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Healthy dietary habits: Persuasive technology model for dietary management

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Abstract

Unhealthy eating habits are a major public health issue, deeply affecting individual well-being. Their consequences go beyond immediate health problems, leading to long-term risks such as obesity, heart disease, and diabetes. Poor dietary choices significantly contribute to the prevalence of non-communicable diseases like cancer, obesity, and diabetes. The widespread use of technology presents a unique opportunity to enhance public health, particularly by encouraging healthier eating behaviors. By integrating behavioral science, innovative technology design, and user-centered strategies, persuasive technologies hold great potential to guide individuals toward adopting and maintaining healthier dietary habits over time. This study aimed to create a persuasive technology to promote healthy dietary habits by leveraging algorithms developed from Kaggle datasets. These algorithms analyzed individual dietary preferences, cultural influences, and lifestyle factors while incorporating mechanisms for providing timely feedback and monitoring user progress. A mixed-method approach was employed, combining qualitative and quantitative techniques for collection of data and analysis. The model was built using Xamarin's mobile authoring tools for the user interface and SQL Server for backend data management, following the Object-Oriented Methodology (OOM). The application achieved a performance matrix with accuracy rate of 91%, precision rate of 93%, and an F1 score rate of 87%.

Keywords: Healthy Dietary; Persuasive Technology; Kaggle Datasets; Fogg Behavior

1. Introduction

Tackling unhealthy eating practices requires a comprehensive approach that incorporates education, policy changes, and innovative strategies. One effective method for encouraging healthier dietary decisions is leveraging persuasive technology [1]. With the rise of inclusion of technology into our day to day activities, it provides a powerful tool to improve public health, particularly by fostering healthier eating behaviors. By merging insights from behavioral science, advanced technological innovation, and user-centered design, persuasive technologies offer a promising way to help individuals adopt and sustain healthier dietary habits over time [2]. Unhealthy eating patterns represent a major public health issue, with significant impacts on individual well-being. These effects go beyond immediate health concerns, leading to long-term risks such as obesity, cardiovascular disease, and diabetes. Such systems are envisioned as dynamic platforms that engage users in meaningful ways and offer personalized recommendations to encourage healthier eating practices [3].

Harnessing the power of AI and natural language processing, conversational systems present an innovative way to drive behavioral change in dietary choices and consumption patterns. By seamlessly integrating nutritional knowledge, individual preferences, and contextual factors, these systems empower users to accept and sustain healthier eating habits, reducing the negative impacts of unhealthy dietary practices on public health [4].

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Unhealthy eating behaviors often lead to significant adverse effects. On the other hand, simple habits, such as eating more slowly, are linked to positive outcomes, including enhanced satiety during meals and reduced calorie consumption. Surprisingly, such easily adoptable habits could play a role in addressing widespread societal health challenges [5]. Rather than directly persuading individuals to change their actions, researchers have introduced the concept of "jolting," a subtle technique that influences grassroots decisions toward desirable outcomes while preserving individual freedom of choice. Nudges can take various forms [6] and require proven effectiveness across different contexts [7].

2. Review of Related Literatures

Given the complex nature of food-related decision-making, the concept of "shoving" plays a significant role in encouraging healthier eating behaviors [8]. One common strategy for nudging individuals toward healthier choices of food is through product placement [9]. For example, positioning a healthier chocolate bar between two options that is low in nutritious on a shelf can increase the likelihood of its selection [10]. A study conducted at a train station found that stores placing healthy items near checkout counters experienced a rise in sales of those products, even when unhealthy options remained available [11]. Additional approaches that usually influences the choice of food include emphasizing the scarcity of certain items [13], creating lunch lines that exclusively offer healthy foods [14], and making nutritious options more accessible and prominent on menus.

As noted by [14], persuasive technology is a rapidly growing and expansive field, incorporating a range of concepts including computer-human interaction, information systems, emotion AI, pervasive and mobile computing, interaction design and captology. This dynamic area of study is reshaping our behavior and actions towards feeding. According to [15], computer technology has a profound impact on our thoughts and behaviors. It explores the creation of a powerful persuasive technology platform designed to help individuals make more informed and health-conscious food choices. Grounded in computer-human interface principles and behavioral economics, this technology aims to provide personalized interventions, recommendations, and real-time feedback, fostering positive changes in dietary habits [16].

Through intuitive user interfaces, seamless integration with wearable devices, the proposed technology seeks to actively engage users on their journey toward achieving and sustaining a healthier routine [17]. The goal is to explore how persuasive technology can effectively motivate individuals, shifting their perspectives to a more positive outlook by identifying the key factors influencing behavior change. In [18], the effect of persuasive techniques on the maternal health behavior of rural women was analyzed. The study aimed to develop a comprehensive model of maternal health behavior and used three persuasive strategies from the model to guide the design of an application aimed at encouraging consistent and timely antenatal, intra-partum, and post-partum behaviors among rural women.

According to [19], a retrospective analysis was conducted to examine the significant advancements in persuasive health, with the aim of highlighting future opportunities that could be unlocked through a more comprehensive theoretical framework and practical methodologies. A taxonomy is provided to categorize contributions in this field, including health behavior theory, cybernetic action-behavior models, social cognitive theory, and control theory. In a large-scale study involving hundreds of participants, the researchers explored how individuals at different stages of change respond to various behavior change techniques [20]. They also investigated the reasons behind the efficiency of these tactics using the incentive model. The results revealed that an individual's feeding procedures significantly influences how persuasive they find different techniques, with each approach motivating behavior for distinct reasons.

In the work of [21], current methods for developing persuasive dieting chatbots were examined, highlighting several significant unresolved challenges. Drawing from previous research, the study pointed out gaps in existing approaches, revealing shortcomings in addressing specific scenarios.

The PROMISS trial explored the use of persuasive technology in a dietary intervention aimed at improving protein consumption and physical function in adults that have low protein intake, with the goal of promoting healthy aging [22]. The sub-study findings revealed insights into technology observance, intake of protein, participant experiences with the technology and dietary procedures, as well as the impact on the awareness of protein gamification. It presented results with positive evaluations of the tablet, but negative assessments of the food box. While recent advancements in recommender systems offer the potential for personalized services to assist users in their decision-making processes [23], traditional systems often fail to incorporate health-related factors such as dietary guidelines and food allergies. A study by [24] highlighted that behavior variation is deeply connected to existential concerns, influenced by a complex array of life circumstances, and unfolds gradually over time. However, the technology used by participants in the work primarily focused on immediate target behaviors, neglecting the broader context of their life circumstances and the passage of time, and provided limited support in assisting users make sense of these factors [25].

3. Material and methods

3.1. Model Design

This research utilizes a mixed-methods approach, combining both qualitative and quantitative data collection and analysis techniques. By integrating these methods, the study offers a thorough understanding of the development process of persuasive technology and its influence on individuals' dietary habits. Purposive sampling techniques were employed to select participants for this study. We recruited individuals with varying dietary preferences, cultural backgrounds, and lifestyle factors to ensure a diverse and representative sample. This approach allowed us to gather detailed insights from participants with unique perspectives on dietary routines and the application of persuasive technology.

3.2. Analysis of the System

The current system provides personalized recipe recommendations tailored to the eating habits and favorites of users. Users can interact through various modes, such as selecting predefined responses through natural language conversations. This multi-modal interaction enhances the user experience and accommodates diverse preferences. Testing showed that offering these options improves users' perception of the system's usability and effectiveness. The modules in the system include:

- **User Interaction Module:** The User Interaction Module enables seamless user engagement through options-based interaction. It allows users to navigate the system intuitively, ensuring a user-friendly experience. By offering a clear and accessible interface, this module enhances the overall usability of the system, fostering positive and efficient user interactions.
- **Personalized Recommendation Module:** The Personalized Recommendation Module analyzes eating habits of users and preferences to generate customized recipe suggestions. It takes into account factors such as dietary restrictions and individual preferences, ensuring that the recommendations align with each user's specific needs. By leveraging user-specific data, this module delivers tailored and relevant recommendations that cater to a variety of dietary requirements.
- **Natural Language Understanding (NLU) Module:** The NLU module extracts communicative intentions and key entities from users' utterances. It performs activities like lemmatization, dependency parsing, and part-of-speech (POS) tagging, using Python libraries like NLTK and SpaCy to analyze the input and understand the user's intent.
- **Natural Language Generation (NLG) Module:** The NLG module generates natural language responses based on a lookup table, allowing the system to reply to users in an engaging and conversational manner.
- **Dialog Management Module:** The Dialog Management Module functions as a finite state machine, processing inputs such as the user's intent, entity type, entity, and valence extracted from their utterance. Considering the present discussion and a recorded set of rules, the dialog manager determines the appropriate transition to the next state. This certifies that the conversation flows normally, maintaining context and relevance throughout the interaction.

3.3. Steps for the Experimental Setup

3.3.1. Define the Experiment

- Objective: The primary goal of this work is to evaluate the effect of a dietary recommendation system on users' choices of food, in order to promote healthier dietary habits among participants.
- Hypothesis: We hypothesized that utilizing persuasive technology, which offers personalized meal recommendations and nutritional analysis, would lead to an increase in the consumption of healthy foods and an overall improvement in dietary habits among participants.
- Target Audience: Participants were drafted from individuals aged 25-45, with diverse dietary preferences and lifestyles, residing in urban areas.
- Informed Consent: Ethical approval and informed consent were obtained from all participants prior to the start of the experiment, ensuring transparency and respect for participants' rights.
- Baseline Data: Initial data collection involved assessing participants' current dietary habits through surveys and dietary logs, providing a baseline for comparison throughout the study.

3.3.2. Develop the Persuasive Technology

- Platform Selection: We developed a web-based solution using C# and .NET Core, providing accessibility across multiple devices.
- Feature Development: in the system, we incorporated features such as personalized meal recommendations based on nutritional needs and preferences, real-time nutritional analysis of meals, and progress tracking to monitor dietary improvements over time.

3.3.3. Setup Tools and Instruments

- **Software Development:** Visual Studio, paired with .NET Core, was employed for both frontend and backend development, providing a robust, scalable, and efficient architecture for the application.
- **Machine Learning Integration:** ML.NET was incorporated to create machine learning models for personalized meal plan recommendations and the analysis of user feedback. This allows the system to continually refine its dietary suggestions based on users' preferences and behaviors.
- **Database Integration:** SQL Server was deployed to manage data storage and retrieval, ensuring efficient handling of user profiles, dietary logs, and system analytics, which supports smooth system operation and data accessibility.

3.3.4. Conducting the Experiment

- **Training and Instructions:** Participants were trained to effectively use the dietary recommendation system. The training focused on the importance of healthy eating, understanding nutritional feedback, and leveraging the system's features to make well-informed dietary decisions.
- **Data Collection:** We collected user interaction data, including dietary logs and feedback, to evaluate participant engagement with the system and their adherence to the dietary recommendations provided.
- **Monitoring:** Continuous monitoring of both participant engagement and system performance was conducted throughout the study. This ensured the experiment's integrity and reliability, enabling real-time adjustments to conserve the accuracy level and consistency of the results.

3.3.5. Data Collection, Cleaning and Analysis

- **Data Handling:** C# was used for data preprocessing tasks, including cleaning and formatting structured and unstructured data from CSV files containing dietary logs. This process ensured the consistency and quality of the data, enabling accurate and reliable analysis.
- **Machine Learning Analysis:** ML.NET algorithms were applied to analyze user data, predict dietary preferences, assess the effectiveness of personalized recommendations, and identify patterns in users' dietary behavior over time.
- **Evaluation:** The experiment's outcomes were assessed using both quantitative metrics such as changes in dietary traditions and adherence to recommendations and qualitative insights gathered from user feedback. This thorough evaluation offered a holistic understanding of the system's effect on participants.

3.4. Training the Datasets

- **Step I: Data Collection and Preprocessing:** The development and training of an intelligent dietary mobile app using ML.NET, guided by the Fogg Behavior Model, started with the objective of promoting healthy dietary habits through personalized recommendations, real-time feedback, and motivational interventions. To achieve this, data was collected from users via surveys, gathering information about their dietary habits, preferences, cultural dietary outlines and nutritional intake. In addition, data from existing dietary databases was built into the system. The collected data was then preprocessed by handling missing values, normalizing the data, and encoding categorical variables to ensure a clean and well-structured dataset for analysis.
- **Step II: Defining Parameters and Setting Up ML.Net:** After installing ML.Net and setting up a new .NET project, the next step was to define the core parameters of the Fogg Behavior Model: *motivation*, users' capability to access and prepare healthy food, and prompts or reminders that encourage healthy eating. These parameters were integrated into the data model to ensure their proper representation for both analysis and prediction within the system.
- **Step III: Data Loading and Transformation:** The collected data was loaded into the ML.Net pipeline. Several data transformations were then applied, including splitting the data into training and testing sets to prepare for model training. A pipeline was created to concatenate the features (motivation and ability) and normalize

the data for consistency. After the data transformation, it was divided into training and testing sets, enabling accurate evaluation of the model's performance during both the training and testing phases.

- **Step IV: Machine Learning Training Model:** The next step was to select a suitable training model for the machine learning algorithm. A regression trainer in ML.Net was deployed to predict the success of adopting a better and adequate eating lifestyles, based on the parameters from the Fogg Behavior Model (motivation, ability, and triggers). The model was trained by fitting with the training datasets and its performance was evaluated using test data to ensure both accuracy and reliability.
- **Step V: Model Evaluation and Saving:** The model's performance was assessed using evaluation metrics such as R-squared and root mean squared error. Once the model met the desired accuracy criteria, it was saved for integration into the mobile app. This trained model was then used to provide real-time dietary recommendations and feedback based on user input, allowing for personalized, dynamic dietary guidance.
- **Step VI: Continuous Learning and Improvement:** The final step focused on ensuring continuous learning and improvement by collecting ongoing data from user interactions. This data was utilized to improve the model over time. Regular retraining with updated data ensured the model stayed accurate, relevant, and responsive to users' changing needs and preferences.
- By implementing these steps, a robust and intelligent dietary mobile app was developed, leveraging ML.Net and the Fogg Behavior Model to effectively promote healthy dietary habits.

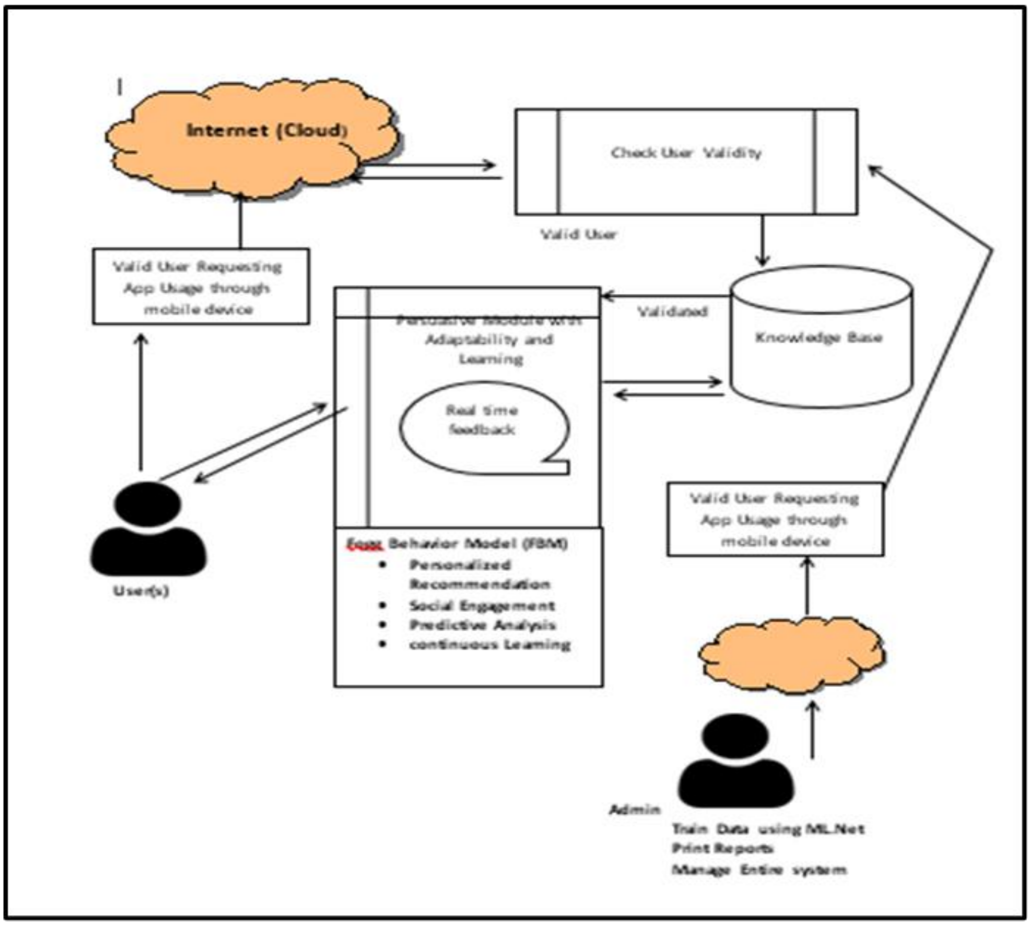

Figure 1 The System's Architecture

3.5. Components of the Architecture

The architecture of the entire system is divided into the following domains:

3.5.1. User

The user engages with the persuasive technology platform to receive personalized dietary recommendations, track eating practices and obtain feedback on their progress toward healthier eating. Users provide key information such as dietary preferences, health goals, and cultural background. The system uses this data to tailor recommendations and support behavior change efforts. The user experience is designed to be motivating and interactive, empowering individuals to improve on their choice of food and sustain positive changes in their day to day consumption habits.

3.5.2. Administrator

The administrator is responsible for managing the overall operation of the persuasive technology platform. This includes maintaining the database of food options and nutritional information, managing user accounts and profiles, and monitoring system performance. Administrators ensure data privacy and security while also analyzing user engagement metrics and feedback to improve the platform's effectiveness. Their role is essential in optimizing the system's operation, ensuring it continues to support users' dietary goals and facilitate durable change of feeding attitude.

3.5.3. Knowledgebase

The knowledgebase acts as the foundation of the persuasive technology platform, containing a comprehensive repository information provided to users with correct and appropriate dietary recommendations. It includes data on nutrition guidelines, healthy recipes, ingredient profiles, cultural dietary practices, and evidence-based strategies for promoting an improved eating procedures. The knowledgebase is continuously updated to reflect the latest research, dietary trends, and public health recommendations, ensuring that users receive the most current and reliable information.

3.5.4. Persuasive Technology or Adaptability and Learning

The system's component encompasses the adaptive and learning capabilities of the platform. Utilizing algorithms of machine learning and adaptive strategies, the system analyzes user interactions, feedback, and outcomes to continually refine and personalize recommendations and interventions. The platform learns from individual user preferences, dietary habits, and behavior patterns to deliver more tailored guidance. By doing so, it aims to optimize user engagement and effectiveness in promoting sustainable, healthy dietary habits over time. This dynamic adaptability is key to ensuring long-term success in performance transformation, particularly in diverse user populations.

3.6. Tools for Design

Designing a dietary mobile app to promote healthy eating habits using machine learning involves leveraging a variety of tools to ensure a robust, user-friendly, and effective system. These tools include:

- **Train Dataset Using ML.Net:** The datasets is trained by the administrator by using ML.Net. This involves collecting and preprocessing data on users' dietary habits, preferences, and nutritional intake. These data are then fed into the ML.Net pipeline, where algorithms of machine learning are applied to develop predictive models. These models generates personalized dietary recommendations, which are continuously improved through ongoing data collation and retraining. Admins must ensure the data is truthful, up-to-date, and significant to the target demographic, focusing on Nigerian nutritional designs and cultural preferences**.**
- **Send Motivational Notifications:** The administrator sends motivational notifications to users, aimed at encouraging them to adhere to their dietary plans and make healthier food choices. These notifications may include helpful tips, reminders, and motivational messages personalized according to each user's progress and preferences. The timing, frequency, and content of these notifications are essential and must be customized to ensure maximum engagement and effectiveness. Machine learning algorithms can assist in refining the timing and content of these messages by analyzing user behavior and feedback.
- **Add New Meal:** The new meals are added to the app's database by the administrator, which involves inputting detailed information about each meal, including its ingredients, nutritional values, and preparation methods. It is very significant for administrator to make sure that the meals are diverse, culturally relevant, and cater to various dietary preferences and restrictions. Additionally, they should categorize the meals correctly and update the database frequently to offer users a broad variety of healthy meal options.
- **Generate Reports:** Administrators create reports to assess the app's performance and usage. These reports may include metrics such as user engagement, the effectiveness of dietary recommendations, and overall health improvements. The insights gained from these reports enable admins to make informed decisions to improve the app's features. The reports also assist in identifying trends, understanding user behavior, and evaluating the app's impact on users' dietary habits.
- **Manage Users:** Administrator play a critical role in managing user accounts, addressing user inquiries and concerns, and ensuring a seamless experience within the app. They monitor user activity to identify any abnormal behavior or potential misuse of the platform. Additionally, admins handle user feedback, implement necessary adjustments, and offer support to help users navigate the app efficiently. A key responsibility also

involves safeguarding privacy of user and securing sensitive data, ensuring the protection of personal information within the app.

- By carrying out these tasks, admins enable users to make the most of the app's features, providing personalized guidance, motivation, informed food choices, progress tracking, and support to help users meet their health and nutrition objectives.
- **Chat AI for Healthy Eating:** Users engage with the chat AI to receive tailored guidance and recommendations for maintaining a healthy diet. The AI initiates conversations to gather information about the dietary choice of users, wellbeing goals, and any specific restrictions they may have. Based on this input, it offers personalized meal suggestions, nutritional advice, and tips for choice healthier food. Users can ask questions, seek clarification, and get real-time feedback from the AI, helping them stay on track in their determination of better nutrition.
- **Receive Notifications:** The app sends users notifications to keep them informed and motivated as they work towards their dietary goals. These notifications can include reminders to log meals, prompts to explore recommended meal options, updates on progress, and motivational messages to encourage consistency with improved eating lifestyles. Users have the option of customizing the settings of their notification, selecting the frequency and its types that best suit their needs, ensuring ongoing engagement and support throughout their journey.
- **View Recommended Meals:** Users can explore a curated list of meal recommendations tailored to their dietary preferences and health goals. Each meal comes with detailed descriptions, ingredient lists, nutritional information, and user reviews. The app categorizes meals into options such as breakfast, lunch, dinner, and snacks, allowing users to easily find meals that suit their tastes and nutritional needs. Recommendations are regularly updated based on user feedback and interaction patterns, ensuring relevance and variety.
- **Update Their Progress:** Users can login and monitor their improvement of the application to stay on track with their journey toward healthier eating. This includes recording meals, tracking daily food and intake of water intake and noting physical activities or exercises. They can personalized their setting, control the intake of calorie, track weight changes, and view progress charts for a clear visualization of their achievements. This feature helps users stay engaged, accountable, and motivated while gaining valuable insights into their eating habits and general progress toward their health objectives.
- **Logout:** Users can log out of the app after completing their session or when switching accounts. This feature enhances account security by protecting personal information and preventing unauthorized access. Exiting the model is done through the app's settings or profile menu by selecting the logout option. By providing a seamless and secure logout process, the app ensures users maintain control over their account privacy, contributing to a safe and user-friendly experience.

3.7. Data Analysis

Data analysis has to do with examining, refining, converting and reshaping of the dataset to extract valuable insights, facilitate informed decision-making, and address complex problems. It encompasses various techniques and methodologies aimed at exploring, interpreting and presenting data in a flawless and organized way.

3.8. Dataset

The dataset used for this analysis was obtained from the Kaggle repository, a widely recognized platform for accessing and sharing diverse datasets across multiple domains. This dataset includes detailed and relevant information aligned with the objectives of our research. In our analysis, we used three key metrics to evaluate the importance of features within the dataset: Chi-Squared Score, Information Gain and MF Score. These indices are essential for determining the relevance and predictive strength of individual features in relation to the expected variable.

The Chi-Squared Score measures the independence between categorical variables and the expected variable by assessing how much the observed frequencies differ from the expected frequencies under the assumption of independence. A higher score signifies a stronger association between the variables.

Information Gain evaluates a feature's predictive power by calculating the reduction in entropy of the target variable when that feature is known. Features with higher Information Gain values are deemed more informative and relevant for prediction.

The MF Score, or Mutual Information Score, measures the shared information between two variables, reflecting their level of dependency. A higher score indicates an improved relationship between the expected variable and features, highlighting its importance in predictive modeling.

4. Result and Discussion

This study aimed at promoting healthy dietary habits was evaluated using the Fogg Behavior Model (FBM). The FBM, behavior change is achieved when Motivation, Ability, and Prompt are aligned. The system's performance was assessed based on key metrics including accuracy rate, precision rate, recall rate, F1-score rate, training time, and execution time.

- **Accuracy Rate (91%)**: Accuracy refers to the ratio of correct predictions (both true positives and true negatives) out of the sum cases analyzed. The dietary recommendation system achieved an impressive accuracy of 91%, meaning it correctly predicted users' choices of food in 91% of instances. This represents a notable improvement over existing systems, which typically maintain accuracy around 85%. The high accuracy underscores the system's effectiveness in guiding users toward healthier dietary decisions while successfully applying the laws of the FBM.
- **Precision Rate (93%)**: Precision refers to the ration of true positive outcomes out of all the positive outcomes made by the model. With a precision rate of 93%, the system demonstrates a high level of reliability in predicting healthy food choices. This means that when the system recommended a healthy choice, it was correct 93% of the time. Compared to existing systems, which often struggle with precision rates around 80-85%, the system's high precision minimizes false positives, giving users with more trustworthy recommendations.
- **Recall Rate (81%)**: Recall indicates the rate of true positive outcomes among all actual positive instances. The system achieved a recall rate of 81%, meaning it correctly identified 81% of all healthy food choices. While slightly lower than the precision rate, this recall still outperforms many existing systems to achieve recall rates around 75%. This indicates that the system is effective at identifying and recommending an improved healthy feeding arrangements to users, though it may occasionally miss some.
- **F1-score Rate (87%)**: The F1-score is a metric used to measure a model's accuracy, balancing precision and recall. It is particularly useful for evaluating classification models when the data is imbalanced. With an F1-score of 87%, the system demonstrates strong performance in both accurately identifying healthy food choices and minimizing false positives. When comparing it with other systems, F1-scores in the range of 78-83%, this system shows superior overall effectiveness in promoting healthy dietary habits.
- **Training Time (5 minutes)**: This is the amount of time taken to train a model in machine learning. The system achieved a training time of just 5 minutes, indicating high efficiency. This rapid training time is a important advantage over many existing systems that may take considerably longer to train. This system has produced a better, reliable, and faster to deploy and update, enhancing its scalability and responsiveness to evolving dietary recommendations.

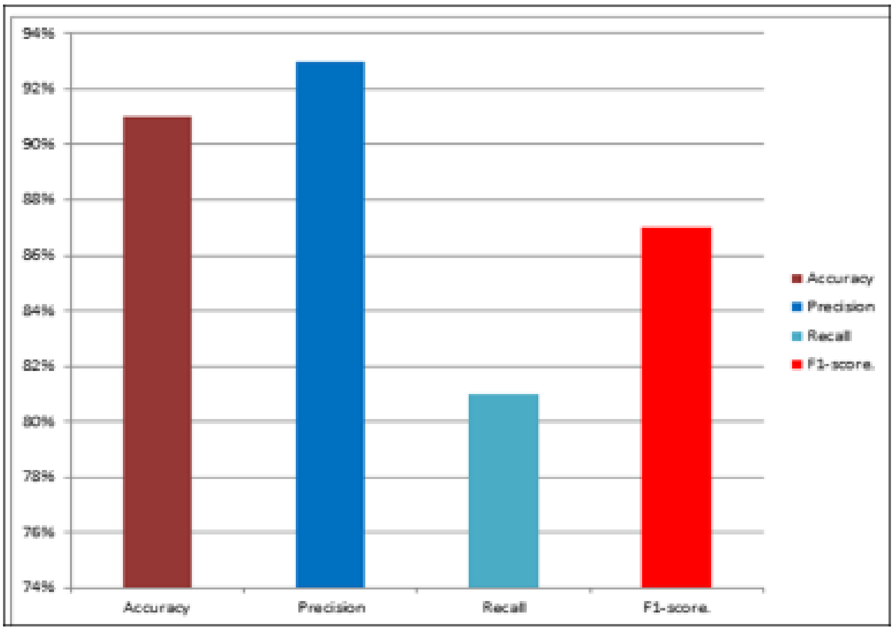

Figure 2 Bar Chart for Performance Metrics

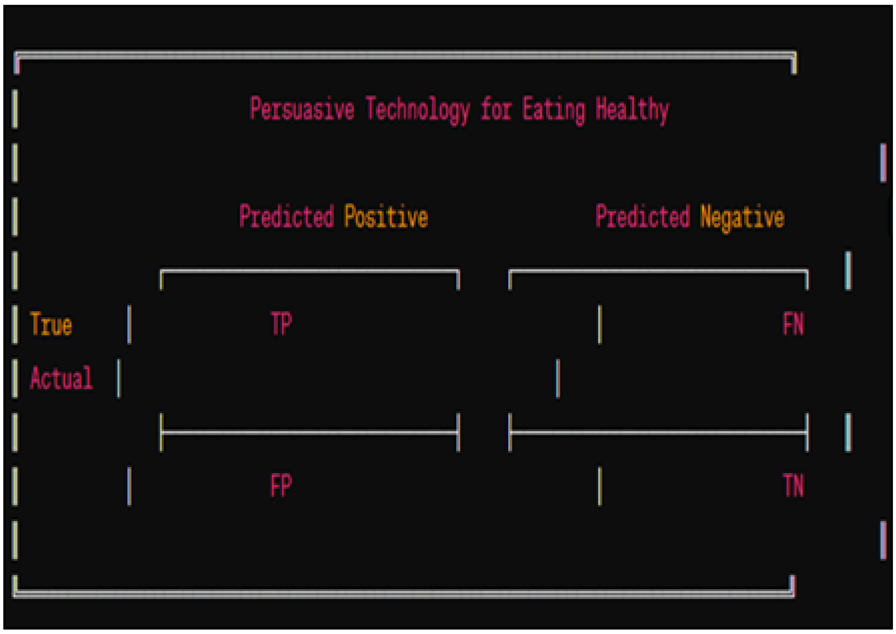

Figure 3 Truth Table Output

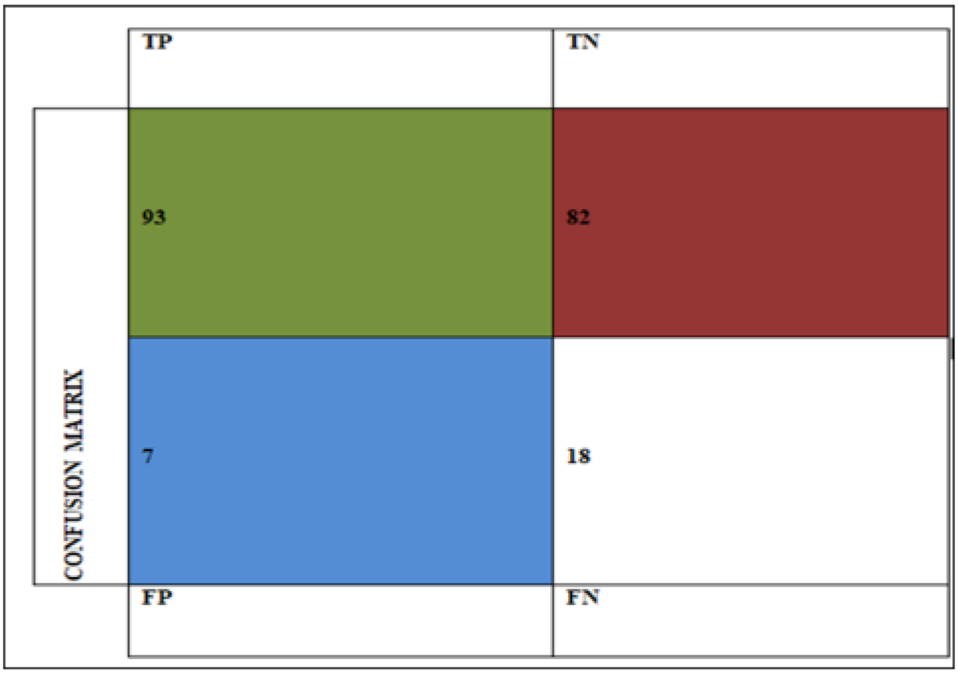

Figure 4 Confusion Matric Table

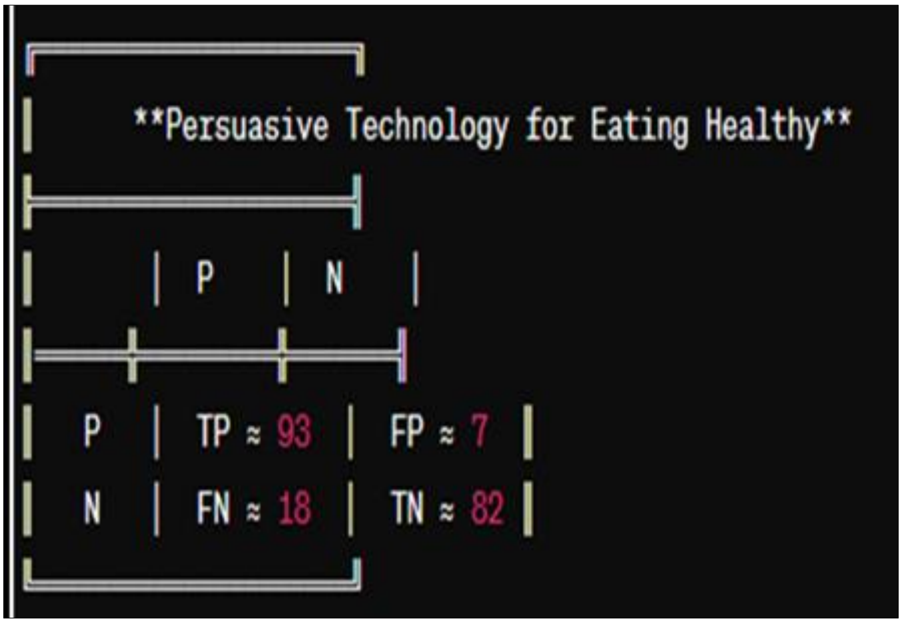

Figure 5 Testing Data Output

Table 1 Fogg Behavior/Performance Table

Model	Accuracy	Precision	Recall	F1-score.	Training time (seconds)
Fogg Behavior Model	91%	93%	81%	87%	5 mins

5. Conclusion

In conclusion, the evaluation of the system's performance underscores its effectiveness in promoting healthy dietary habits through persuasive technology. The system's impressive precision, accuracy, and overall balanced performance across key metrics demonstrate its ability to drive positive dietary changes and support better health outcomes. These findings have important implications for public health, highlighting the potential of technology in addressing critical health challenges. Moving forward, continuous research and development will be crucial in further enhancing the system's capabilities, maximizing its potential to influence healthier eating behaviors. With the previsions of persuasive technology, we can empower individuals to make informed choices about their diet and lifestyle, ultimately fostering healthier lives and communities.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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