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MACHINE LEARNING DRIVEN HEALTH AWARE FOOD RECOMMENDATION SYSTEM

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ABSTRACT

Maintaining a healthy and balanced diet is increasingly difficult in modern, fast-paced lifestyles. Consumers frequently struggle to select suitable meals because traditional food service environments lack personalized, health-focused guidance. This paper presents a machine learning-driven health-aware food recommendation system designed to provide personalized meal suggestions based on individual physiological data. By capturing basic user inputs such as age, gender, height, weight, and activity level the system calculates critical health indicators like Body Mass Index (BMI), Basal Metabolic Rate (BMR), and Total Daily Energy Expenditure (TDEE). A Random Forest classification model is then utilized to evaluate this health profile and predict the most optimal meal plan category for the user. The model demonstrates a high prediction accuracy, offering a robust alternative to static menu browsing. The resulting web application bridges the gap between convenience and nutritional awareness, empowering users to make data-driven dietary choices.

KEYWORDS: Machine Learning, Food Recommendation, Random Forest Classifier, Personalized Nutrition, Health-Aware System**.**

1. INTRODUCTION

Customer satisfaction in the food service industry relies heavily on convenience and personalization. As the variety of available menu options expands, customers often experience decision fatigue when trying to align their meal choices with their personal lifestyle and dietary goals. Traditional fast-food environments, such as burger shops, typically present static menus that offer no guidance tailored to the individual's nutritional requirements.

This research introduces an intelligent recommendation system that shifts the ordering process from manual browsing to guided, health-aware decision-making. Instead of relying on past purchase history or generic popularity metrics, the proposed system evaluates a user's unique physical parameters to suggest menu items that fit their specific metabolic profile. This approach not only reduces the time spent navigating a menu but also promotes healthier eating habits by transparently mapping meal macros to the user's calculated energy needs.

2. Literature Review

Traditional food service systems rely on static, menu-based ordering where customers manually browse options without personalized guidance. Existing recommendation models often fail to consider individual nutritional needs or lifestyle factors, making them unsuitable for health-conscious users. However, there is a recognized shift toward health-aware models. Recent advancements emphasize using personal metrics such as Body Mass Index (BMI), Basal Metabolic Rate (BMR), and Total Daily Energy Expenditure (TDEE) to generate nutritionally relevant suggestions. By evaluating these factors alongside activity levels, modern systems can move beyond generic choices to tailor specific meal plans to individual body types.

To effectively process this multi-dimensional health data, modern frameworks leverage supervised machine learning algorithms over rigid, rule-based methods. The Random Forest Classifier, a robust ensemble learning algorithm, is highly effective for these classification tasks. By combining multiple decision trees, it significantly reduces the overfitting typically seen in single tree models, ensuring higher prediction accuracy. Furthermore, it efficiently handles the mixture of numerical and categorical data inherent in health profiles without complex transformations. Despite these technological strengths, a distinct gap remains in applying dynamic, predictive machine learning directly to the fast-food industry. Implementing a predictive model that instantly adjusts recommendations based on real-time biometric inputs provides a highly accurate, scalable solution for personalized nutrition.

3. Proposed System Architecture

The proposed system consists of three main components: Data Acquisition Layer, Data Processing Layer, and User Interface Layer.

Data Acquisition Layer The data acquisition layer includes a secure, interactive web-based form where users input their essential physiological parameters. These parameters collect basic user information such as age, gender, height, weight, and daily activity level. This layer serves as the initial interaction point, ensuring all necessary data is gathered securely before system processing.

Data Processing Layer The data processing layer consists of a Python-based backend server and a database system (MongoDB) that securely store and manage user and nutritional data. This layer automatically calculates derived health metrics—such as BMI, BMR, and TDEE—and feeds them into a Random Forest Classifier machine learning model. The trained model then analyzes these processed metrics to accurately predict the most suitable meal plan category for the individual.

User Interface Layer The user interface layer includes a dynamic, React JS-based web dashboard that allows users to seamlessly view their personalized food recommendations. This layer presents the recommended dishes alongside detailed nutritional information (calories, protein, fats, carbs) and a personalized daily diet plan in a clear

4. METHODOLOGY

The methodology of the proposed system encompasses a structured pipeline consisting of data collection, preprocessing, model training, and real-time deployment. Initially, a comprehensive dataset featuring basic user biometrics (age, gender, height, weight, activity level) and derived health metrics (BMI, BMR, TDEE, Body Fat, Lean Body Mass) is collected and preprocessed to eliminate inconsistencies and encode categorical variables into numerical formats. Following this, a Random Forest Classifier is trained and evaluated using an 80:20 train-test data split. This specific algorithm was selected for its robust ensemble learning capabilities, which effectively minimize overfitting while processing complex, multi-dimensional health parameters. Finally, the trained predictive model is deployed via a Python-based API integrated with a React JS frontend and a MongoDB database. During real-time operation, the system captures dynamic user inputs, computes the necessary physiological metrics, and processes them through the model to instantly classify and output the optimal, personalized meal plan.

Methodology Flowchart

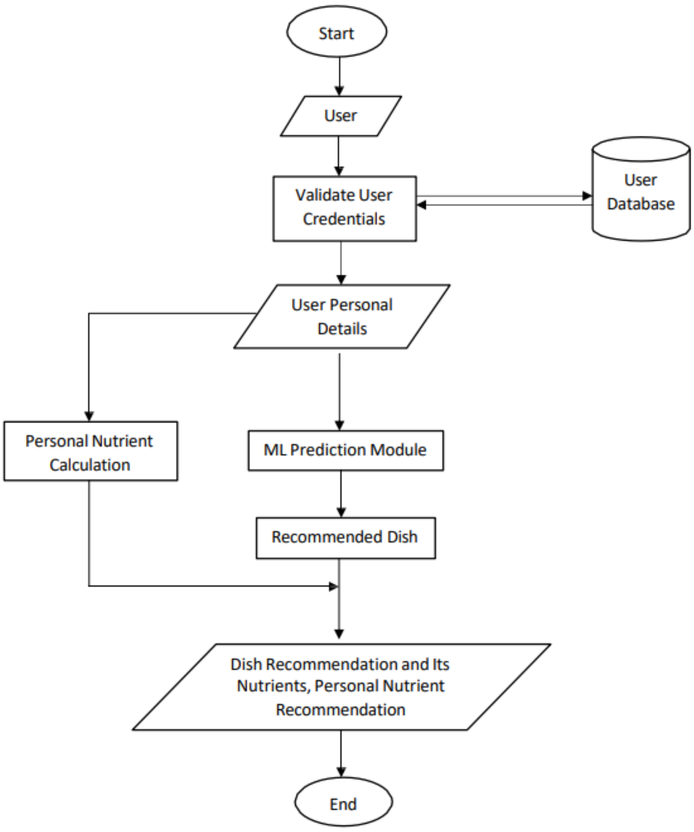

Figure 1: Methodology Flowchart.

4.1 Input Design

The input design of the proposed recommendation system focuses on creating a secure, user-friendly interface to efficiently collect accurate biometric data for machine learning processing. The entry point is a secure login module that authenticates users through email and encrypted passwords, applying strict validation constraints to prevent unauthorized access. Once authenticated, users access a personalized data entry form designed to capture essential health metrics, specifically age, gender, height, weight, and daily activity level. To ensure data integrity, the interface employs structured input methods, utilizing dropdown menus for categorical variables like gender and activity level, alongside strictly constrained numeric fields for physical measurements. Upon submission, the system automatically validates this raw data and computes derived physiological metrics—such as Body Mass Index (BMI), Basal Metabolic Rate (BMR), and Total Daily Energy Expenditure (TDEE)—which are seamlessly passed to the Random Forest model for real-time meal plan prediction.

4.2 Output Design

The output design of the recommendation system focuses on presenting the processed machine learning predictions and nutritional data in a clear, highly structured, and user-centric format. Upon receiving the predicted meal plan category from the backend, the React JS-based frontend dynamically renders a personalized nutrition dashboard. The primary interface displays specific, health-optimized burger recommendations within visually engaging card layouts, complete with dish names and category descriptions. To ensure dietary transparency, the system provides a comprehensive breakdown of each recommended dish's nutritional profile, explicitly detailing its total calories, protein, carbohydrates, fats, and fiber content. Furthermore, the output extends beyond single meal suggestions by generating a customized daily dietary plan based on the user's derived physiological metrics. This plan presents the user's target daily calorie requirements and optimal macronutrient percentage distributions. Ultimately, this responsive and intuitive output design not only facilitates immediate food selection but also empowers users with actionable, science-backed health insights.

4.3 Machine Learning Model

The core of the system uses a Random Forest Classifier, an algorithm chosen for its high accuracy in handling health data. The dataset is split into 80% for training the model and 20% for testing it. This method works by building multiple decision trees and combining their results, which prevents errors and improves overall prediction consistency. By analyzing the user's physical parameters, the model accurately predicts the best meal plan category for their body type. During testing, the model achieved an exceptional accuracy of 99.2%, proving it is highly reliable for making real-time food recommendations.

5. RESULTS AND DISCUSSION

The performance of the Random Forest Classifier was evaluated using a reserved 20% testing dataset. The model demonstrated exceptional reliability, achieving an overall prediction accuracy of 99.2%. Standard metrics showed high precision, recall, and F1-score values—approaching 0.99 and 1.00—across all target body type classes, including Lean, Normal, Overweight, and Obese. The Confusion Matrix revealed minimal errors, with only minor misclassifications between closely related categories like Lean and Normal. Furthermore,the system successfully processed dynamic user inputs to classify and generate personalized dietary recommendations within a fraction of a second. These results confirm the model is highly accurate, responsive, and practical for real-world food service applications.

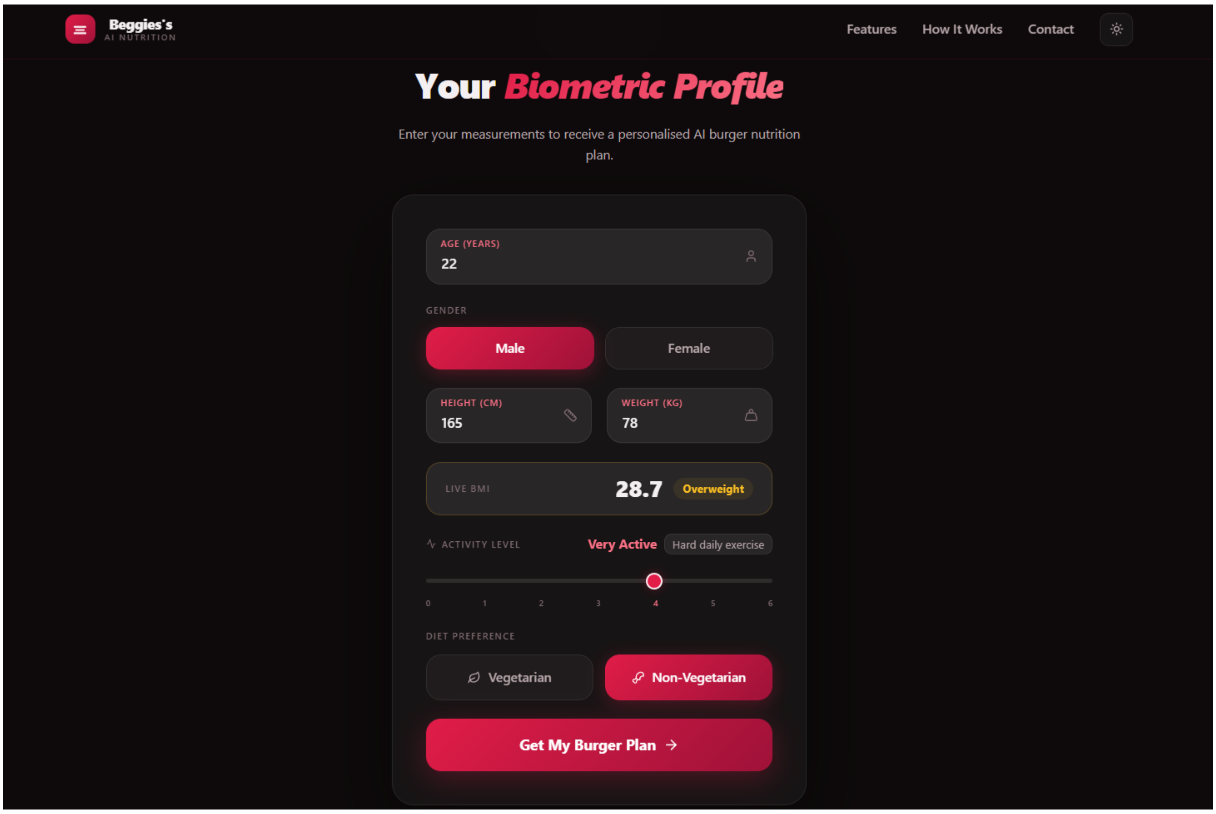

Figure 2: Biometric input page.

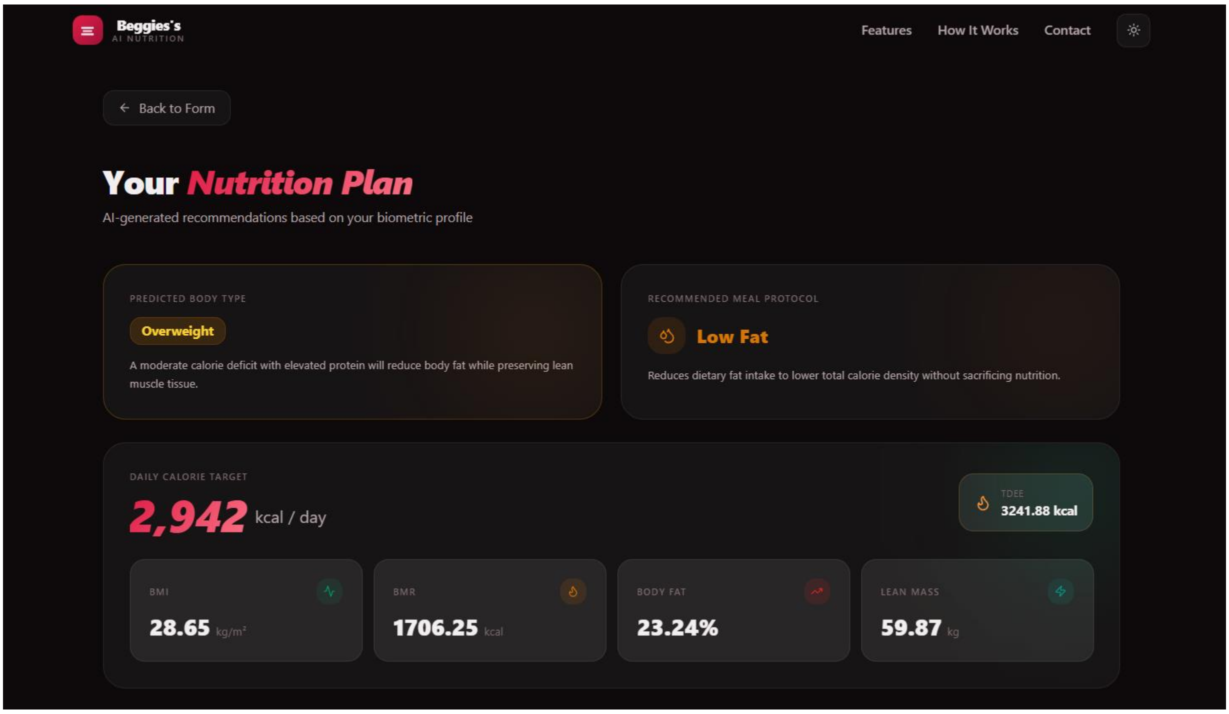

Figure 3: Diet Suggesiion page.

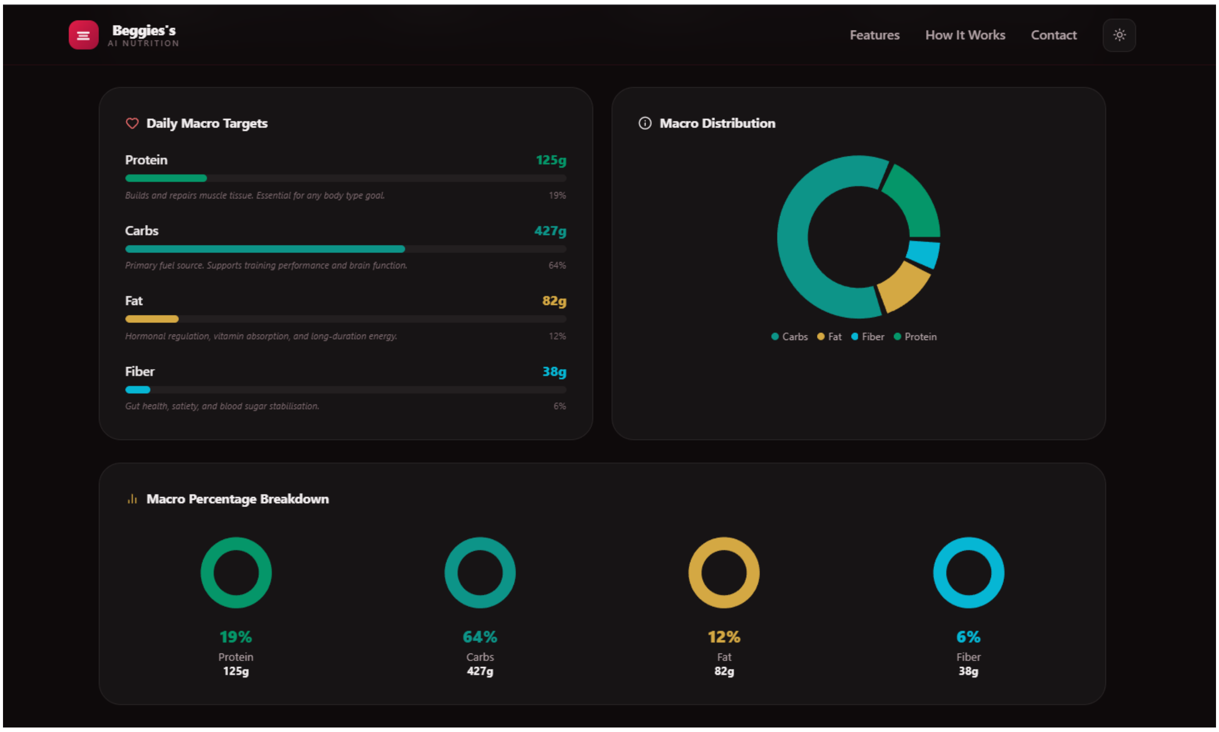

Figure 4: Daily Macro page.

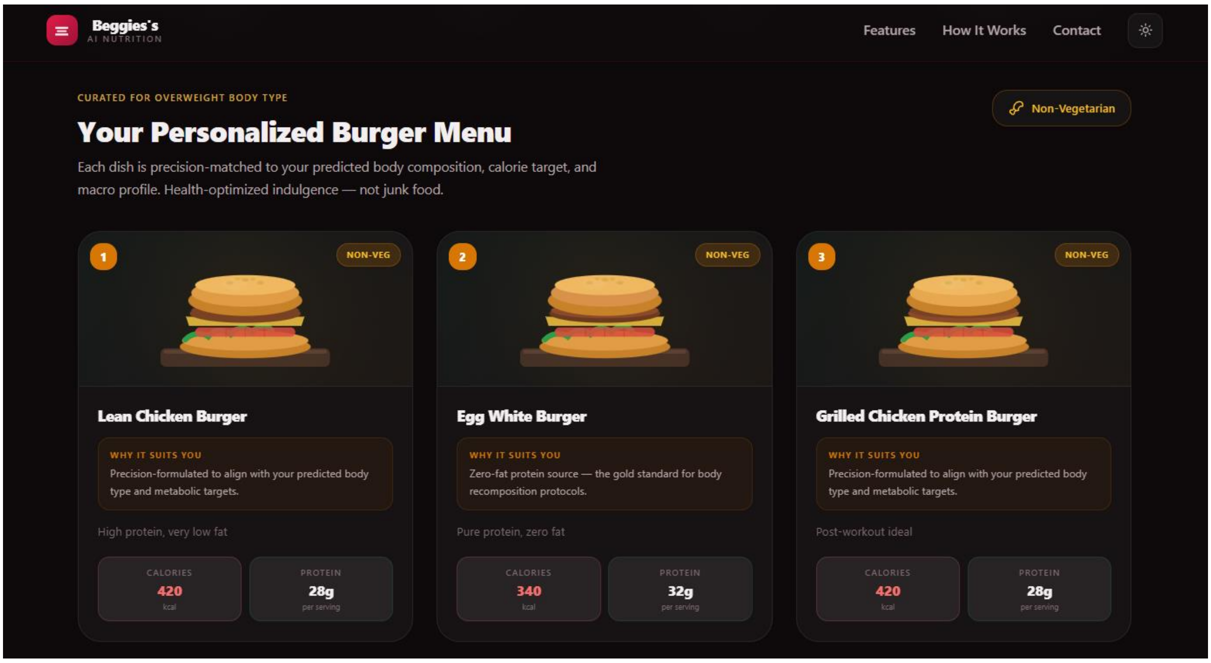

Figure 5: Food Recommendation page.

6. CONCLUSION

The ML-Driven Health-Aware Food Recommendation System successfully demonstrates the powerful integration of machine learning with modern web technologies to deliver highly personalized nutritional guidance. By bridging the gap between static food menus and individual physiological needs, the project offers a dynamic, user-centric solution that promotes healthier dietary choices. The system efficiently captures essential biometric data to calculate derived health metrics, which are then processed by a robust Random Forest Classifier. This data-driven approach ensures exceptional prediction accuracy and stability, allowing the system to instantly map users to optimal meal plan categories. Ultimately, this complete end-to-end application—combining a responsive frontend, a secure backend, and an intelligent predictive model—highlights the immense practical potential of AI in transforming the fast-food industry. It establishes a strong, scalable foundation for future advancements in smart, health-conscious dietary recommendation platforms.

7. FUTURE WORK

Future improvements to the system may include:

Integrate an AI-powered chatbot to provide interactive and conversational meal recommendations based on user health data and preferences, Develop a dedicated mobile application to improve accessibility and allow users to receive personalized food recommendations anytime, Implement location-based recommendation features to suggest nearby burger shop outlets and available menu items, Expand the system by incorporating larger datasets to improve prediction accuracy and recommendation quality, Introduce advanced machine learning models to further enhance personalization and adaptability of the recommendation system.

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