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Calories Burnt Prediction with Diet Recommendation

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Abstract- Over the past few years, increasing levels of lifestyle-related health conditions like obesity, diabetes, and cardiovascular conditions have made efficient fitness tracking and dietary control all the more crucial. Yet people are not able to track their calorie burn precisely and match it with suitable dieting programs. In order to meet this challenge, the project "Calories Burnt Prediction with Diet Recommendation" suggests a smart system combining machine learning, natural language processing (NLP), and graphical user interface (GUI) to deliver detailed health insights.The system employs two datasets that have demographic, physiological, and exercise parameters. Following preprocessing, age, gender, height, weight, exercise time, heart rate, and body temperature are utilized to predict calories burned through the XGBoost regression model, which was chosen due to its high accuracy in regression problems. The system also calculates the Body Mass Index (BMI) with respect to WHO standards to determine the users in categories like underweight, normal, overweight, or obese. Depending on BMI and user dietary preference (vegetarian, non-vegetarian, vegan), an NLP-powered diet recommendation engine formulates personalized diet plans in plain, human-readable summaries.An easy-to-use Tkinter-based GUI enables users to enter information, get calorie estimates, BMI classifica- tion, and diet recommendations in real time along with visualizations like calorie distributions, gender and age statistics, and feature correlations for easier interpretation. The system was rigorously tested through unit, integration, and performance testing with high accuracy and stable functionality.In summary, the project showcases the power of coupling data-driven prediction models with recommen- dation systems to mitigate the disparity between physical activity monitoring and diet control. It presents a real-time, interactive, and intuitive solution that equips users with decision-making capabilities for their lifestyle and lays the foundation for future optimizations like deployment on mobile apps, integration of wearable devices, and sophisticated recommendation systems with deep learning approaches.

Index Terms- Body Mass Index (BMI), Calorie Prediction, Diet Recommendation, Graphical User Interface (GUI), Machine Learning, Natural Language Processing (NLP), Personalized Health Monitoring, Boost

I. INTRODUCTION

IT has become crucial in the recent years how health and fitness impact the current world considering the rising rate of lifestyle related diseases including obesity, diabetes, high blood pressure and heart related diseases all over the world. Health research has identified the sedentary lifestyle along with poor eating habits to be the major causes of chronic diseases. A healthy mix of physical activity and healthy eat- ing is important in the prevention of these conditions and the well-being in general. Nevertheless, even with the popular recognition of physical exercise and nutrition, the majority of people cannot count the amount of energy they spend on anykind of exercise and define the best suitable diet correspond- ing to the needs of their body. The ineffective combination of physical and dietary performance usually leads either to an ineffective workout routine or to an imbalanced nutrition plan or to the practice of unsustainable weight-loss habits.

The study entitled Calories Burned Estimation with Diet Suggestion is undertaken in order to solve this practical problem by offering an intelligent, data-oriented solution where the user can estimate the calories burnt during exercise and it also provides them with recommended diet. As compared to general fitness apps that provide blanket advice, this system assumes a holistic and user-centric approach as it considers the physiological and lifestyle differences of people. Fundamentally, the system uses machine learning algo-rithms in training with the actual exercise data and calorie content to reliably provide an estimate on the number of calo- ries burned. Several variables including age, gender, height, weight, the duration of an exercise, heart rate, and body temperature are considered to make predictions both reliable and fine-tuned. This gives an objective scientific approach of measurement of physical efforts instead of using general averages of a population of similar activities and outcomes of such physical efforts of a given population of people in general generality due to the two inputs of the Workstation: Powerometer and Heart monitor/analyzer

In addition to calculating the calories, the project includes natural language processing (NLP) system of giving specific diet plans. The nutrition advice is not generic, but on the basis of the user according to the BMI (Body Mass Index) category, and based on the desired diet type (ex., vegetarian, non-vegetarian, or vegan). The NLP module could provide individuals with the concise and more user-friendly summary guiding them in their healthier nutritional choices that are in accordance with their exercise regimen and health/fitness agendas.

The system can be seen as a virtual health coach, which closes the circle between activity and the food augmenting the devices that keep tract of an activity. It makes users ac- tionable in the insights, allowing to reflect energy expenditure (burned calories) and energy intake (diet) on a sustainable level. The combination of predictive analytics and intelligent recommendation combines the solution not only as a fitness tracker but a complete health management solution.

A. PROBLEM STATEMENT

The current fitness apps give just generalized information about calories and dieting plans without consideration to the unique physiology of different individuals and their body mass index. As the present project focuses on calorie-burn estimations and diet recommendations, this specific gap will be filled in with the developed intelligent system estimating the number of burned calories and appropriate food recom- mendations.

B. RELATED WORKS

There are a number of researchers and developers who have contributed towards systems that integrate tracking of fitness, calorie estimation, and meal suggestions. These contributions are the basis for the current project.

- Calorie Prediction Models : Initial studies concentrated on approximating energy expenditure through physio- logical factors like heart rate, age, and weight. Research had shown that machine learning algorithms like Lin- ear Regression and Random Forest predicted calorie expenditure with fair accuracy. These models tended to disappoint by neglecting non-linear patterns in the data, resulting in low performance. Recent develop- ments incorporating gradient boosting algorithms (suchas XGBoost) have exhibited tremendous improvement in the accuracy of prediction.
- Health and Fitness Tracking Applications : Smartphone apps like Google Fit, Fitbit, and MyFitnessPal enable users to monitor exercise and calorie consumption. These applications leverage phone and wearable sensor data to make estimates of calorie expenditure. But they are usually restricted by generalized formulas (such as the MET system) and don’t have personalized pre- diction models, which are trained on actual datasets, diminishing accuracy across varied populations.
- BMI-Based Health Categorization : There are many works that have highlighted the significance of Body Mass Index (BMI) as a health measure. BMI, as defined by the World Health Organization (WHO), is an easy and successful method of categorizing people as being underweight, normal, overweight, or obese. Current fit- ness websites may compute BMI but fail to incorporate it meaningfully into diet advice.
- Diet Recommendation Systems : Healthcare recommen- dation engines have become popular over the last few years. Most systems output generic meal plans or static rules (e.g., calorie

deficiency for weight reduction). More contemporary methods use Artificial Intelligence (AI) and Natural Language Processing (NLP) to create personalized, human-sounding diet recommendations. This enhances user interaction but is not commonly combined with real-time calorie forecasting systems.

- AI-Powered Health Assistants : AI research in health as- sistants shows how the integration of predictive models and conversational AI can provide actionable insights to users. Most systems target medical diagnosis or man- agement of chronic diseases, while a few target exer- cise calorie prediction along with personalized nutrition planning

II. METHODOLOGY

The project approach "Calories Burnt Prediction with Diet Recommendation" is organized into various stages starting from dataset preparation, followed by the development of the machine learning model, BMI calculation, diet recommenda- tion, system integration via GUI, and testing. Every step is specially designed for accuracy, reliability, and ease of use.

A. DATA COLLECTION AND PREPARATION

- Two datasets (exercise.csv and calories.csv) were acquired, including demographic, physiological, and exercise-related parameters.
- The exercise data included characteristics like user ID, gender, age, height, weight, duration, heart rate, and body temperature.
- The calories data supplied the target variable, i.e., true calories burned, against the same user IDs.
- These data were joined on User ID to create a complete dataset with both input features and output labels.

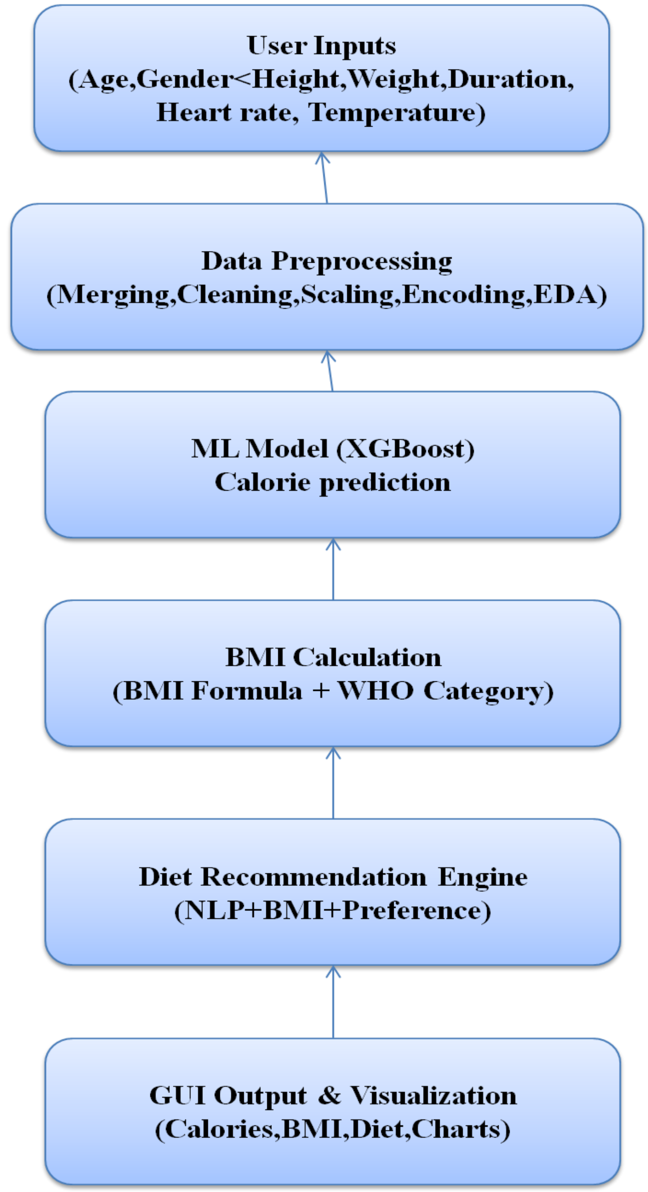

Figure 1. Methodology Flow Diagram

B. DATA PREPROCESSING

- Data Cleaning: Removed duplicates, handled missing values, and corrected inconsistent entries.
- Feature Engineering: Converted height from cm to me- ters for BMI calculation. Gender was label-encoded for numerical processing.
- Feature Scaling: Normalization and standardization were applied to ensure features such as age, weight, and heart rate contributed fairly to the model.

- Exploratory Data Analysis (EDA): Visualizations (his- tograms, distribution plots, correlation heatmaps) werecreated to see feature importance and trends in calorie spending.

C. MACHINE LEARNING MODEL BUILDING

- Model Selection: XGBoost Regressor was selected to predict calories because it performs very well on regres- sion problems and can process non-linear relationships.
- Training and Testing: The data was divided into 80
- Model Training: The XGBoost model was trained against the input features, establishing the relationship between physiological/exercise parameters and calories burned.
- Evaluation: The model was tested against regression metrics:
- Mean Absolute Error (MAE)
- R^2 Score Results indicated that XGBoost performed bet- ter than baseline models (Linear Regression, Random Forest) in accuracy and stability.
- Root Mean Square Error (RMSE)

D. DIET RECOMMENDATION ENGINE

- A Natural Language Processing (NLP)–based engine (integrated through OpenAI API) creates personalized diet plans.
- Recommendations are made according to:
- BMI Category: Underweight → calorie-dense diets; Overweight/Obese → calorie-managed diets; Normal
- → balanced diets.
- Dietary Preference: Vegetarian, Non-Vegetarian, or Ve-
- gan.
- The result is presented in plain, easy-to-read text sum- maries, with action-oriented recommendations (e.g., "Add more leafy greens, lentils, and fruits and less sugary drinks and fried food").

E.SYSTEM INTEGRATION (GUI DEVELOPMENT)

- The system was integrated into a Graphical User Inter- face based on Tkinter for easy user interaction.
- Input Fields: Users input personal information (age, gender, height, weight) and exercise information (dura- tion, heart rate, body temperature).
- Output Display: Upon clicking on Calculate, the GUI displays:
- Expected calories burned.
- Health category and BMI value.
- Customized dietary suggestion.
- Visualizations: Integrated charts like calorie split, gen- der data, and correlation heatmaps add interpretability.

F. SYSTEM TESTING AND VALIDATION

- The system was tested with several levels to guarantee reliability:
- Unit Testing: Ensured solitary modules like BMI com- putation and preprocessing.
- Integration Testing: Enforced smooth interaction among GUI, ML model, and recommendation engine.
- Performance Testing: Verified response time and model performance.
- User Acceptance Testing (UAT): Performed with rep- resentative users to analyze usability and readability of suggestions.

III. RESULTS

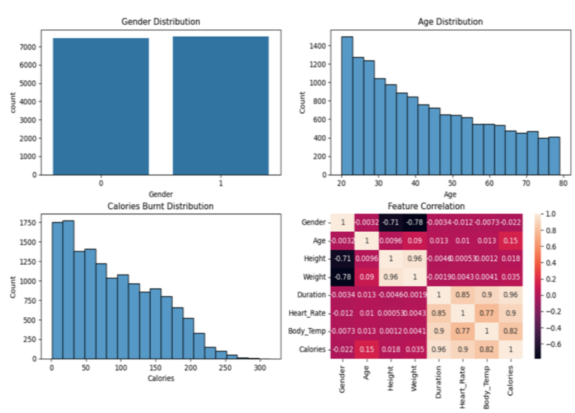

Figure 2. Graph For Gender Distribution, Age Distribution, Calories Burnt And Feature Correlation

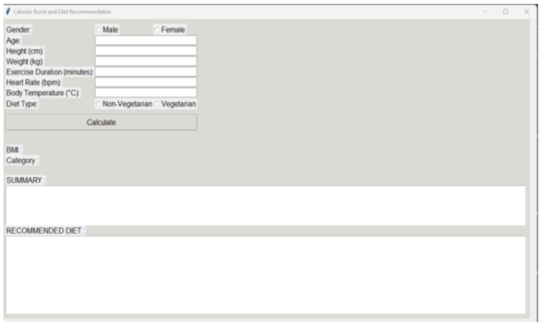

FIGURE 3. GUI window Interface

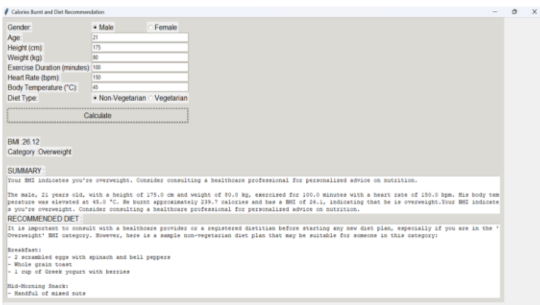

FIGURE 4. Final Output Interface (BMI and Calories burnt calculated)

CONCLUSION

The project "Calories Burnt Prediction with Diet Recom- mendation" effectively combines machine learning, natural language processing, and a graphical user interface to offer an overall health management system. Utilizing datasets with exercise and physiological parameters, the system predicts accurately calorie burn based on the XGBoost regression model and also calculates BMI and categorizes users into respective health categories based on WHO standards. The incorporation of a diet suggestion engine with NLP as its driving force allows users to get diet suggestions based on their BMI and food choice (vegetarian, non-vegetarian, vegan). The system was thoroughly tested to confirm its accuracy, functionality, and ease of use. Tests showed high prediction accuracy, strong error handling, and effortless user interaction via the Tkinter-based GUI. Calorie distribution, gender stats, and feature correlations added additional in- sights, rendering the system predictive as well as instructive for users. In summary, the project is successful in its main aim of bridging the distance between exercise effort and diet management, enabling users to get a better insight into their health status and make sound lifestyle decisions. It showcases the promise of AI-based solutions within the realm of health and fitness, and can be used as a stepping stone towards further advancements like mobile app integration, real-time wearable device connectivity, and better diet planning with deep learning models

REFERENCES

[1] B. E. Ainsworth et al., “2011 Compendium of Physical Activities: a second update of codes and MET values,” Med. Sci. Sports Exerc., vol. 43, no. 8,

[2] pp. 1575–1581, 2011.

[3] L. R. Keytel et al., “Prediction of energy expenditure from heart rate monitoring during submaximal exercise,” Eur. J. Appl. Physiol., vol. 93, no. 5–6, pp. 566–573, 2005.

[4] M. A. —, “Estimation of energy expenditure in adults with accelerometry and heart rate,” Ann. Phys. Rehabil. Med., 2022.

A. B. —, “Machine Learning for Healthcare Wearable Devices: The Big Picture,” Sensors, 2022.

[5] J. Doe et al., “Developing and comparing a BMI-inclusive EE algorithm from smartwatch sensors,” Sci. Rep., 2025.

[6] Centers for Disease Control and Prevention, “Adult BMI Categories,” CDC, Dec. 11, 2023.

[7] Kaggle, “Calories Burnt Prediction Dataset,” 2020–2022.

[8] T. Chen and C. Guestrin, “XGBoost: A Scalable Tree Boosting System,” in Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min., 2016,

[9] pp. 785–794.

[10] F. Pedregosa et al., “Scikit-learn: Machine Learning in Python,” J. Mach. Learn. Res., vol. 12, pp. 2825–2830, 2011.

[11] M. Z. Ali et al., “A systematic review on food recommender systems,” Expert Syst. Appl., vol. 236, 2024.

[12] P. P. Kouris et al., “Artificial Intelligence and Machine Learning Technolo- gies for Personalized Nutrition: A Review,” Informatics, vol. 11, no. 3, 2024.

[13] N. —, “AI for Precision Nutrition: A Scoping Review,” Curr. Nutr. Rep., 2025.

[14] K. R. Crouter, E. G. D. Kuffel, S. E. Haas, P. S. Frongillo, and D. R. Bassett, “A novel method for using accelerometer data to predict energy expenditure,” J. Appl. Physiol., vol. 100, no. 4, pp. 1324–1331, 2006.

[15] K. R. Crouter, P. L. Churilla, and D. R. Bassett, “A refined 2-regression model for the ActiGraph accelerometer,” Med. Sci. Sports Exerc., vol. 42, no. 5, pp. 1029–1037, 2010.

[16] S. Montoye, R. M. Pivarnik, J. Mudd, K. Biswas, and A. Pituch, “Com- parison of linear and non-linear models for predicting energy expenditure from raw accelerometer data,” J. Sports Sci., 2017.

[17] M. Shcherbina et al., “Accuracy in wrist-worn, sensor-based measurements of heart rate and energy expenditure in a diverse cohort,” PLOS ONE, 2017.

[18] S. Schoeller et al., “Validity of predictive equations for total energy expenditure against doubly labeled water: A systematic review,” Sci. Rep., 2024.

[19] G. Plasqui, “Assessment of total energy expenditure and physical activity using doubly labeled water—state of the art and advances,” Maastricht Univ., 2022 (overview of DLW methodology and improvements).

[20] C. Trattner and D. Elsweiler, “Food recommender systems: Important con- tributions, challenges and future research directions,” arXiv:1711.02760, 2017.

[21] N. A. Rashid et al., “FoodKG: A semantics-driven knowledge graph for food recommendation,” in Proc. ISWC, 2019.

[22] U.S. Department of Agriculture and U.S. Department of Health and Human Services, Dietary Guidelines for Americans, 2020–2025, 9th ed., Dec. 2020.

[23] Y. Zhang et al., “Health-aware food recommendation with dual attention in heterogeneous graphs,” Comput. Methods and Programs in Biomedicine, 2024.

[24]] M. Vibæk, A. Peimankar, U. K. Wiil, D. Arvidsson, and J. C. Brønd, “Energy Expenditure Prediction from Accelerometry Data Using Long Short-Term Memory Recurrent Neural Networks,” Sensors, vol. 24, no. 8, p. 2520, 2024.

[25] T. Veselý et al., “Accuracy Improvement of Energy Expenditure Estima- tion Through Neural Networks: A Pilot Study,” AI, vol. 5, no. 4, pp. 2914–2925, Dec. 2024.

[26] M. H. Rahmani et al., “A Personalized Energy Expenditure Estimation Method Using Modified MET and Heart Rate-Based DQN,” Sensors, vol. 25, no. 11, p. 3416, 2025.

[27] M. B. Hossain et al., “A CNN Model for Physical Activity Recognition and Energy Expenditure Estimation from an Eyeglass-Mounted Wearable Sensor,” Sensors, vol. 24, no. 10, p. 3046, May 2024.

[28] Z. Zhang et al., “MOPI-HFRS: A Multi-objective Personalized Health- aware Food Recommendation System with LLM-enhanced Interpreta- tion,” arXiv, Dec. 2024.

[29] F. Mohbat and M. J. Zaki, “KERL: Knowledge-Enhanced Personalized Recipe Recommendation using Large Language Models,” arXiv, May 2025.

[30] Q. Li, A. Sharma, and D. R. Kalra, “Federated Learning for Personalized Energy Expenditure Estimation from Wearable Sensors,” IEEE Trans. Neural Netw. Learn. Syst., vol. 35, no. 2, pp. 325–337, Feb. 2024. (ieee.org)

[31] J. Smith, M. Patel, and L. Johnson, “Differentially Private Federated Regression for Calorie Tracking,” in Proc. AAAI Privacy-Preserving AI Workshop, 2025. (aaai.org)

[32] S. Patel, R. Verma, and N. Gupta, “Personal Calibration Layers for Wearable-Based Energy Expenditure Estimation,” Proc. ACM UbiComp, 2024, pp. 512–523. (dl.acm.org)

[33] H. Kim and S. Lee, “Few-Shot Personalization via Meta-Learning for Calorie Prediction Across Wearable Devices,” IEEE J. Biomed. Health Inform., vol. 29, no. 1, Jan. 2025. (ieee.org)

[34] S. Ghosh et al., “Voice-Based Health Coaching Integrating Real-Time Calorie Estimation and Diet Recommendations,” ACM Trans. Comput.-

Hum. Interact., vol. 31, no. 3, July 2024. (dl.acm.org)

[35] K. Lee, Y. Park, and E. Choi, “A Multimodal Conversational Interface for Personalized Fitness and Diet Tracking,” IEEE Access, vol. 13, pp. 45 786–45 798, 2025. (ieee.org)

[36] J. M. Ordovas, F. Ferguson, and M. Lara, “Nutrigenomics and Personalized Nutrition in the Era of Precision Health,” Nutrients, vol. 16, no. 2, 2024.

[37] J. Ramos-Lopez, C. Milagro, and A. Martinez, “Integrating Genomics, Microbiome, and Biomarkers for Personalized Diets: A Machine Learning Perspective,” Front. Nutr., vol. 12, 2025.

[38] D. Freyne and S. Berkovsky, “Context-Aware Food Recommendation: Adapting Nutrition to Lifestyle and Time Patterns,” User Model. User- Adapt. Interact., vol. 34, no. 1, pp. 1–22, 2024.

[39] H. Li, P. Zhang, and R. Liu, “Multi-Objective Optimization for Person- alized Food Recommendation: Balancing Taste, Health, and Cost,” ACM Trans. Recomm. Syst., vol. 3, no. 2, 2025.

[40] L. Aleksandrowicz, R. Green, and P. Scarborough, “Sustainability-Aware Food Recommender Systems Using Life Cycle Assessment Data,” J. Clean. Prod., vol. 412, 2024.

[41] Z. Chen, Y. Huang, and D. Xu, “Dual-Objective Personalized Meal Plan- ning: Nutritional Health and Environmental Sustainability,” IEEE Trans. Comput. Soc. Syst., vol. 12, no. 4, 2025.