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Smart Fitness Insights: Predicting Exercise Calories with Explainable AI

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Abstract: Accurate estimation of energy expenditure and calories burned during exercise is essential for fitness tracking and health monitoring. Reliable calorie estimation enables professionals to design personalized fitness plans and helps individuals optimize their workouts. This study proposes a machine learning approach to predict calories burned based on physiological and exercise-related features such as gender, age, height, weight, exercise duration, heart rate, and body temperature. Several ensemble regression models are employed, including Gradient Boosting Decision Trees Regression (GBDTR), Extreme Gradient Boosting Regression (XGBOOSTR), Stacking Regression (STACKINGR), Random Forest Regression (RFR), Bagging Regression (BAGGINGR), and Voting Regression (VOTINGR). Among these models, XGBOOSTR demonstrates the highest performance with a Mean Squared Error (MSE) of 14.224, Mean Absolute Error (MAE) of 2.022, R-squared (R^2) value of 0.9964, Peak Signal to Noise Ratio (PSNR) of 37.41, and Signal to Noise Ratio (SNR) of 29.29. Explainable Artificial Intelligence (XAI) techniques, including Local Interpretable Model Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP), are applied to interpret model predictions and identify the most influential features, such as exercise duration, heart rate, and body temperature. The findings of this research provide valuable insights for developing wearable health applications, enhancing personalized fitness tracking, and assisting medical professionals in promoting healthier lifestyles.

Keywords: Machine Learning, XAI, Regression, Prediction.

I. INTRODUCTION

Physical activity plays a vital role in maintaining fitness, preventing chronic diseases, and improving overall well-being. The number of calories burned during exercise serves as a key indicator of workout effectiveness and varies based on several factors such as age, gender, body composition, heart rate, body temperature, and duration of activity. Accurate estimation of calorie expenditure not only supports personal fitness goals but also assists healthcare professionals in prescribing tailored exercise programs.

Exercise intensity and duration are among the most significant factors influencing calorie burn. According to previous studies, a 30-minute session of moderate to intense exercise can burn between 150 and 400 kilocalories [1]. However, accurately estimating calorie expenditure remains challenging due to individual physiological differences. Overestimation may lead to nutritional imbalance, while underestimation can hinder fitness progress. These challenges highlight the need for reliable, automated prediction methods.

Machine learning (ML) has emerged as a powerful tool for analyzing health data and predicting energy expenditure. Several studies have demonstrated the effectiveness of ML techniques in improving calorie estimation and exercise tracking. For instance, Panwar et al. [9] employed regression models such as Support Vector Regression (SVR) and XGBoost to estimate calorie burn from physiological and activity-related features. Alfred et al. [10] applied Random Forest models to enhance prediction accuracy using demographic and biometric data. Similarly, Basavaraj et al. [11] utilized ensemble learning approaches such as XGBoost and Random Forest, achieving better performance than traditional statistical methods.

Motivated by the need for precise and personalized calorie estimation, this study uses a dataset of 1,500 exercise records containing various physiological and activity-based attributes. Several ensemble regression models, including Random Forest Regression (RFR), Extreme Gradient Boosting Regression (XGBOOSTR), Stacking Regression (STACKINGR), and Gradient Boosting Decision Trees Regression (GBDTR), are implemented and evaluated. Comprehensive preprocessing techniques are applied to ensure data quality, while model performance is assessed using cross-validation

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methods. Furthermore, Explainable Artificial Intelligence (XAI) techniques such as Shapley Additive Explanations (SHAP) and Local Interpretable Model Agnostic Explanations (LIME) are employed to interpret the most effective model and highlight the importance of influential features. The main contributions of this study are as follows:

- A comprehensive evaluation of ensemble regression models for predicting calorie burn during exercise.
- An exploration of model interpretability using XAI techniques to understand the influence of key features such as body temperature, heart rate, and exercise duration.

The remainder of this paper is structured as follows: Section II presents the proposed methodology, Section III discusses the results and analysis, and Section IV concludes with key findings and implications.

II. METHODOLOGY

The main objective of this study is to develop an advanced ML-based approach for accurately predicting calories burned during exercise. This section describes the methodological framework, including dataset description, data analysis and visualization, preprocessing, feature selection, model development, model evaluation, and interpretability. The overall system architecture is presented in Figure 1.

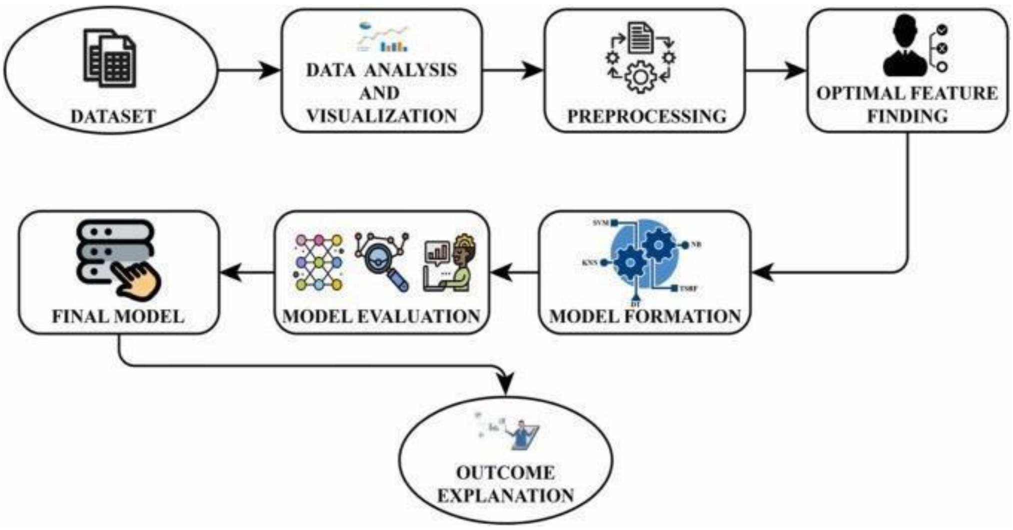

Fig. 1 Architecture of the Research

A. Dataset

This study uses a dataset [8] containing 1,500 records with eight predictive features and one target variable (Calories). The features include demographic and physiological factors such as Gender, Age, Height, Weight, Duration of exercise, Heart Rate, and Body Temperature. These parameters form the basis for predicting calorie expenditure during exercise. A detailed description of the dataset is provided in Table I.

TABLE I FEATURES OF THE DATASET

Features	Description	Variable Type	Unit
User ID	Participant ID number	Numerical	-
Gender	Participant gender (0=Male, 1=Female)	Nominal	-
Age	Participant age	Numerical	Years
Height	Participant height	Numerical	cm
Weight	Participant weight	Numerical	kg
Duration	Exercise duration	Numerical	Minutes
Heart Rate	Average heart rate	Numerical	bpm
Body Temp	Body temperature	Numerical	°C
Calories	Calories burned (Target variable)	Numerical	kcal

B. Data Analysis and Visualization

Visualization techniques, such as histograms with density plots, and heatmaps, were used to analyse the dataset. These

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methods help identify feature distributions, patterns, and possible outliers, which are essential for understanding the data and improving model performance.

Histograms with density plot were generated for each feature (Figure 2). To show the frequency distribution of values histogram is used. Where, gender displays a clear binary distribution (0 = Male, 1 = Female). Age shows a right-skewed pattern, with most participants between 20 and 50 years old. Height and Weight are nearly normally distributed, while Duration and Calories are right-skewed, indicating that most exercise sessions were short and burned fewer calories. Density plots are used to show the probability density of key features. Variables such as Age, Body Temperature, and Calories have right-skewed distributions, while Height, Weight, and Heart Rate show near-normal patterns. The Duration feature appears uniformly distributed, covering a wide range of exercise times.

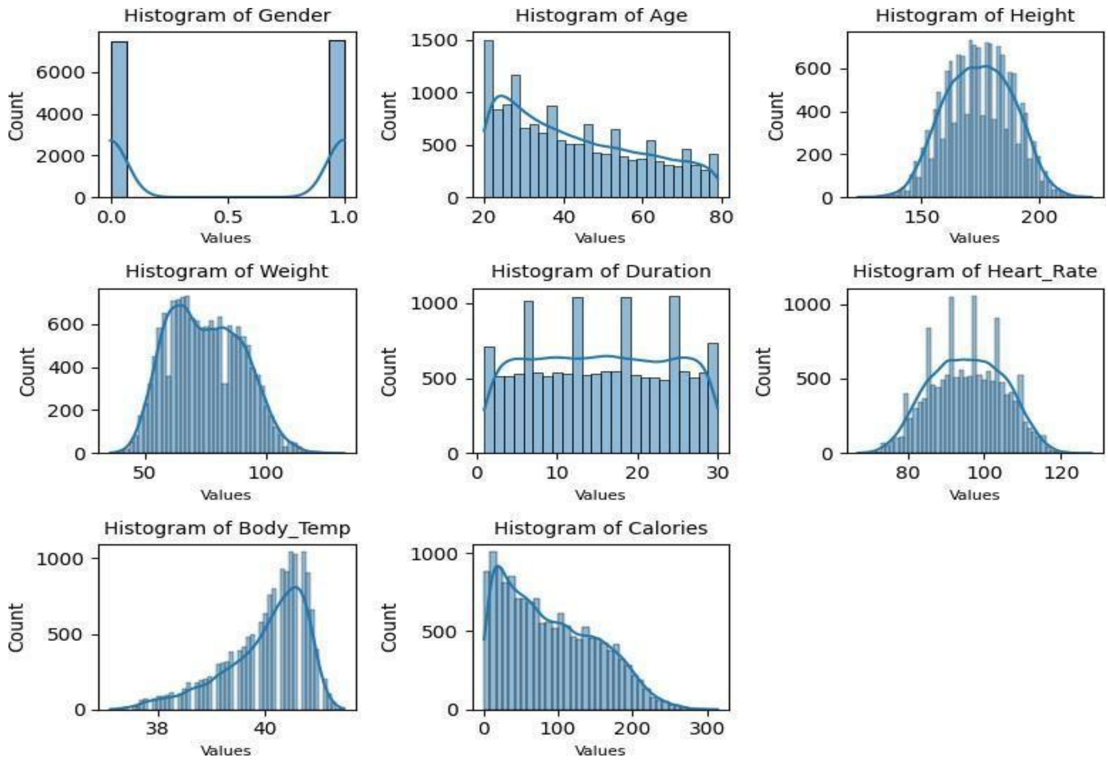

Fig. 2. Histogram with density plot illustrating the distribution of different features

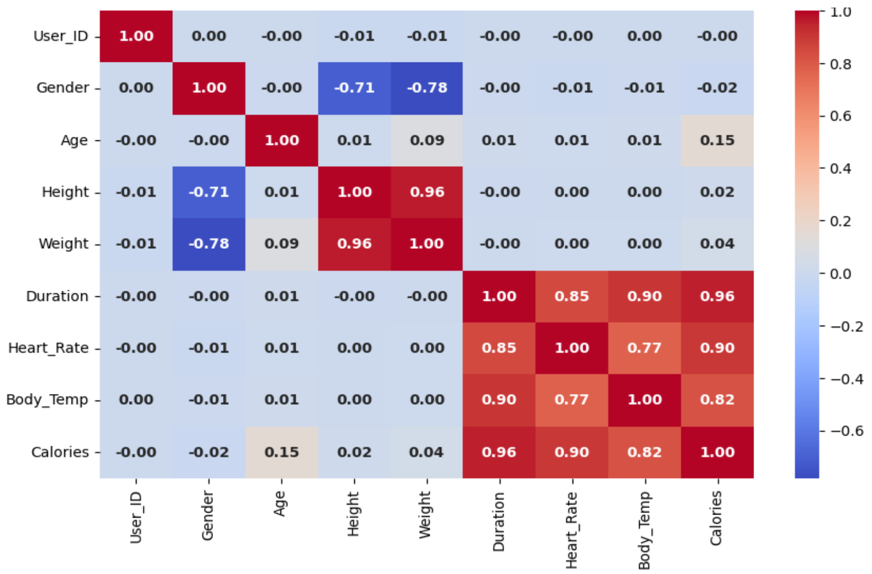

Fig. 3 Heatmap visualizing the intensity of relationships across the features.

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A heatmap (Figure 3) displays the correlation between variables. Strong positive correlations are found between Weight, Duration, and Calories, indicating that these are key predictors. Weaker correlations, such as that between Age and Calories, suggest less impact. This correlation analysis also helps identify multicollinearity among variables and supports effective feature selection.

C. Preprocessing

Several preprocessing steps were applied to ensure data quality and model readiness. The User ID column, having no predictive value, was removed. The Gender feature, originally represented by text ("Male", "Female"), was encoded into binary form (0 = Male, 1 = Female). These preprocessing operations improved data consistency and model compatibility [16].

D. Optimal Feature Finding

Feature selection was carried out to reduce redundancy and improve model accuracy. Correlation analysis and feature-importance ranking identified Weight, Duration, Heart Rate, and Body Temperature as the strongest predictors, while Gender and Age had less influence. Tree-based models such as RFR and GBDTR further confirmed these findings. The final feature set focused on the most predictive attributes to enhance learning efficiency and model performance.

E. Model Formation

In this study, several ensemble regression techniques were implemented, including BAGGINGR [5], RFR [6], VOTINGR [12], XGBOOSTR [7], STACKINGR [13], and GBDTR [14], to predict calorie expenditure. Among these, XGBOOSTR achieved the best performance and provided the most reliable results.

XGBoost is a gradient boosting framework optimized for efficiency and scalability. It builds an ensemble of decision trees sequentially, where each new tree corrects the residuals of the previous ones. Regularization techniques are used to prevent overfitting and improve generalization. The basic equation of XGBoost regression is:

$$F(x)=F_{previous}(x)+\eta\cdot h(x) \qquad (1)$$

where $F(x)$ is the updated prediction, $F_{previous}(x)$ is the previous prediction, η is the learning rate, and $h(x)$ is the output of the current decision tree.

F. Model Evaluation

To evaluate model performance, five standard regression metrics were used: Mean Squared Error (MSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), Peak Signal-to-Noise Ratio (PSNR), and Signal-to-Noise Ratio (SNR). These metrics measure prediction accuracy and generalization ability. Ideally, R^2, PSNR, and SNR should be maximized, while MSE and MAE should be minimized.

G. Final Model

Based on performance comparisons, XGBOOSTR demonstrated the highest accuracy and robustness among all ensemble regression models. Therefore, it was selected as the final model for predicting calorie expenditure during exercise.

H. Model Interpretability

To ensure interpretability and transparency, XAI techniques, SHAP and LIME, were applied to the final model. SHAP provides a unified measure of each feature's contribution to model predictions, showing that Body Temperature, Heart Rate, and Duration have the most significant influence on calorie estimation. LIME focuses on local interpretability by explaining individual predictions using simpler surrogate models [15]. Together, SHAP and LIME help make the model's predictions more understandable and trustworthy for both fitness tracking and medical applications.

III. RESULT ANALYSIS

This section presents the performance analysis of all regression models used in this study. Table II summarizes the comparative results of the ensemble regression models in terms of MAE, MSE, R^2, PSNR, and SNR.

TABLE II PERFORMANCE COMPARISON OF REGRESSION MODELS

Model	MAE	MSE	R^2	PSNR	SNR
BaggingR	1.7327	7.7437	0.9980	40.51	31.86
RFR	1.7279	7.6858	0.9981	40.54	31.89

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GBDTR	2.7357	14.7690	0.9963	37.70	29.06
XGBOOSTR	1.2941	3.9176	0.9990	43.47	34.82
VotingR	3.9490	31.8454	0.9919	34.37	25.72
StackingR	1.7964	8.1578	0.9979	40.28	31.63

Among all models, XGBOOSTR demonstrated the best overall performance, achieving the lowest error rates (MAE = 1.29, MSE = 3.91) and the highest accuracy metrics (R^2 = 0.9990, PSNR = 43.47, SNR = 34.82). These results indicate that XGBOOSTR provides superior predictive accuracy and robustness compared to the other ensemble models. Although BaggingR, RFR, and StackingR also performed well with high R^2 values and relatively low errors, VotingR showed the weakest performance, recording the highest error values (MAE = 3.9490, MSE = 31.8454) and the lowest R^2 (0.9919). Therefore, XGBOOSTR was identified as the most suitable model for accurate calorie burn prediction.

To further assess the reliability and consistency of XGBOOSTR, 10-fold cross-validation was conducted. The fold-wise results are presented in Table III. The analysis shows that Fold 4 achieved the best performance with the lowest MAE (1.880), lowest MSE (9.870), and highest R^2 (0.9974), PSNR (38.78), and SNR (30.70). This indicates that the model generalizes well and produces highly accurate predictions across different data partitions. In contrast, Fold 7 displayed slightly weaker performance, with the highest MSE (17.561) and lowest R^2 (0.9954), suggesting minor variations due to data distribution.

TABLE III 10-FOLD RESULTS FOR THE BEST MODEL (XGBOOSTR)

Fold	**MAE**	**MSE**	**R^2**	**PSNR**	**SNR**
1	2.082	16.684	0.9959	37.72	28.68
2	2.056	14.301	0.9964	37.26	29.27
3	1.975	13.238	0.9966	37.34	29.61
4	1.880	9.870	0.9974	38.78	30.70
5	1.917	11.470	0.9971	38.00	30.20
6	1.982	13.897	0.9963	36.84	29.30
7	2.177	17.561	0.9954	36.77	28.32
8	2.053	14.555	0.9964	37.19	29.07
9	2.031	14.235	0.9963	37.16	29.21
10	2.069	16.428	0.9957	37.00	28.54

The SHAP plot for the final XGBOOSTR model (Figure 4) provides insight into the most influential features in calorie burn prediction. The analysis shows that Duration and Heart Rate are the most significant predictors, followed by Weight and Body Temperature. Longer exercise duration and higher heart rate values are associated with increased calorie expenditure, confirming physiological expectations. This visualization enhances the interpretability of the model by clearly showing the direction and magnitude of feature impacts.

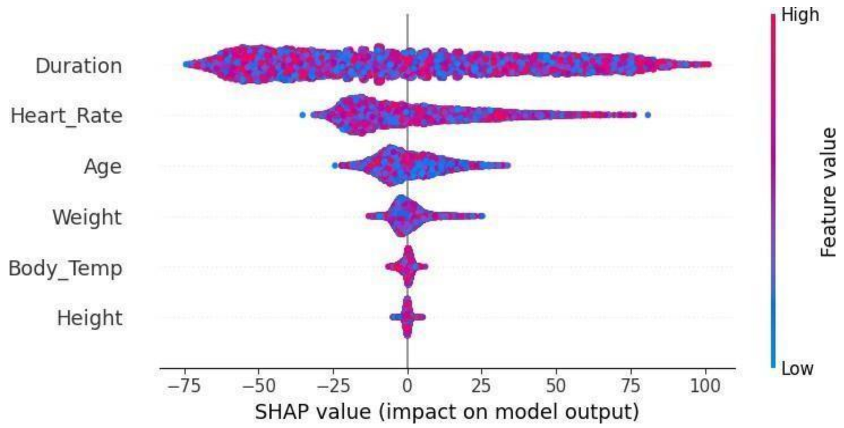

Fig. 4. The impact of various features on the model's output.

Additionally, the LIME plot (Figure5) illustrates how specific features influence individual predictions. By explaining localized decision boundaries, LIME helps interpret the model's reasoning for specific data points, improving transparency and trust in the predictive framework. Together, SHAP and LIME analyses provide both global and local interpretability, allowing a clearer understanding of model behaviour.

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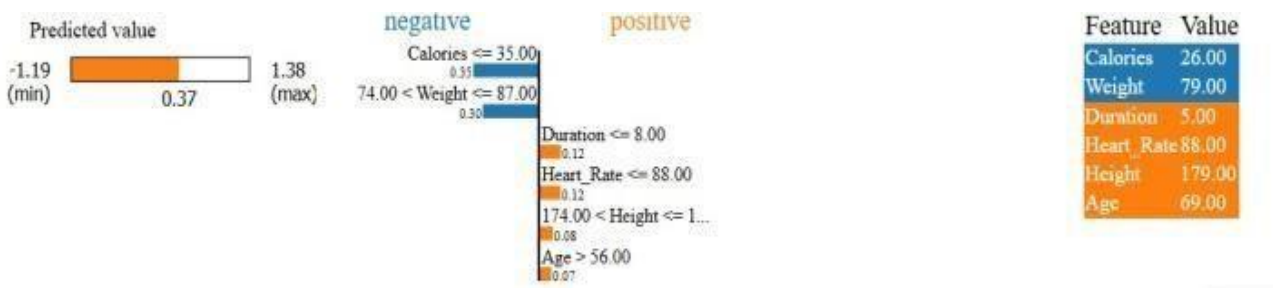

Fig. 5 LIME analysis with key features influencing a specific model prediction.

Table IV compares recent calorie-prediction approaches based on dataset size, optimal model choice, feature optimization, and achieved performance. Studies [9] and [8] used similar datasets with seven attributes, where LightGBM [8] slightly outperformed XGBoost [9]. Paper [7] extended the feature space to nine attributes and applied a hybrid RF + XGBoost model with SHAP-based interpretability, reaching $R^2 \approx 0.98$. The proposed work, trained on fifteen-thousand samples with seven features, applies XGBoost along with feature selection, yielding MAE = 1.2941, MSE = 3.9176, and $R^2 = 0.9990$, showing improved accuracy over prior studies.

TABLE IV COMPARISON OF CALORIE PREDICTION METHOD

Paper [No.]	Dataset (Samples × Attributes)	Best Model Used	Optimal feature finding	Performance Metrics
[9]	15,000 × 7	XGBoost	No	MAE = 1.48
[8]	15,000 × 7	LightGBM	No	MAE = 1.27
[7]	~15,000+ × 9	Hybrid RF + XGBoost	Yes (SHAP, Gini importance)	$R^2 \approx 0.98$, MAE ≈ 1.2–1.3, RMSE < 2.0
Proposed	15,000 × 7	XGBoost	Feature selection	MAE=1.2941, MSE=3.9176, R2=0.9990

IV. CONCLUSION

This study combines ML ensemble models with XAI techniques to improve the prediction of calorie expenditure during exercise. Multiple regression ensembles, including GBDTR, XGBOOSTR, STACKINGR, RFR, BAGGINGR, and VOTINGR, were applied to a dataset of 1,500 samples containing features such as Age, Gender, Weight, Height, Body Temperature, Heart Rate, and Calories burned. After cross-validation, the XGBOOSTR model achieved the highest prediction accuracy among all models. Using LIME and SHAP, this study also identified the most important features affecting calorie burn, such as Body Temperature, Heart Rate, and Duration. The results show that ML with XAI can enhance personalized fitness tracking and assist healthcare professionals in creating better exercise plans. Future work will aim to expand the dataset, include more physiological factors, and apply the models in real-time wearable applications for improved health monitoring.

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