Exertion (RPE).

Heart Rate Monitoring: Incorporate heart rate monitors to provide better estimates of exercise intensity.

GPS Tracking: Use GPS devices to effectively track distance and time, especially for cycling and outdoor running.

Advanced Procedures:

Metabolic Equivalent of Task (MET): Utilize MET values to assess the energy cost of activities compared to resting, allowing for a more precise estimation of calorie burn.

Learning the Calculator: Implement learning techniques to analyze individual data (like user behaviour and preferences) and refine kilocalorie projections over time.

Individualized Guidance: Set personalized kilocalorie goals by considering factors such as age, gender, and activity level to create tailored nutritional advice.

Dietetic Support: Offer dietary recommendations to help users navigate their health journey, avoiding restrictive practices while integrating advanced features into the calorie calculator. This will enable users to make well-informed decisions about their fitness and dietary goals.

CONCLUSION

This research successfully integrates the Mifflin St. Jeor equation into a more comprehensive system for estimating calories, considering various physical activities like walking, running, cycling, and swimming. Here are the key takeaways and conclusions:

Accurate Baseline Predictive Representation: The Mifflin St. Jeor equation serves as a reliable foundation for measuring resting metabolic rates and offers a scalable multiplier for different activity levels. When combined with specific activity parameters, it leads to effective baseline calorie estimations.

Enhanced Precision through Machine Learning: The findings show that advanced machine learning techniques, such as XG Boost and Random Forest, significantly outperform traditional linear methods, achieving accuracy levels of 98.43% and 98.09%, respectively. These technologies account for individual variations and uncover complex relationships among factors like exercise type, intensity, and duration.

Technical Insights and Data Understanding: Variables such as exercise type, environmental factors, and activity-specific metrics (like rate and duration) enhance prediction accuracy. This aligns with current fitness-tracking technologies and supports personalized applications.

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