2023 Global Conference on Information Technologies and Communications (GCITC)
Karnataka, India. Dec 1-3, 2023

2023 Global Conference on Information Technologies and Communications (GCITC) | 979-8-3503-0816-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/GCITC60406.2023.10426098

Food Recommendation System Using K-means Clustering and Random Forest Algorithm

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***Abstract*—A balanced diet is a cornerstone of a healthy lifestyle, with far-reaching effects on overall well-being and the prevention of chronic diseases. In our increasingly health-conscious world, the importance of tailored dietary choices has never been more apparent. However, achieving and maintaining a balanced diet can be a complex task. To address this challenge, we introduce a novel recommendation system integrated into the ”WeCare” platform. Leveraging machine learning techniques, including K-Means clustering and the Random Forest algorithm, this system generates personalized diet plans based on an individual's unique physical attributes, health goals, and special dietary needs, such as those of athletes, bodybuilders, and pregnant women. By considering factors such as body mass index (BMI), calorie requirements, and health objectives, this system empowers individuals to make informed dietary decisions that align with their long-term well-being. This paper outlines the development and implementation of this comprehensive recommendation system, highlighting its potential to enhance lives through data-driven dietary guidance.**

***Index Terms*—Machine Learning, K-Means, Random Forest Algorithm, Recommendation System, Diet Plan,BMI,Calories.**

I. Introduction

In the present era, various health issues plague humanity, with improper diets and insufficient nutrition being significant culprits. The World Health Organization (WHO) reports that globally, inadequate and imbalanced dietary intake is responsible for 9% of heart attack deaths, 11% of ischemic heart disease fatalities, and 14% of gastrointestinal cancer related deaths. Troublingly, 0.25 billion children suffer from Vitamin-A deficiency, 0.2 billion grapple with iron deficiency (anaemia), and 0.7 billion endure iodine deficiency. This project seeks to address these health concerns by developing a personalized diet recommendation system. This system utilizes user data including height, age, weight, gender, body fat percentage, and preference for weight loss, weight gain, or specific physical activities like gym workouts. It follows a three-stage process: Information Collection, Learning, and Recommendation. The system compiles relevant information, draws insights, and ultimately provides tailored dietary recommendations based on the user's physical attributes, preferences, and Body Mass Index (BMI), striving to enhance individual well-being.

II. PROBLEM STATEMENT

Introducing WECARE, a cutting-edge web-based recommender system revolutionizing nutrition delivery. Tailored for both the health-conscious and those battling chronic diet-related ailments, it constructs personalized health profiles and delivers precision nutrition recommendations. Elevate your quality of life with WECARE's adaptive approach to wellness through nutrition.

III. OBJECTIVES

A. Comprehensive User-Centric Approach

The primary objective of this study is to adopt a holistic approach by considering various crucial aspects of the user's lifestyle. It aims to ensure that these factors are taken into account while the system works towards creating and recommending a healthy and nutritious diet plan tailored to the individual user.

B. Unlocking Holistic Health

The study recognises that a good nutritious and balanced diet, supplemented by a modest degree of physical exercise, plays an important role in maintaining a healthy weight. However, it emphasizes that the advantages of proper nutrition extend far beyond weight management. The objective here is to emphasize the broader health benefits associated with good nutrition.

C. The 70/30 Rule for Fitness

The objective of this statement is to introduce the concept of the ”70/30 rule” to maintain fitness. According to this rule, staying healthy involves a dual focus: 70% on one's dietary intake and 30% on physical activity and exercise. This objective aims to highlight the significance of nutrition as a predominant factor in achieving and sustaining fitness, while also acknowledging the role of physical activity.

IV. Related Work

Age-Based Nutritional Predictions: Researchers have delved into the realm of age-based dietary predictions, employing fuzzy logic-based membership functions to ascertain nutritional requirements based on user age groups. This insightful contribution was made by Arushi Singh and collaborators [2].

Smart Systems and User Interfaces: Numerous systems prioritize user-friendly interfaces and incorporate intelligent system layers. These systems often encompass features such as menu suggestions, dietary deficit analysis, and user activity tracking. Such advancements were introduced by Butti.Gouthami [3].

Virtualized Food Recommendation: Virtualized food recommendation systems, typified by Diet-Right, offer dynamic recommendations that are influenced by user interactions. These systems take into account a multitude of factors, including nutritional diversity, cost considerations, and patient scheduling. Faisal Rehman and co-authors shed light on this area of research [6].

Machine Learning and Deep Learning Approaches: Recent investigations integrate machine learning and deep learning techniques into dietary recommendation systems. These sophisticated models factor in various attributes, including age, gender, body weight, and nutritional values, to propose suitable meal plans, particularly tailored to individuals with specific health conditions. Suleman Khan, Shubham Singh Kardam, and their team have contributed significantly to this field [4] [15].

Multidisciplinary Approach: Recognizing the intricate nature of dietary recommendations, some researchers advocate for a multidisciplinary approach, merging insights from nutrition, food science, psychology, biology, anthropology, and sociology. This holistic perspective, championed by Weiqing Min, aims to enhance the effectiveness of dietary recommendation tools [17].

Challenges in Recommender Systems: Additionally, Mani Madhukar underscores the challenges associated with developing recommender systems, including those focused on dietary choices. These challenges encompass issues such as data scarcity, system complexity, response time, and data quality [1].

Mobile-Based Approaches: Researchers have explored mobile-based solutions to enhance the accessibility of nutritional information. Certain systems empower users to capture images of their meals, subsequently providing nutritional insights and estimations. Raza Yunus has contributed valuable insights to this mobile-based approach [13].

Ontology Modeling for Personalization: In the quest for personalized dietary recommendations, ontology modeling has emerged as a promising avenue. This approach aims to generate context-specific recommendations tailored to individual users and their unique settings, as articulated by Ishita Padhiar and her team [7].

Management of Diabetic Diets: Researchers have addressed the complexities of managing diabetic diets by employing algorithms such as SOM and K-means Clustering. These methods effectively manage diets by focusing on key components that influence individuals with diabetes. Maiyaporn Phanich's work in this area is noteworthy [8].

Recipe-Based Recommendation Systems: Lastly, some researchers have introduced recipe-based recommendation systems. These systems leverage advanced algorithms for meal creation and assessment, incorporating user feedback and extensive recipe collections to propose a diverse range of meals aligned with individual preferences. This innovative approach was pioneered by Devis Bianchini and collaborators [5].

V. Existing System

A. Food Recommendation system (FRS)

This technology is particularly built for diabetes individuals. It analyses food clustering using K-means clustering and Self-Organizing Map algorithms. The system suggests replacement foods based on nutritional and dietary factors. However, it doesn't adequately address the dynamic nature of diabetes, as the disease level can vary throughout the day or in different patient situations, potentially requiring varying food recommendations.

B. Andriod-based Food recommender system with tags and latent factors

An Android-based food recommender system that leverages user-generated tags and ratings to provide personalized recipe recommendations. In its approach, this system uses latent feature vectors and matrix factorization to improve prediction accuracy by aligning suggestions with user preferences. However, it does not consider the nutritional aspects necessary to balance a user's diet according to their specific needs.

C. Content-based food recommender system

This system focuses on recommending food recipes based on user-provided preferences. It disassembles the user's preferred recipes into ingredients, assigning ratings based on

stored user preferences. Recommendations are made by matching ingredients in preferred recipes with those in the database. However, this system overlooks nutrition factors and diet balance, and it may also lead to repetitive recommendations since user preferences may not change daily.
These existing diet recommendation systems have specific focuses. Some cater to patients with particular diseases, while others aim to balance diet plans. However, they exhibit limitations such as not considering the dynamic nature of disease levels, neglecting essential nutrition factors, and potentially providing repetitive recommendations without accounting for dietary balance. These shortcomings underscore the need for a more comprehensive and adaptable diet recommendation system.

VI. PROPOSED SYSTEM

The proposed system operates within a Machine Learning environment, employing advanced algorithms to calculate user-specific data and deliver tailored diet recommendations. To achieve this, the system utilizes a carefully curated dataset, which is divided into three distinct categories for precision:

- Lunch Data
- Breakfast Data
- Dinner Data

Each category serves as a unique source of information to train the machine learning model, enabling it to generate highly customized diet plans based on the user's preferences and goals.

A. Algorithms Utilized:

1) K-means: K-Means clustering is employed to group foods with similar nutritional profiles and characteristics. This algorithm assists in organizing and categorizing foods effectively, enabling the system to make informed recommendations.

2) Random Forest: The Random Forest algorithm is used to refine and enhance the precision of diet plan recommendations. It processes and analyzes the user's data, considering a multitude of factors, and generates optimized diet plans that align with the user's chosen goal, whether it be pursuing a healthy diet, weight gain, or weight loss

B. User-Centric Approach

The proposed system offers a user-centric approach, allowing individuals to make a choice aligned with their health objectives. Depending on whether the user selects options related to maintaining a healthy diet, gaining weight, or losing weight, the system dynamically adapts its recommendations. It takes into account the specific user data, the category of meals chosen (breakfast, lunch, or dinner), and applies the relevant machine learning algorithm to generate a personalized diet plan.
In essence, this system aims to provide a seamless and tailored solution for users seeking improved dietary choices. By effectively combining data-driven insights and advanced algorithms, it empowers users to make informed decisions about their nutrition, thereby promoting their overall health and well-being.

VII. K-MEANS ALGORITHM

The K-Means algorithm, a sophisticated iterative approach, tries to split a dataset into unique, non-overlapping clusters. Each data point is assigned to a single cluster, with the goal of making the data points inside a cluster as comparable as feasible while keeping the clusters different. It accomplishes this by minimising the sum of squared distances between data points and the centroid of their cluster (the mean of all points in that cluster). In the proposed work , we used K-Means to divide our dataset into three unique meal categories: lunch, breakfast, and dinner. This clustering procedure allowed us to isolate the data for subsequent training and testing. Random Forest technique was used to develop predictive model, ensuring a robust and data-driven approach..

VIII. RANDOM FOREST ALGORITHM

The Random Forest algorithm is used for supervised classification. It gets its unique name from the way it builds a forest of decision trees with a random element. Random Forest distinguishes itself from traditional decision trees by harnessing the strength of numerous trees. In essence, the more trees there are in the forest, the more accurate and robust the results become. Here's a high-level summary of how Random Forest works: Random Forest is essentially a collection of decision trees that function together. Each tree is trained on a random subset of the data, maintaining diversity in the various trees.Random Forest uses a majority voting process to make predictions. Each tree in the forest votes, and the class with the most votes wins.Reduced Overfitting: The randomness supplied throughout the training process aids in the reduction of overfitting, making Random Forest a viable option for a variety of datasets. Random Forest now serves as the conductor of this classification symphony in the context of our research, where we've rigorously categorised our dataset into three particular meal groups (lunch, breakfast, and dinner). Consider it a collection of decision trees, each one dedicated to interpreting the characteristics and labels in our training dataset. To make predictions, these individual trees create their own set of rules.

IX. HARRIS-BENEDICT FORMULA

We utilised Harris Benedict's technique to calculate the user's daily calorie needs depending on their gender and physical activity. The Harris Benedict Formula is a frequently used technique for estimating an individual's daily calorie needs based on their age, gender, weight, and activity level. The formula is available in two major forms:

1. Original Harris-Benedict Formula (1919): - For Men: BMR = 66.5 + (13.75 x weight(kg) + (5.003 x height(cm) - (6.75 x age(years)) - For Women: BMR = 655.1 + (9.563 x weight(kg)) + (1.850 x height(cm)) - (4.676 x age(years))

2. Revised Harris-Benedict Formula (Harris-Benedict Principle - 1919/1919/1919): - For Men: BMR = 88.362 + (13.397

x weight(kg)) + (4.799 x height(cm)) - (5.677 x age(years)) - For Women: BMR = 447.593 + (9.247 x weight(kg)) + (3.098 x height(cm)) - (4.330 x age(years))

Once you've calculated your Basal Metabolic Rate (BMR) using the appropriate formula, you can determine your daily calorie needs by multiplying your BMR by an activity factor that represents your daily activity level:

- Sedentary (little or no exercise): BMR x 1.2 - Lightly active (light exercise or sports 1-3 days a week): BMR x 1.375 - Moderately active (moderate exercise or sports 3-5 days a week): BMR x 1.55 - Very active (hard exercise or sports 6-7 days a week): BMR x 1.725 - Super active (very hard exercise, physical job, or training twice a day): BMR x 1.9

This will give you an estimate of the number of calories you need to maintain your current weight. To lose weight, you should consume fewer calories, and to gain weight, you should consume more calories than this estimated number. Keep in mind that individual variations may exist, and it's important to monitor your progress and adjust your calorie intake accordingly.

X. IMPLEMENTATION AND DESIGN

A. User Flow

Users will engage with our system by sharing their physical information, and in return, our cutting-edge machine learning model will craft personalized diet recommendations. These meticulously tailored plans will encompass a delectable trio of breakfast, lunch, and dinner options, revolutionizing the way you nourish your body.

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1) User Initiation: The user initiates the interaction with the diet recommendation system by accessing the system through a web or mobile application.
2) User Input: The user is prompted to provide their physical information, which typically includes details such as age, gender, height, weight, and possibly other relevant factors like body fat percentage.
3) User Goals and Preferences: Additionally, the system may inquire about the user's dietary goals and preferences. For example, the user might indicate whether they are looking to maintain their current weight, lose weight, or gain weight. They might also specify any dietary restrictions, allergies, or food preferences they have.
4) Data Submission: After inputting all the required information and preferences, the user submits the data to the system.
5) Data Analysis: The system's machine learning model, which includes the K-Means clustering and Random Forest algorithms, analyzes the user-provided data. The K-Means algorithm categorizes the data into relevant clusters or categories, such as breakfast, lunch, and dinner, based on the user's profile and preferences.
6) Personalized Diet Generation: Within each category (breakfast, lunch, dinner), the Random Forest algorithm generates personalized diet recommendations. These recommendations are tailored to the user's physical information, dietary goals, and preferences. For instance, if the user aims to lose weight, the system will create a diet plan that aligns with this goal.
7) Diet Plan Presentation: The system compiles the recommendations into a comprehensive diet plan that includes specific food items or meal ideas for breakfast, lunch, and dinner. The diet plan may also provide nutritional information, such as calorie counts, macronutrient breakdowns, and suggested portion sizes.
8) User Feedback and Adjustments: The diet plan is presented to the user through the application's interface. The user has the option to review the recommendations and make any desired adjustments or substitutions based on their personal preferences or dietary restrictions.
9) Final Diet Plan Acceptance: Once satisfied with the diet plan, the user can accept it, and it becomes their personalized diet recommendation.
10) Regular Usage and Updates: The user can continue to interact with the system for ongoing dietary guidance. They can provide updates on their progress, and the system can adjust the diet plan as needed to help them achieve their goals.
11) User Monitoring: Over time, the user's progress can be tracked through the system. The user can input weight changes, activity levels, or other relevant data, allowing the system to adapt and provide continuous support.
12) Diet Plan Execution: The user follows the recommended diet plan in their daily life, incorporating the suggested meals for breakfast, lunch, and dinner.
13) Achieving Health Goal: By adhering to the personalized diet plan, the user works towards their health and dietary goals, whether it's maintaining a healthy weight, losing weight, or gaining weight in a controlled manner.

This user flow outlines the seamless interaction between the user and the diet recommendation system, which combines machine learning algorithms with user-provided data to offer personalized and effective dietary guidance.

B. System Architecture

1) User Engagement: Users input essential details (age, gender, weight, etc.) via the website.

2) Machine Learning Magic: Our system employs advanced techniques:

3) K-Means Clustering: Organizes food items by calorie content.

4) Random Forest Classifier: Predicts suitable food items based on user input.

5) Data-Driven Insights: The system delivers:

6) BMI & Health Status: Users receive their BMI and current health assessment (Overweight, Underweight, Healthy). Tailored Recommendations: Three dietary categories (breakfast, lunch, dinner) are suggested based on user input.

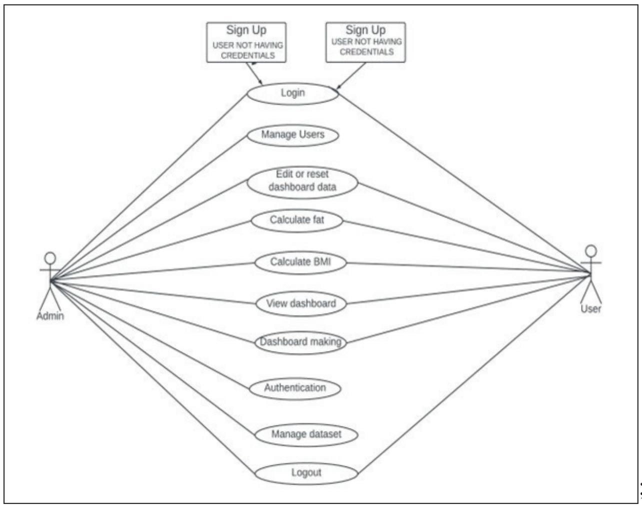

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Fig. 1. Use Case Diagram

7) Freedom of Choice: Users can select from multiple recommended items to create their personalized diet plan.

8) Calorie Conscious: The system calculates selected food calories, comparing it to daily consumption requirements.

9) Empowered Decision-Making: Armed with insights, users finalize their diet plans, making informed choices for a healthier lifestyle.

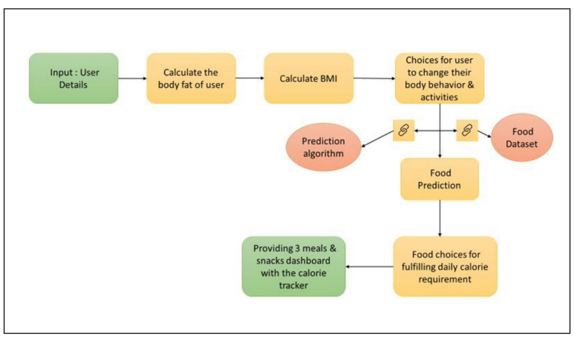

Fig. 2. System Architecture

XI. Results and Analysis

In this section, we present the results of our study, which aimed to develop and evaluate the "We Care Food Recommendation System." We employed various machine learning algorithms to enhance the accuracy and effectiveness of our system. Among these algorithms, Random Forest and K-means played pivotal roles. The following subsections detail our findings, with a focus on the selection of the Random Forest algorithm for implementation.

A. Algorithm Performance Evaluation

We started our research by evaluating the performance of several machine learning techniques, such as Support Vector Machine , Random Forest, k-Nearest Neighbours , and Logistic Regression. We assessed these algorithms using three crucial metrics: AUC, Accuracy, and Precision. The table summarises the findings :

TABLE I
Algorithm Performance Metrics

Model	**AUC (Area Under Curve)**	**Accuracy**	**Precision**
SVM	0.544	0.857	0.75
Random Forest	0.917	0.938	0.853
kNN	0.685	0.687	0.65
Logistic Regression	0.897	0.91	0.785

As evident from the table I, the Random Forest algorithm outperformed other models in terms of AUC, Accuracy, and Precision. The Random Forest model achieved an impressive AUC score of 0.917, indicating its robustness in distinguishing between recommended and non-recommended food items. Moreover, it exhibited high accuracy (0.938) and precision (0.853), making it the algorithm of choice for implementing food recommendation system.

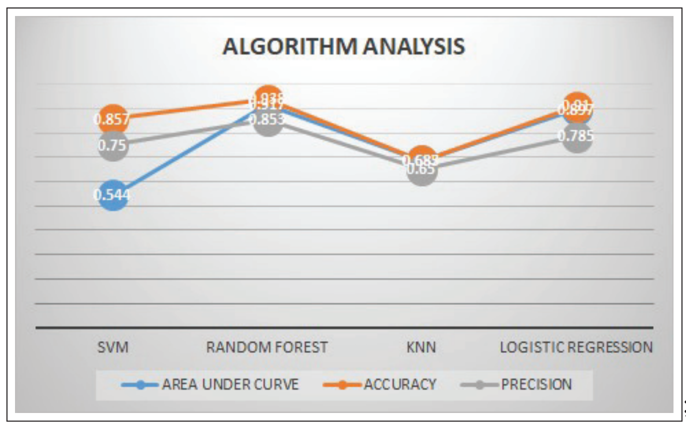

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Fig. 3. Algorithm analysis of models

B. Random Forest Algorithm Implementation

Having identified Random Forest as the most promising algorithm for our project, we proceeded with its implementation. This ensemble learning method was employed to predict suitable food items for users based on their input and dietary requirements. Random Forest excelled in handling complex feature interactions and exhibited remarkable predictive performance.

C. K-means Clustering for Nutrient Segregation

In addition to Random Forest, we leveraged the K-means clustering algorithm to group food items into nutrient-based clusters. This step was crucial for categorizing food items into Breakfast, Lunch, and Dinner options, thereby streamlining dietary recommendations. K-means clustering effectively grouped foods into clusters based on their nutrient profiles, enabling our system to offer tailored meal plans aligned with user preferences and health goals.

D. Overall System Functionality

The "We Care Food Recommendation System" seamlessly integrates these algorithms to provide users with a holistic dietary experience. Key functionalities include:

- User Input and BMR Calculation: Age, gender, and activity level data are utilized to calculate users' Basal Metabolic Rate (BMR), forming the foundation of personalized diet plans.
- Meal Segregation: Food items are categorized into Breakfast, Lunch, and Dinner options, simplifying meal planning for users.
- Nutrient Clustering: K-means clustering ensures food items are grouped based on nutrient profiles, facilitating healthier meal recommendations.
- BMI and Health Status: Our system calculates users' Body Mass Index (BMI) and categorizes them as Overweight, Underweight, or Healthy, offering valuable health insights.
- Balanced Diet Plans: Personalized diet plans are generated for each meal, taking into account BMI and health goals.
- User Selection and Customization: Users have the flexibility to select and customize food items according to their preferences and dietary restrictions.
- Calorie Comparison: Our system compares selected calorie intake to daily requirements, enabling users to make informed dietary choices.
- Ongoing Support and Adaptability: Users receive continuous guidance and can adjust their diet plans as needed to achieve long-term health objectives.

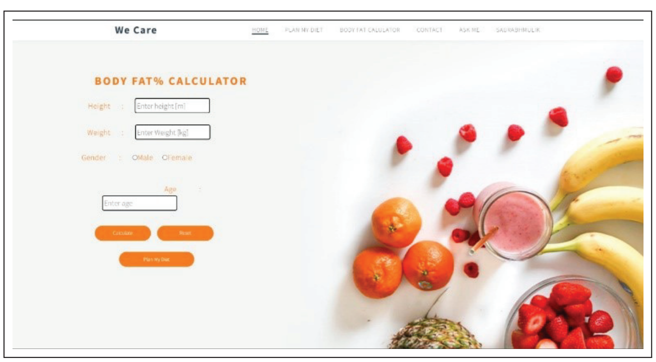

Fig. 4. Body Fat Calculator

XII. Conclusion

In a technology-driven era marked by the transformative power of Machine Learning and Artificial Intelligence, our website stands as a pioneering contribution in the Information Technology sector. It addresses the ever-growing awareness of the vital role nutrition plays in our lives.

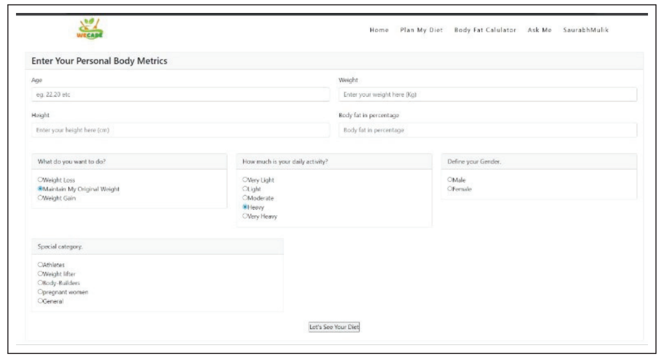

Fig. 5. User Inputs

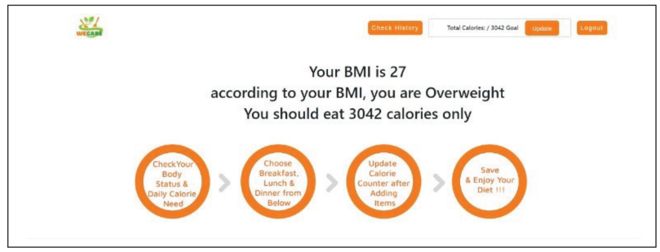

Fig. 6. Calorie Calculation According to BMI

By seamlessly integrating advanced technologies, we have created a dynamic platform capable of delivering personalized nutritional guidance tailored to individual user profiles and health objectives. Beyond being a repository of dietary recommendations, our website serves as a gateway to a more informed and healthier lifestyle.

Our unwavering commitment remains focused on empowering individuals on their journey toward improved health and fitness. As we continue to harness the potential of cutting-edge technologies, our vision is to foster healthier and happier lives in an increasingly health-conscious world.

In conclusion, our website represents a significant milestone in the evolving landscape of the Information Technology sector, particularly in the realm of health and well-being. It symbolizes innovation and progress, and as we look to the future, we anticipate its continued positive impact on individuals seeking to make healthier choices and achieve their wellness aspirations.

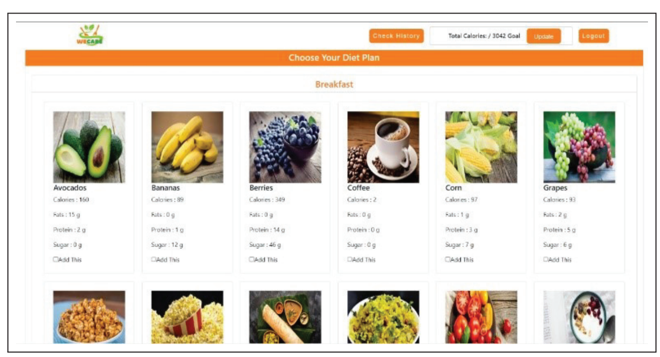

Fig. 7. Breakfast Recommendation

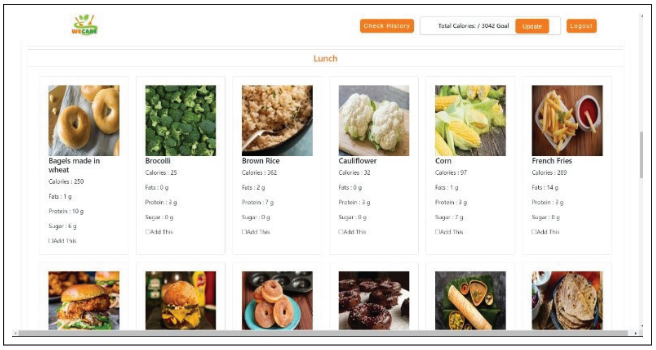

Fig. 8. Lunch Recommendation

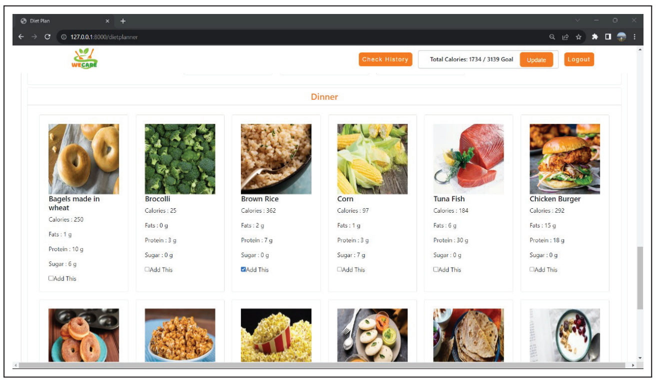

Fig. 9. Dinner Recommendation

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