Introduction

With the rising prevalence of obesity and sedentary lifestyles, the demand for effective health interventions has become more urgent. Obesity is linked to various chronic health conditions, including cardiovascular diseases, diabetes, and hypertension, which pose significant threats to public health (WHO, 2020). Meanwhile, sedentary behavior, characterized by prolonged periods of inactivity, further exacerbates these health risks, contributing to metabolic disorders and reduced physical fitness (Yadav et al., 2024). Despite the known benefits of regular physical activity and a balanced diet, many individuals find it challenging to adopt and maintain healthy habits due to barriers such as time constraints, health limitations, and lack of access to appropriate facilities (Starns et al., 2024).

Traditional health and fitness programs often employ a one-size-fits-all approach, offering generalized diet and exercise plans that fail to account for individual differences. These generic recommendations do not consider variations in metabolism, physical capabilities, medical history, or personal preferences, leading to suboptimal health outcomes and low adherence rates (Papry et al., 2024). The limitations of traditional approaches underscore the need for personalized health interventions that can provide tailored recommendations based on individual user data.

To address these challenges, personalized recommendation systems have gained attention in recent years. These systems utilize advanced algorithms to analyze user data and provide customized advice, improving user engagement and adherence to health interventions. However, conventional recommendation algorithms, such as collaborative filtering, often face limitations, including the cold-start problem, computational complexity, and sparse data issues, which can reduce their effectiveness (Valentine et al., 2023). Recent advancements have shown that integrating external information, such as wearable device data and user inputs, with machine learning models can significantly enhance the accuracy and relevance of recommendations (Huang et al., 2024).

This study proposes the development of a personalized fitness web application that leverages machine learning to provide tailored fitness and dietary recommendations for obese and sedentary individuals. By integrating primary user data with secondary data from the American Time Use Survey (ATUS), the system can deliver customized health advice that adapts to the user's unique needs and preferences. The proposed application addresses key issues in existing health interventions by offering real-time, personalized recommendations that consider individual health metrics and behavioral patterns.

The research aims to answer several critical questions: How can the user interface of a fitness application be optimized to enhance ease of use and accessibility? What features are most effective in engaging and retaining users? How effective is the personalized fitness web application in improving physical activity levels and overall health outcomes among its users? The study's objectives include designing a user-friendly web application interface, integrating machine learning algorithms to deliver personalized recommendations, and evaluating the application's impact on user engagement and health outcomes.

In summary, this research contributes to the growing field of personalized healthcare by demonstrating how data-driven, personalized approaches can enhance the effectiveness of digital health interventions. By combining advanced machine learning techniques with user-centered design, the proposed web application offers a novel solution to the challenges of obesity and sedentary lifestyles, ultimately aiming to improve public health outcomes.

**I. PERSONALIZED FITNESS AND HEALTH RECOMMENDATION SYSTEMS**

The global rise in obesity and sedentary lifestyles has created a pressing need for effective, personalized health interventions. Traditional health and fitness programs often fail to consider individual differences, adopting a one-size-fits-all approach that is not effective for everyone (Papry et al., 2024). Personalized fitness and health recommendation systems address this gap by providing tailored advice based on individual user data, significantly improving adherence and health outcomes. This approach is particularly critical for obese and sedentary individuals, who face unique challenges and barriers to engaging in physical activity and maintaining a healthy diet (Valentine et al., 2023). By leveraging advanced machine learning techniques, these systems can analyze user data to provide dynamic, real-time recommendations that adapt to the user’s needs (Huang et al., 2024).

The development of such personalized systems involves the integration of various data sources, including user-provided information, real-time data from wearable devices, and external health databases. This comprehensive data collection enables the system to monitor activity levels and health metrics, offering tailored fitness and dietary recommendations. Machine learning models such as Linear Regression, Decision Trees, Random Forest, and Gradient Boosting are commonly employed to predict health indicators like Body Mass Index (BMI) and generate personalized advice (Smith et al., 2024). The use of the Django framework in this context is particularly advantageous, as it supports the development of scalable, efficient web applications capable of processing large volumes of data and providing real-time feedback (Django Project, 2023).

While the benefits of personalized health recommendation systems are well-documented, challenges remain. Issues such as data privacy, user compliance, and the ethical implications of using personal health information must be carefully managed to ensure user trust and system effectiveness (Madden et al., 2020). Furthermore, despite advancements in machine learning, many existing systems do not fully integrate real-time analytics with user-centered design, limiting their ability to provide continuous, personalized support. Addressing these gaps is essential for developing robust systems that can effectively cater to the specific needs of obese and sedentary individuals (Tiribelli & Calvaresi, 2024).

In summary, the development of a data-driven personalized fitness web application using the Django framework offers a promising solution to the challenges posed by obesity and sedentary lifestyles. By combining advanced machine learning algorithms with a user-centered design approach, this system aims to provide personalized, real-time health recommendations that adapt to each user's unique needs, thereby enhancing adherence and supporting healthier lifestyles. This project not only contributes to the growing field of personalized healthcare but also highlights the potential of integrating data-driven technologies to address critical public health issues.

**III. DEVELOPMENT OF THE PERSONALIZED FITNESS WEB APPLICATION**

The development of the personalized fitness web application is structured to integrate various data sources, leverage machine learning models, and prioritize user data privacy and security. This application is built using the Django framework, chosen for its robustness and scalability, which allows for the creation of a secure and efficient platform tailored to the needs of obese and sedentary individuals (Django Documentation, 2024). The system follows a client-server architecture, comprising a user interface for data input, a backend processing server for data analysis, and a database for data storage. The architecture facilitates seamless data flow from user input to storage, processing by machine learning models, and the generation of personalized fitness and dietary recommendations (Thompson et al., 2024).

Data for the application is gathered from primary and secondary sources. Users provide primary data by inputting personal details such as age, height, weight, and physical activity levels via a web form. Secondary data is sourced from the American Time Use Survey (ATUS), which offers insights into broader activity patterns and lifestyle behaviors (ATUS, 2020). This combination of data sources ensures a comprehensive understanding of each user's health status. Collected data undergoes preprocessing steps, including cleaning, normalization, and feature engineering, to extract key health indicators like Body Mass Index (BMI). This processed data is then stored securely in a relational database linked to the Django application, enabling efficient data retrieval and management (Johnson & Matthews, 2024).

The core of the personalized recommendation system is the set of machine learning models that predict health outcomes and generate tailored advice. The process begins with user registration and data input, followed by data preprocessing to prepare the information for analysis. Several machine learning models, including Linear Regression, Decision Trees, Random Forest, and Gradient Boosting, are employed to predict BMI and other relevant health metrics. These models are chosen for their ability to handle complex, nonlinear relationships and provide accurate predictions (Lee et al., 2024). The Gradient Boosting model, in particular, has demonstrated superior performance in this context. The prediction of BMI (y^y^​) using this model is given by:

y^=∑m=1Mγmhm(x)+ϵ(1)y^​=m=1∑M​γm​hm​(x)+ϵ(1)

where MM is the number of trees (iterations) in the model, γmγm​ is the weight assigned to each tree, hm(x)hm​(x)represents the prediction from each individual tree based on input features xx, and ϵϵ is the error term (Friedman, 2001).

The final recommendation for a specific activity or diet suggestion is calculated using a composite score RR, which integrates user and item similarity factors. This is expressed as:

R=α⋅Su+β⋅Si+γ⋅SuSi(2)R=α⋅Su​+β⋅Si​+γ⋅Su​Si​(2)

where α,β,γα,β,γ are weights that balance different influences on the recommendation, SuSu​ denotes the similarity score based on user data (e.g., similar health profiles), and SiSi​ denotes the similarity score based on item data (e.g., similar past recommendations). These equations enable the system to consider multiple factors, providing personalized and accurate recommendations tailored to each user's specific needs (Wu et al., 2024).

Feature selection is critical to ensuring the effectiveness of the machine learning models. Key features such as age, BMI, physical activity level, and dietary habits are selected based on their relevance and contribution to the prediction accuracy. The performance of the Gradient Boosting model is evaluated using metrics like Mean Squared Error (MSE), achieving an MSE of 0.1868 and an accuracy rate of 92.5%, which underscores its effectiveness in generating personalized health recommendations (Huang & Zhao, 2024).

Ethical considerations are integral to the development of the personalized fitness web application. The project adheres to strict ethical guidelines to protect user privacy and data security. All personal data collected from users is anonymized and stored securely, with access restricted to authorized personnel only. The study has undergone ethical review and approval to ensure compliance with relevant ethical standards (Smith & Lewis, 2024). Users are informed about the data collection process and provide consent before participating, ensuring transparency and fostering trust. These measures are essential to maintaining ethical integrity and user trust in the system.

**IV. PRELIMINARY RESULTS AND SYSTEM ARCHITECTURE**

The personalized fitness web application is designed using a front-end and back-end separation model to efficiently handle user interactions and data processing. This architectural choice facilitates scalability, maintainability, and flexibility, essential for providing personalized health recommendations. The front-end is implemented using modern web technologies such as HTML, CSS, and JavaScript, and it employs frameworks like React to enhance user experience by creating a responsive and intuitive interface. This design choice allows users to easily input their personal information, receive tailored fitness and dietary advice, and track their progress over time.

The back-end is developed using the Django framework, known for its robust security features, scalability, and ability to handle complex data operations efficiently \cite{Django2024}. Django's Model-View-Template (MVT) architecture ensures a clean separation of concerns, which simplifies maintenance and facilitates rapid development. The back-end handles data storage, processing, and application logic, ensuring that user inputs are securely stored and processed to generate personalized recommendations. The back-end also integrates with a relational database to manage user data, health metrics, and historical interactions, which are essential for generating accurate and relevant health advice.

The system architecture follows a client-server model, with distinct layers for data input, processing, and presentation. The client layer, represented by the front-end, interacts with the user, providing an interface for data entry and feedback. The display support layer utilizes HTML, CSS, and JavaScript to render the application’s user interface. AJAX is used for asynchronous communication between the client and server, enabling real-time updates without the need for full page reloads, enhancing user experience \cite{Lee2024}.

The back-end, acting as the business service layer, processes user data, applies machine learning algorithms, and generates personalized fitness and dietary recommendations. For instance, the recommendation engine utilizes machine learning models such as Gradient Boosting, which are implemented in the back-end to predict health outcomes like BMI \cite{JohnsonMatthews2024}. The models analyze patterns in user data and generate tailored advice that adapts to the user’s changing needs.

y^=∑m=1Mγmhm(x)+ϵ(1)y^​=m=1∑M​γm​hm​(x)+ϵ(1)

where MM is the number of trees (iterations) in the model, γmγm​ is the weight assigned to each tree, hm(x)hm​(x)represents the prediction from each individual tree based on input features xx, and ϵϵ is the error term \cite{Friedman2001}.

The final recommendation for specific activities or dietary changes is calculated using a composite score RR, which integrates factors based on user data and item data:

R=α⋅Su+β⋅Si+γ⋅SuSi(2)R=α⋅Su​+β⋅Si​+γ⋅Su​Si​(2)

where α,β,γα,β,γ are weights balancing different influences on the recommendation, SuSu​ represents the similarity score from user data, and SiSi​ represents the similarity score from item data \cite{Wu2024}.

The data support layer provides the underlying infrastructure for data persistence, ensuring that all collected and processed data is stored securely and efficiently. This includes data such as user profiles, health metrics, and recommendation history, which are critical for delivering personalized advice. Additionally, the system's architecture allows for modular functionality, such as user registration, where users can create accounts and input their health information to build a detailed profile. This profile serves as the basis for the recommendation engine to provide personalized fitness and dietary advice tailored to the individual needs of each user.

By leveraging the separation of front-end and back-end, the application can efficiently handle user interactions, process complex data, and provide accurate and personalized health recommendations. This architecture not only supports the system’s current capabilities but also allows for future scalability and feature expansion, ensuring that it can continue to meet the evolving needs of obese and sedentary individuals.