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Artificial intelligence-powered predictive modeling for calorie burns in underserved regions

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Abstract

Background: Tracking caloric expenditure in relation to the intensity, rate, and duration plays an important role in healthcare and nutrition, with a focus on underserved regions where access to nutritional support and health tracking tools are limited. This study aims to bridge the gap and emphasize the nuances in the predictive capacity of machine learning models and the development of cost-effective and applicable models in tracking calorie burn in these regions.

Methods: This study utilized a publicly available Calories Burnt Prediction dataset (Kaggle) comprising 15,000 records with variables like age, sex, height, weight, duration of exercise, heart rate and body temperature. Data preprocessing steps included categorical encoding, feature scaling, and feature selection based on importance ranking followed by the training and evaluation of XGBoost (Xtreme Gradient Boosting)), Ridge Regression and Random Forest machine learning frameworks performance was assessed using mean absolute error (MAE), mean squared error (MSE) and coefficient of determination (R^2).

Results: The CaloModel (XGBoost) demonstrated the best overall performance, with the lowest prediction error and highest explained variance (MAE: 10.18; MSE: 167.21; R^2: 0.95). Ridge Regression and Random Forest also showed strong predictive performance but were comparatively less favorable. Feature importance analysis identified exercise duration, heart rate, and body temperature as the most influential predictors of calorie expenditure.

Conclusion: These findings support the potential utility of machine learning- based calorie burn estimation in low resource regions with the CaloModel showing a strong potential for estimating calorie burn using easily obtainable physiological and activity-related variables. However, further validation is required using independent datasets to improve robustness and generalizability to ensure safe integration into clinical and public health settings.

Keywords: Calorie Burn, Machine Learning, Predictive Modeling, CaloModel, Underserved Regions, Fitness Tracking, Nigeria

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Background

According to the World Health Organization, 2.5 billion adults (≥ 18 years) are said to be overweight (Body Mass Index (BMI) ≥ 25) with 890 million living with obesity (BMI≥ 30), with the prevalence of overweight being 31% in WHO Southeast Asia and Africa alone in 2022 [1]. This culminated in the adoption of the WHO Acceleration plan to stop obesity [2] by the 75th World Health Assembly in 2022. Obesity results from an imbalance between caloric intake and expenditure. Caloric expenditure plays an important role in influencing health metrics, maintaining overall well-being, preventing cardiovascular diseases and metabolic syndrome [3]. However, access to fitness trackers, tailored fitness regimen, adequate health check and nutritional framework are limited in low-resource settings [4,5]. This prevents individuals from monitoring their calorie intake and burn effectively. This leads to an increased risk of cardiovascular disease, obesity, type 2 diabetes mellitus, and metabolic imbalance [7]. Traditional methods for estimating calorie expenditure include metabolic equations, wearable sensor-based approaches, and indirect calorimetry [6,17,8]. While metabolic equations such as the Harris–Benedict and Mifflin–St Jeor formulas are widely used, they often fail to account for individual variability in physiological responses [18, 20]. Wearable devices that integrate motion and heart rate data provide real-time estimates but may require consistent access to specialized hardware [6,19,21]. Indirect calorimetry remains the gold standard; however, it depends on laboratory-based equipment and controlled environments, limiting its practical use in many settings [22]. These limitations highlight the need for alternative approaches that rely on accessible and easily measurable variables, particularly in resource-limited settings. AI-driven models have demonstrated significant success in predicting health metrics, including disease detection, fitness monitoring, and nutritional assessments [8,9,10]. Machine learning and deep learning frameworks, such as decision trees, support vector machine, random forest and pytorch, tensor flow have been widely applied in predictive healthcare. These models have been deployed for use as motion sensors [21] heart rate measurement [24], food recognition and calorie prediction. These advancements demonstrate potential applications in healthcare [14]. Several studies have explored AI-based models for calorie estimation, focusing on deep learning, regression models, and hybrid approaches. However, there is a paucity of studies that outline the benefits of AI-based models in calorie predictions. Furthermore, the dearth of studies exploring the under-utilization of fitness tracking device in underserved regions provide a stronger justification for this study to be executed. The health for all goal of the WHO [23] cannot be achieved if these regions are left out [14]. Two previous studies explored calorie estimation utilizing computer vision on meals commonly consumed by high income countries but failed to take into cognizance meals consumed in underserved regions [26, 27]. Consequently, making the model lack validation in these regions. These models may struggle to recognize meals from low-income countries thereby lacking the capacity to estimate calorie intake in these regions. Additionally, another study outlined a wearable sensor on the neck capable of estimating calorie intake. But this study failed to present its validation in low resource settings as well, where meal options differ [28]. Furthermore, two studies explored the prediction of physical activities using wearable devices integrating XGBoost, machine learning framework and achieved an accuracy level of 99.67% and 91% respectively [27, 34] showing signs of a possible overfitting which raises credibility concerns in the study. This highlights the need to craft a more methodical, credible and thorough approach in the development of a machine learning models with a superior predictive ability and reduced impact of overfitting that can estimate calorie burn more accurately. This study develops CaloModel, an XGBoost machine learning framework [10, 11, 12] to design a model trained with an open-source dataset from Kaggle [13] which contains demographics and activity related features making it suitable for this study. Publicly available datasets, such as those from Kaggle, may originate from controlled or experimental environments, the findings should be interpreted cautiously and require validation using real-world data [15, 16, 17]. The findings of this study may inform future research and potential applications in preventive health strategies. This study aimed to address several gaps including poor emphasis on the applicability of AI-powered calorie estimation models tailored for underserved populations; under-utilization of wearable fitness trackers is grossly under-studied [10]; and failure of previous studies to evaluate models using meals in low-resource settings [24, 25, 26].

Methods

Data collection and preprocessing

A publicly available calorie-burn dataset [13] comprising 15,000 records was obtained from Kaggle. The dataset includes demographic and physiological variables such as age (years), sex (binary), height (cm), weight (kg), duration of exercise (minutes), heart rate (beats per minute), and body temperature (°C). The target variable represents estimated calorie expenditure. Preprocessing was executed under the following:

Scanning: Using Pandas module, a scan of missing values yielded none.

Feature Selection: Feature importance ranking was performed using the Random Forest algorithm. All input variables were initially considered, and features contributing most significantly to prediction were retained based on their importance scores. The final selected features included age, sex, height, weight, duration of exercise, heart rate, and body temperature. No recursive feature elimination was applied.

Conversion: The conversion of Gender, a categorical variable to numerical variable was done for ease of model training and evaluation.

Standardization: Using Standard Scaler, numerical variables were scaled to ensure uniformity.

Train-Test Data Split: The dataset was divided into training and testing subsets using a 70/30 split. This approach aligns with standard machine learning practice, ensuring sufficient data for model training while preserving an independent test set for evaluating performance on unseen data.

Model selection and evaluation

Algorithms Used: A comparative analysis of three regression models; XGBoost, Ridge Regression and Random Forest were implemented to determine the model with the best predictive performance.

Hyperparameter Tuning: Model parameters were optimized using Grid Search CV and Randomized Search CV to identify the best-performing configurations for each algorithm.

Cross-Validation: Model robustness was evaluated using 10-fold cross-validation. The dataset was partitioned into 10 subsets, with each subset used once as a validation set while the remaining subsets were used for training. Cross-validation was performed using the K Fold method with shuffling enabled and a fixed random state (random state = 42) to ensure reproducibility. Model performance across folds was assessed using the coefficient of determination (R^2).

Evaluation Metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and coefficient of determination (R^2) values were used to assess the model performance.

Overfitting Mitigation: Regularization techniques, including L2 regularization and sub-sampling, were applied to reduce the risk of overfitting and improve model generalizability.

Data Analysis: Descriptive and statistical analyses were conducted to explore relationships among variables and understand data distribution.

Statistical Analysis: Computation of mean, median, standard deviation and data distribution

Feature Correlation Analysis: Pearson correlation coefficient was used to demonstrate the linear relationships between important features

Visualization: To reveal statistical patterns and trends, histograms, bar charts, box plot, scatter plot were used.

Ethical Considerations: This study utilized a publicly available and anonymized dataset obtained from Kaggle. No identifiable human participant data were accessed; therefore, institutional ethical approval was not required.

Results

Dataset Characteristics

The dataset comprised 15,000 observations with demographic and physiological features. The mean age of participants was 42.79 ± 16.98 years. The sex distribution was nearly balanced, with 49.65% males and 50.35% females. The mean height and weight were 174.47 ± 14.26 cm and 74.97 ± 15.04 kg, respectively. The calculated mean body mass index (BMI) was 24.34 ± 1.56 kg/m², indicating that the population falls within the normal BMI range on average. Exercise duration ranged from 1 to 30 minutes, with a mean of 15.53 ± 8.32 minutes, reflecting varying levels of physical activity. The mean heart rate and body temperature were 95.52 ± 9.58 bpm and 40.03 ± 0.78°C respectively. The summary is shown in table 1 below.

Table 1. Dataset Characteristics

Variable	Value (Mean ± SD / Range / %)
Sample size	15,000
Age (years)	42.79 ± 16.98
Sex (Male)	49.65%
Sex (Female)	50.35%
Height (cm)	174.47 ± 14.26
Weight (kg)	74.97 ± 15.04
BMI (kg/m²)	24.34 ± 1.56
Duration (minutes)	15.53 ± 8.32 (Range: 1–30)
Heart Rate (bpm)	95.52 ± 9.58
Body Temp (°C)	40.03 ± 0.78

Model performance metrics

Model performance was assessed under the following metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), R^2 score. The synopsis of each model's performance is seen in table 2 below.

Table 2. Model performance metrics

Metric	CaloModel	Ridge Regression	Random Forest
MAE	10.18	11.60	12.02
MSE	167.21	195.41	212.35
R^2	0.95	0.94	0.93

Cross-Validation Results

Cross-validation results demonstrated consistent model performance across folds. The XGBoost model (CaloModel) achieved the highest mean R^2 value (0.9508 ± 0.0020), followed by Ridge Regression (0.9386 ± 0.0035) and Random Forest (0.9334 ± 0.0038), indicating strong predictive performance and minimal variability across validation sets [28, 29, 30].

Data visualization

Feature Importance plot

Analysis of feature importance indicates that duration of exercise and Heart rate were the most important determinants of calorie burn. As showed in Figure 1.

Distribution of Calories

The analysis of calorie distribution in this study indicates the participants engaged in low-intensity activities which explains lower calorie burn between 0-150 on Y-axis and only a few engaged in high intensity activities which explains higher calorie burn between 150-300 on the X-axis as shown in Figure 2.

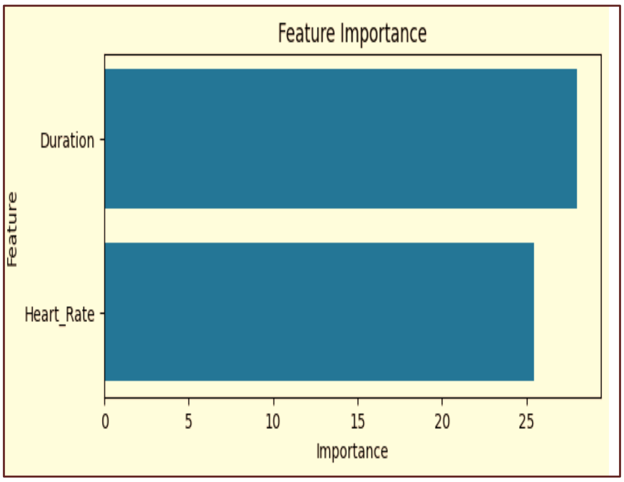

Figure 1: Feature Importance Plot highlighting the determinants of calorie burn with duration of exercise as the most predominant determinant of calorie burn closely followed by Heart rate.

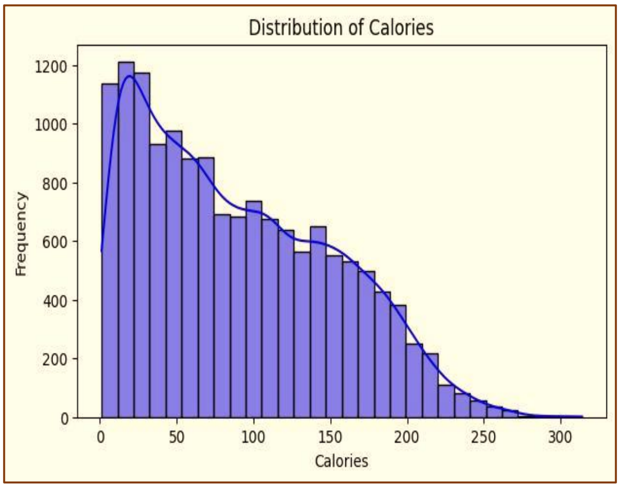

Figure 2: Histogram plot showing Calorie distribution.

Heatmap of feature correlates

Heat map of feature correlates plot as showed in Figure 3 below explains the order of importance evident in the strong correlation between duration and body temperature, heart rate, at 0.85 and 0.9 respectively.

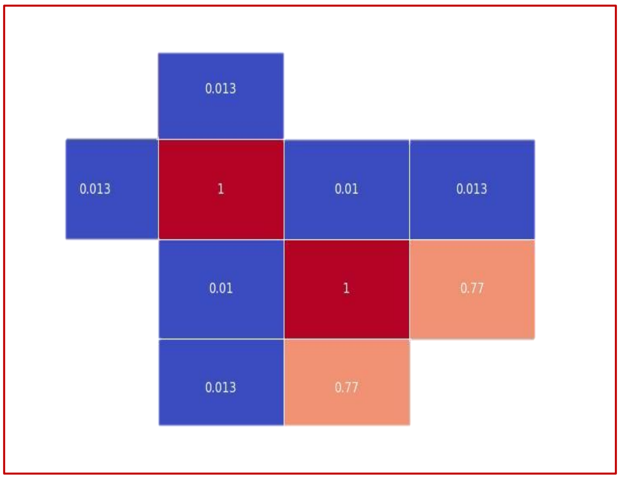

Figure 3: A heatmap visualizing the correlations amongst different predictors of calorie burn.

Model performance plot (MAE)

A visual analysis of the models used for this study shows a lower MAE for CaloModel indicating the best performing Model among the three. This is demonstrated by Figure 4.

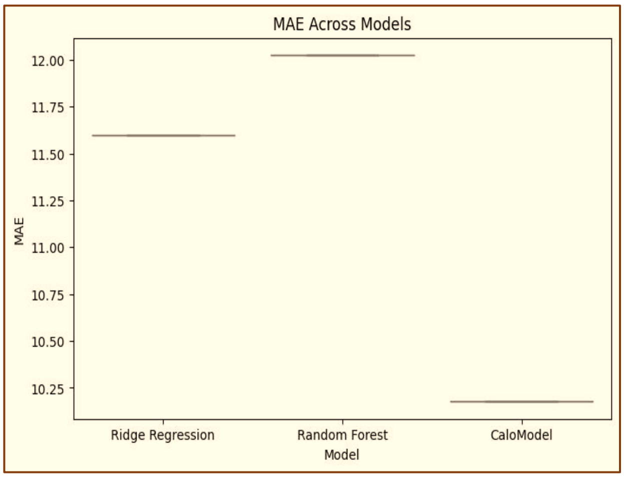

Figure 4: A box plot for Mean Absolute Error of each Model used for this study.

Model performance plot (R^2 Analysis)

This demonstrates the proportion of variance exhibited by each model during evaluation. A higher R^2 value (closer to 1) makes a Model a better fit for prediction. The CaloModel shows the closest value to 1. A visual representation of this is shown by figure 5.

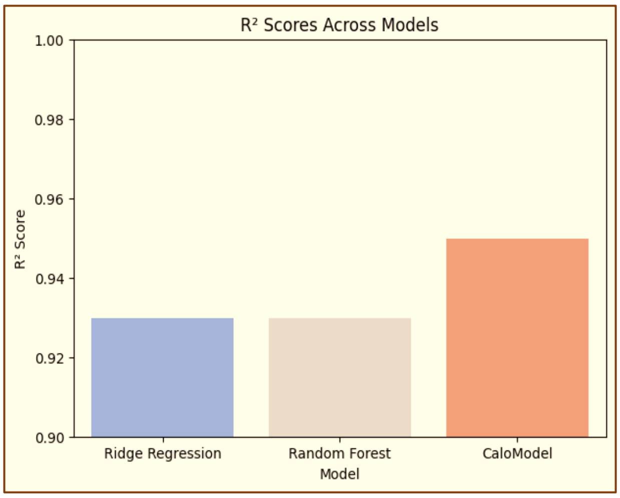

Figure 5: A bar chart for R^2 values of each model used for this study.

Residual Plot for CaloModel

This explores the level of underestimation or overestimation in the predictive ability of the model. The errors made by the model are not large errors with a +/_ 20 margin of error on the average as evidenced by the heavy concentration of the dots close to the zero line of perfection as shown in Figure 6 below.

Discussion

This study developed and evaluated CaloModel, an XGBoost-based machine learning model amongst other models for predicting calorie expenditure using common variables both demographics and physiological. The consistency observed between cross-validation and test results suggests that the model is stable and capable of generalizing within the dataset. This demonstrated strong performance may be attributed to the inherent capacity of XGBoost to capture non-linear relationships between variables.

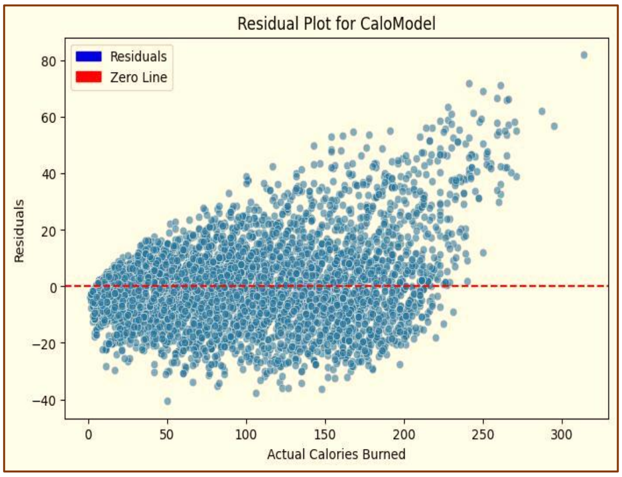

Figure 6: Residual plot of CaloModel estimating the margin of error in prediction.

Previous studies have shown promising outcomes with the integration of machine learning models for energy expenditure prediction as seen by [35] which compared gradient boosting models with linear regression frameworks and reported the XGBoost to have outperformed traditional linear models. Likewise, another study [36] explored multiple machine learning frameworks, including XGBoost, Random Forest and stacking models and found XGBoost to have outperformed the other models across evaluation metrics. Other studies have utilized machine learning for estimating energy expenditure using wearable sensors, patches, motion tracking, and physiological signals. Although ensemble models have been found to demonstrate strong performance in controlled environments, some still rely on continuous sensor inputs such as motion data and real time monitoring which impacts their applicability in broader contexts while this study supports the possibility of using available data to make predictions without reliance on wearable devices or specialized equipment. This presents a strong argument for how a simpler and data driven approach can be deployed for calorie estimation [31, 32, 33]. The gross under-utilization and inaccessibility of wearable fitness trackers in low-resource regions have created the need for an alternative approach tailored to close the gaps in these regions. The incorporation of CaloModel if clinically validated, may provide AI based solutions empowering residents of these regions to take charge of their fitness plan and nutrition.

Clinical implication

The findings of this study suggest a potential application of the model in both clinical and non-clinical settings. Upon a successful clinical trial, energy expenditure estimation may be supported while using this model. This may be of help for management of obesity and metabolic disorders. Additionally, if successfully validated, integration with established digital and mobile health tools may be considered to improve accessibility. It is important to note that this model is not meant to replace clinical experts or serve as a diagnostic tool but as a potential support system if validated successfully.

Limitations of study

The dataset used in this study may contain inherent biases, reflect controlled or simulated conditions rather than real-world populations. The dataset may also have potential imbalance in demographic diversity, which can affect model performance. This study is limited by lack of external validation using an independent dataset which may impact the robustness of the model. Further studies should utilize independent dataset to test model robustness. Further works will consider integration with a telegram bot after a successful external validation for easy access. Cloud deployment should be considered for model optimal functioning if integration with Telegram bot is executed.

Future directions

Incorporation of ensembles learning for model fine-tuning. Incorporation of deep learning frameworks for further evaluation. Further evaluation with independent dataset to test model robustness. Clinical deployment pending a successful external validation.

Policy recommendations

Increase awareness programmes geared towards encouraging individuals to take charge of their fitness, thereby preventing cardiovascular and metabolic diseases. Increase funding to support AI-based research geared towards innovative solutions for health challenges in resource-challenged settings. Incorporate AI based Predictive models for fitness tracking across primary health centers.

Conclusion

This study highlights the potential AI-based models have in the prevention of cardiovascular diseases via efficient calorie tracking in low resource centers where fitness tracking devices are nonexistent or grossly under-utilized.

Abbreviation

AI: Artificial Intelligence; WHO: World Health Organization; XGB: Extreme Gradient Boosting; XGBoost: Extreme Gradient Boosting; MAE: Mean Absolute Error; MSE: Mean Squared Error; R^2: Coefficient of Determination; BMI: Body Mass Index

Declaration

Acknowledgment

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Availability of data and materials

The dataset used in this study is publicly available on Kaggle (Calories Burnt Prediction Dataset) https://www.kaggle.com/datasets/ruchikakumbhar/calories-burnt-prediction. For further inquiry: drmichael17atgmail.com

Authors' contributions

Babatunde Ogunmiloro (BO) conceived the study, performed data analysis, developed the model, and wrote the manuscript. The author had read and agreed to the published version of the manuscript.

Ethics approval and consent to participate

This study utilized a publicly available and anonymized dataset. No identifiable human participant data were accessed; therefore, institutional ethical approval was not required. The study was conducted in accordance with the principles of the Declaration of Helsinki.

Consent for publication

Not applicable

Competing interest

The author declares that he has no competing interests.

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