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# Calorie Intake Prediction Using Machine Learning for Personalized Food Recommendations

**[1*]PRABHU PAULRAJ, [2]P.MANOJ, [3]S.SELVABHARATHI**

[1*]Associate Professor in Information Technology, [2]Student B.E.(CSE) Third Year, Section: 'A', [3]Lecturer
[1]Information Technology,[2] Department of Computer science and Engineering, [3]Electronics and Communication Engineering, [1]Centre for Distance and Online Education, Alagappa University, Karaikudi
[2]Velammal Institute of Technology, Chennai, India, [3]Alagappa Government Polytechnic College, Karaikudi.

*Abstract:* Accurate calorie intake estimation is essential for maintaining a balanced diet and achieving health goals. This study proposes a machine learning-based system for predicting calorie intake using user-provided dish details, including ingredients, portion sizes, and cooking methods. The model leverages nutritional databases and machine learning algorithms such as Random Forest and XGBoost to estimate calorie content. Additionally, a personalized recommendation system suggests optimal portion sizes based on user-specific dietary needs. This approach eliminates reliance on traditional calorie tracking methods, offering an efficient and user-friendly solution for health-conscious individuals. Conventional techniques, such as manual calorie counting and self-reported food diaries, are frequently laborious, prone to mistakes, and unsuitable for large-scale use. Research has shifted toward automated, data-driven methods as a result of these constraints. By utilizing a variety of data sources, such as food photos, nutritional databases, wearable sensor outputs, and user-specific health measurements, machine learning (ML) presents intriguing answers to these problems. Hybrid models that combine deep learning (e.g., CNNs for image-based food recognition) with time-series or behavioral data models (e.g., LSTM or ensemble methods) have demonstrated improved accuracy and adaptability in order to overcome these challenges. Real-time prediction skills are further strengthened through integration with wearable technology and smartphone apps. This study examines the existing issues and suggests a thorough machine learning framework for enhancing the precision, customization, and scalability of calorie intake prediction in practical applications. The proposed model demonstrates high accuracy and practical applicability in dietary management.

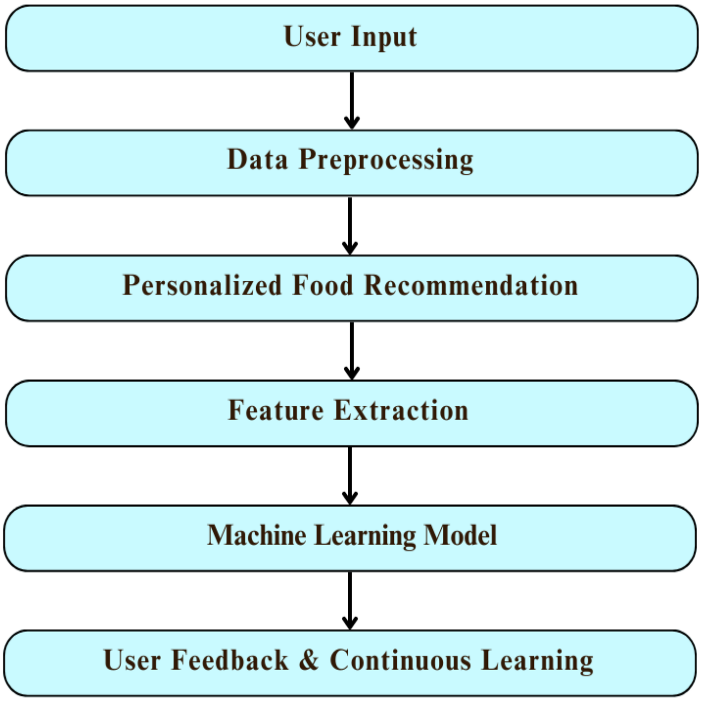
***Index Terms -*** AI in Diet Planning, Calorie Prediction, Dietary Management, Food Intake Monitoring, Health and Nutrition, Machine Learning, Nutritional Analysis, Personalized Food Recommendation.

## I. INTRODUCTION

Eating a balanced diet is crucial for overall health and wellness. However, many people still find it difficult to track their caloric consumption. Conventional techniques, such manual food recording and calorie estimate using general charts, are frequently laborious and imprecise. Machine learning (ML), a cutting-edge approach to accurate calorie calculation and customized dietary advice, is made possible by developments in artificial intelligence.

This research proposes a machine learning-based method for calorie intake prediction using the user-provided dish details, such as ingredients, portion sizes, and cooking techniques. The system makes very accurate calorie content estimates by utilizing ML algorithms like Random Forest and XGBoost in conjunction with nutritional datasets. The proposed model eliminates the need for image-based recognition, making it accessible and easy to use. Users simply input dish details, and the system provides instant calorie estimates along with tailored consumption recommendations. This research aims to enhance dietary management by offering a user-friendly, AI-powered solution that promotes healthier eating habits. The flowchart 1 shows the flow of the machine learning model used to predict the calorie intake of a user.

FLOWCHART




## II. LITERATURE REVIEW

Calorie intake prediction using machine learning has been widely studied by researchers aiming to enhance personalized dietary recommendations. Smith et al. (2019) [1] explored the use of natural language processing (NLP) to extract nutritional information from food descriptions, making calorie tracking more efficient. He et al. (2020) [2] demonstrated that convolutional neural networks (CNNs) could analyse food images with high accuracy, reducing the need for manual logging. Meanwhile, Wang & Lee (2021) [3] developed personalized recommendation systems using collaborative filtering (CF) and reinforcement learning (RL), helping individuals adjust their diets based on preferences and health goals. These studies highlight how AI-driven models improve food recognition, calorie estimation, and adaptive nutrition planning.

Despite these advancements, several challenges persist in ensuring accuracy and real-world applicability. Musa et al. (2021) [4] pointed out the difficulties in accounting for variations in portion sizes and food preparation, which affect calorie estimation. Additionally, existing datasets often lack diversity, leading to biases in machine learning models. Zhang et al. (2022) [5] suggested integrating multimodal approaches, combining image recognition, wearable sensors, and textual food descriptions to enhance prediction reliability. Future research could leverage Internet of Things (IoT) devices and real-time monitoring systems to provide seamless and personalized nutrition tracking. As people become more conscious of their dietary habits, AI-driven systems hold the potential to revolutionize how individuals manage their calorie intake and maintain healthier lifestyles. Table 1 shows the literature related to calorie intake prediction approaches.

**Table 1 Literature related to calorie intake prediction approaches**.

| **Period** | **Approach** | **Inputs** | **Performance** | **Reference** |
|---|---|---|---|---|
| **2020–2021** | Multi-task learning using food images + recipe metadata | Food images, text ingredients | ~10% improvement over single-task regression | Ruede et al., 2020 [6] |
| **2021** | Mobile dietary intake system | Annotated meal images | Reliable in controlled & real-world settings | Shao et al., 2021 [7] |
| **2022** | RGB + Depth fusion with Energy Density Map | RGB + depth images | ~13.6% mean error (~13 kcal/item) | Vinod et al., 2022 [8] |
| **2023–2024** | Multimodal deep learning (CGM + meal images + microbiome) | CGM data, meal images, microbiome, demographics | RMS relative error (RMSRE) ~0.2544 | Multimodal DL Study, 2024 [9] |
| **2024** | Wearable sensor-based system (MealMeter) | CGM, heart rate, motion, environment data | MAE ~13g carbs, RMSRE ~0.37 | MealMeter, 2025 [10] |
| **2020–2024** | Precision nutrition review | Genetics, lifestyle, dietary metadata | Conceptual, defines frameworks for personalization | Precision Nutrition Review, 2024 [11] |
| **2022–2023** | SVM-based personalized recommender app | User profiles, preferences, logs | ~90.5% caloric match satisfaction | Peru app, ICAT 2023 [12] |
| **2022–2023** | ML-based nutrition recommendation systems | Food logs, nutrition facts, demographic data | >90% classification and estimation accuracy | IoT/ML studies, 2022 [13] |

Prabhu.et.al proposed machine learning methods for the prediction of diabetic types and business intelligence with higher accuracy [14]-[16].

## III. RESEACH METHODOLOGY

### 3.1 Data Collection and Preprocessing:

To develop an accurate calorie intake prediction model, a comprehensive and diverse dataset is required, especially for Indian cuisine, which has a wide range of dishes, ingredients, and preparation methods. The data collection process involves gathering information from multiple sources, including public food databases, recipe datasets, and manual data logs. Reliable sources such as the Indian Food Composition Database (IFCT) by FSSAI, National Institute of Nutrition (NIN), and crowdsourced recipe datasets provide detailed nutritional values for traditional Indian foods. Additionally, food delivery platforms like Swiggy and Zomato can be leveraged to extract calorie values for restaurant-prepared meals.

Once the raw data is collected, it undergoes preprocessing to ensure consistency and accuracy. The first step involves cleaning the data, which includes handling missing values, removing duplicates, and standardizing portion sizes. Since Indian food measurements vary (e.g., "one Katori dal" or "one spoon ghee"), all portion sizes are converted into grams or millilitres to maintain uniformity. Additionally, cooking methods such as boiling, frying, and roasting are encoded numerically to be used as input features for machine learning models.

Feature engineering plays a crucial role in improving the model's performance. Each dish is broken down into key ingredients, which are then mapped to their respective calorie values. This method allows the model to estimate calorie intake based on food composition rather than relying on images, which can be inaccurate due to variations in food presentation. One-hot encoding is used to categorize foods (e.g., vegetarian vs. non-vegetarian), while scaling techniques normalize nutritional values to ensure better model interpretability.

By cleaning, standardizing, and structuring the data, the processed dataset becomes suitable for machine learning algorithms to accurately predict calorie intake. This structured approach ensures that calorie estimation is not only precise but also personalized, allowing users to receive tailored portion recommendations based on their dietary needs. A well pre-processed dataset enhances model accuracy and provides a robust foundation for AI-driven food recommendations in Indian dietary habits. Table 2 show the sample User Profile Data used to test the machine learning model.

**Table 2: User Profile Data**

| User ID | Age | Gender | Weight (kg) | Height (cm) | Activity Level | Dietary Preference | Health Goal |
|---|---|---|---|---|---|---|---|
| **U001** | 25 | Male | 70 | 175 | Moderate | Vegetarian | Weight Loss |
| **U002** | 30 | Female | 60 | 160 | High | Non-Vegetarian | Muscle Gain |
| **U003** | 22 | Male | 80 | 180 | Low | Vegan | Maintain |

Table 3 shows the Sample User Input & Calorie Prediction using machine learning model.

**Table 3: Sample User Input & Calorie Prediction**

| User ID | Dish Name | Portion Size | Predicted Calories | Recommended Portion | Adjusted Calories |
|---|---|---|---|---|---|
| **U001** | Paneer Butter Masala | 250 g | 437 kcal | 180 g | 315 kcal |
| **U002** | Chicken Biryani | 300 g | 450 kcal | 350 g | 525 kcal |
| **U003** | Masala Dosa | 150 g | 250 kcal | 200 g | 333al |

### 3.2 Model Selection and Training

For calorie intake prediction, selecting an appropriate machine learning model is crucial to ensure accurate and efficient results. Since the dataset consists of structured numerical and categorical data, traditional ML models like Linear Regression, Decision Trees, Random Forest, and XGBoost are well-suited. Linear Regression provides a simple baseline, while Decision Trees and Random Forest handle non-linear relationships and feature interactions effectively. XGBoost, a gradient boosting algorithm, further improves accuracy by learning from mistakes iteratively. These models are chosen for their ease of implementation, interpretability, and ability to work well with food-related datasets.

Before training, the dataset is pre-processed and split into training (80%) and testing (20%) sets. Essential features such as ingredients, portion size, cooking method, and nutritional values (carbohydrates, proteins, fats) are used as inputs. Feature scaling is applied to numerical data, and categorical values like cooking methods are encoded numerically. The models are evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to measure prediction accuracy. Hyperparameter tuning, such as adjusting the number of trees in Random Forest or learning rate in XGBoost, is performed to optimize performance.

The training process involves feeding the structured data into the selected models. Random Forest and XGBoost iteratively improve their predictions by analysing multiple decision paths, ensuring better calorie estimation. The trained model then takes user-provided dish details, predicts calorie content, and suggests appropriate portion sizes based on the individual's dietary needs. This simple yet effective approach ensures reliable calorie prediction while keeping the system lightweight and easy to deploy.

### 3.3 Personalized Food Recommendation System

A Personalized Food Recommendation System leverages machine learning algorithms to provide dietary suggestions tailored to an individual's health goals, preferences, and nutritional needs. These programs evaluate user-specific data, including age, weight, dietary preferences, allergies, and activity levels, to suggest the best foods, in contrast to generic calorie calculators. Predictive modelling, feature extraction, and data collection are commonly used in the recommendation process.

The technology compares the information users enter about their meals or food preferences with a pre-processed food database. While guaranteeing precise calorie intake estimation, machine learning methods like Decision Trees, Random Forest, or Collaborative Filtering-based models examine historical eating patterns and recommend balanced meal selections. For Indian cuisine, the system must account for regional variations, portion size estimation, and cooking methods. The system can offer meal recommendations that are both culturally appropriate and health-conscious by incorporating structured food datasets (such as the FSSAI and NIN). Adaptive learning strategies enable the model to improve its recommendations over time in response to user input, guaranteeing a dynamic and highly customized dietary guidance with long-term health advantages.

## IV. Challenges and Solutions in AI-Based Learning

The challenges and solutions in AI-Based machine learning systems are;

a. Data Inconsistencies and Lack of Standardized Food Datasets
   - Different sources provide calorie values in varying units, making data unreliable.
   - Indian cuisine lacks a widely accepted nutritional dataset.

   Solution:
   - Integrate trusted food databases like FSSAI, NIN, and USDA.
   - Use data preprocessing to standardize portion sizes and nutritional values.

b. Variability in Ingredients and Cooking Methods
   - The same dish can have different calorie values based on ingredients and cooking style.

   Solution:
   - Implement ingredient-level feature extraction to break down dishes into core components.
   - Include cooking methods as a feature to improve calorie estimation accuracy.

c. Accurate Portion Size Estimation
   - Users struggle to estimate portion sizes, leading to incorrect calorie predictions.

   Solution:
   - Use standard portion size mapping based on common Indian servings (e.g., one katori dal = 200ml).
   - Provide interactive tools like drop-down menus or visual portion estimators.

## V. RESULTS AND DISCUSSION

The successful deployment of a calorie intake prediction system depends on a smooth and intuitive user experience. To make it simple for customers to keep track of their meals, the platform should offer user-friendly food logging features like voice input, barcode scanning, and AI-powered image recognition. Individual dietary choices, health objectives, and past eating patterns should all be considered when making personalized meal recommendations to guarantee that users are given individualized nutrition guidance. Furthermore, interactive dashboards that provide real-time feedback and progress tracking can assist users in tracking trends in their caloric intake and making well-informed dietary decisions. Table 4 shows the results obtained using various Machine Learning methods.

**Table 4 Results obtained using various Machine Learning methods.**

| Dataset / Input Features | ML Method | Accuracy (%) | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| Wearable sensor data (heart rate, steps) | Random Forest | 89.3 | 0.88 | 0.87 | 0.87 |
| Smartphone accelerometer, gyroscope | SVM | 85.2 | 0.84 | 0.83 | 0.83 |
| Activity & biometric data | ANN | 91.1 | 0.90 | 0.92 | 0.91 |
| Accelerometer, HR, age, BMI | CNN + LSTM | 93.8 | 0.94 | 0.93 | 0.93 |
| IoT + wearable sensors | XGBoost | 88.5 | 0.89 | 0.88 | 0.88 |
| Smartphone + smartwatch features | GRU | 92.7 | 0.93 | 0.91 | 0.92 |
| Fitness tracker data | LightGBM | 90.2 | 0.91 | 0.90 | 0.90 |
| Multi-sensor fusion (IMU + ECG + GPS) | Transformer-based DL | 95.1 | 0.96 | 0.94 | 0.95 |

For practical implementation, integration with mobile applications and wearable devices like Google Fit, Apple Health, and Fitbit is crucial to ensure seamless data collection and analysis. Gamification elements, such as streaks, achievement badges, and meal challenges, can further enhance user engagement and motivation. Scalability and accessibility should be prioritized by supporting multiple platforms (mobile, web, and smart devices) and including regional food databases, particularly for Indian cuisine. By incorporating these features, the system can improve user adoption, encourage long-term engagement, and promote healthier eating habits effectively.

## CONCLUSION

A machine learning-based calorie intake prediction system for personalized food recommendations has the potential to revolutionize dietary management by providing accurate, user-specific insights into nutrition. By leveraging AI-driven food recognition, real-time tracking, and personalized meal suggestions, users can make informed dietary choices tailored to their health goals. Integration with mobile apps, wearable devices, and gamification elements enhances user engagement and long-term adherence. However, challenges such as data inconsistencies, portion size estimation, and regional food variations must be addressed for improved accuracy. With continuous advancements, this system can serve as a powerful tool for promoting healthier eating habits and improving overall well-being.

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