Development of Intelligent Nutrition Surveillance System with OpenAI API

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Abstract

Nutrition surveillance is crucial in monitoring public health by identifying dietary deficiencies and tracking nutritional trends. Traditional systems often struggle with data collection and analysis challenges, particularly in crises. Artificial intelligence (AI) offers promising solutions for improving the efficiency and accuracy of such systems. This study aims to develop an intelligent nutrition surveillance system that leverages the OpenAI API to provide personalized dietary recommendations, improve real-time data processing, and enhance nutrition management. The system integrates natural language processing (NLP) and machine learning models for food recognition and nutrient estimation. Data is collected through a user-friendly interface, and personalized meal plans are generated based on user inputs. The system's performance was tested using a combination of manual data entry and food image recognition, with user feedback guiding further refinements. The OpenAI-based system successfully provided real-time, personalized nutrition plans. The NLP model accurately processed user queries, while the food recognition model performed well with simple meals and struggled with complex dishes. User satisfaction was generally high, but some data input guidance and food recognition accuracy improvements were noted. This research demonstrates the practical application of AI in nutrition surveillance, particularly in resource-constrained settings. The system's ability to generate personalized recommendations using real-time inputs represents a significant advancement in public health technology. The study presents a scalable and adaptable framework for integrating AI into nutrition surveillance, showing strong potential for further application in individual and population health. Future research should focus on refining image recognition algorithms and incorporating automated data collection methods to enhance accuracy and applicability.

Keywords

Artificial Intelligence, OpenAI, nutrition surveillance, personal assistance, public health informatics

1. Introduction

Nutrition surveillance is critical in monitoring population health, particularly by tracking dietary intake, identifying nutritional deficiencies, and detecting emerging trends that may indicate broader public health concerns. Effective nutrition surveillance systems can inform policy decisions, guide public health interventions, and prevent malnutrition-related illnesses [1]. However, many existing systems face data collection, processing, and analysis challenges, often relying on self-reported data or surveys that may lack accuracy and timely insights [2]. These limitations underscore the need for more intelligent and adaptable approaches to nutrition monitoring, especially in vulnerable populations.

The problem of nutrition surveillance has become particularly acute during the ongoing full-scale Russian invasion of Ukraine. War and conflict often disrupt food supply chains, displace populations, and limit access to essential resources, contributing to food insecurity and poor nutritional outcomes [3]. In Ukraine, the conflict has severely affected food availability, leading to a rise in malnutrition, especially in regions with limited humanitarian aid [4]. Existing nutrition surveillance systems, already strained by the challenges of the COVID-19 pandemic, have been further hindered by logistical constraints, making it difficult to track and address the nutritional needs of affected

ProfIT AI 2024: 4th International Workshop of IT-professionals on Artificial Intelligence (ProfIT AI 2024), September 25–27, 2024, Cambridge, MA, USA

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populations [5]. These challenges necessitate more advanced systems that can operate effectively in crisis conditions.

The impact of nutrition on public health is well-documented, with poor nutrition being a leading cause of morbidity and mortality worldwide [6]. In the context of the war in Ukraine, malnutrition exacerbates pre-existing health conditions and increases vulnerability to disease outbreaks, such as influenza and other communicable diseases [7]. Adequate nutrition is essential for maintaining immune function and overall well-being, particularly in war-affected regions where healthcare systems are overwhelmed and limited access to food [8]. Addressing nutritional needs is crucial for short-term survival and long-term recovery, highlighting the importance of robust nutrition surveillance systems in managing public health during conflict.

Artificial intelligence (AI) has emerged as a valuable tool for public health, offering solutions to enhance data collection, analysis, and decision-making processes. AI can help bridge the gaps in traditional nutrition surveillance by automating data collection from diverse sources, including social media, satellite imagery, and mobile health platforms [9]. Machine learning models can process large datasets to detect patterns in nutritional intake and predict potential public health crises before they manifest [10]. In conflict zones, AI can support rapid food security and malnutrition assessments by integrating real-time data, providing governments and humanitarian organizations with actionable insights to guide interventions [11].

Large language models (LLMs), such as OpenAI's GPT, have demonstrated significant potential as personal assistants in public health. These models can assist individuals in making informed nutritional decisions by offering personalized dietary recommendations based on available data, preferences, and constraints [12]. In war-torn regions, where access to healthcare professionals may be limited, LLMs can be an accessible resource for individuals and healthcare workers. Their ability to analyze vast amounts of data, respond to queries in natural language, and provide tailored guidance makes them a valuable asset in supporting nutrition surveillance efforts, particularly in resource-constrained settings.

The study aims to develop an intelligent nutrition surveillance system using OpenAI API.

2. Current research analysis

Data-driven nutrition surveillance systems have gained prominence in recent years as technological advancements enable more efficient and accurate collection and analysis of nutritional data. These systems leverage large-scale datasets, including electronic health records, food consumption surveys, and remote sensing data, to monitor real-time population nutrition trends. Using machine learning algorithms and data analytics tools, these systems can identify emerging patterns, predict future nutritional risks, and support targeted public health interventions. Integrating data from diverse sources such as mobile health applications, social media platforms, and geographic information systems (GIS) allows for more comprehensive assessments of dietary behaviours and food accessibility, providing valuable insights into nutritional challenges at the community and individual levels. However, despite these advancements, current data-driven nutrition surveillance systems still face challenges related to data quality, accessibility, and interoperability, particularly in low-resource or conflict-affected settings.

The paper [13] discusses the implementation and impact of a mobile-based nutrition surveillance system to improve accountability and real-time monitoring of nutritional outcomes in India. The Poshan Tracker system, part of the country's Integrated Child Development Services Scheme, provides transparent data on anthropometric outcomes, food distribution, and the functioning of Anganwadi Centers (AWCs). Over the study period, there were significant improvements in the operational consistency of AWCs and the distribution of supplementary food to vulnerable groups. However, the paper highlights limitations in data accuracy, with discrepancies between Poshan Tracker data and the National Family Health Survey, potentially caused by differences in measurement techniques and reporting biases. This indicates the need for further system refinement to ensure more reliable and consistent data for policy-making and program adjustments.

The paper [14] explores the dietary patterns (DPs) that help protect against hypertension (HTN) in a nationwide study of Chinese adults. The researchers used reduced rank and partial least square regression to identify key dietary components of HTN protection. Their findings suggest that diets high in fresh vegetables, fruits, mushrooms, dairy products, and legumes are associated with lower odds of HTN. The study highlights the relevance of adapting dietary patterns to local habits, as traditional Western diets like the DASH diet may not be suitable for Chinese populations. However, a limitation is the potential lack of generalizability to other ethnic groups due to the focus on Chinese adults and the specific dietary patterns derived from their habits.

The chapter [15] explores integrating AI technologies into nutrition and fitness to improve health outcomes. It emphasizes how AI can assist in personalized nutrition and fitness strategies by analyzing large datasets and adapting recommendations based on individual factors such as genetics, lifestyle, and environment. AI applications, such as machine learning algorithms and wearable technologies, are discussed in the context of improving diet, monitoring physical activity, and supporting rehabilitation. However, the paper highlights limitations in the generalizability of AI models due to the complexity and variability of human health data, as well as challenges related to data integration and privacy concerns, which must be addressed for broader implementation.

The paper [16] comprehensively reviews AI nutritionists' current advancements and applications, focusing on software designed for dietary monitoring, food recognition, and nutrient recommendations. The study systematically evaluates 177 AI nutritionists, highlighting their growing importance in personalized nutrition and health monitoring. While AI nutritionists have significantly improved dietary tracking and personalized dietary advice, the paper identifies limitations in the current level of intelligence of these tools, noting that most systems rely on basic algorithms and have yet to fully exploit advanced AI capabilities, such as deep learning or molecular-level food behaviour prediction.

The paper [17] presents a novel system designed to estimate the nutritional content of meals served in compartment trays using image-based technology. The platform employs a depth camera and Raspberry Pi to capture images and depth data, which are then processed by an algorithm that integrates dish recognition, portion-size estimation, and nutrition analysis. Using instance segmentation models like CenterMask with VoVNetV2-99, the system accurately identifies food items and calculates their nutritional value. The study demonstrates that this AI-driven method significantly outperforms dietitians in speed and achieves comparable accuracy in calorie estimation. However, a limitation of the platform is that its performance heavily depends on the quality of the depth information, and further refinement is needed to handle more complex and varied meal types.

The paper [18] explores the development of an AI-powered mobile application designed to provide personalized dietary recommendations based on individual user data, such as body mass index (BMI), age, gender, and food preferences. By utilizing machine learning algorithms, the app generates tailored diet plans that mimic the role of a nutritionist, helping users maintain a healthy diet without requiring professional consultation. The system processes user input to recommend suitable meal plans, saving time and making dietary guidance more accessible. However, the paper notes limitations in the model's ability to account for complex medical conditions and dietary restrictions, which may affect the accuracy of its recommendations. The system also requires further validation in real-world settings to improve its practical applicability and adaptability to diverse user needs.

The paper [19] presents a system that leverages artificial intelligence to provide tailored dietary recommendations and optimize meal planning, particularly in medical settings. The proposed system uses food images taken before and after consumption to estimate nutrient intake through image analysis and segmentation techniques to accurately identify food portions. This approach aims to streamline nutritional assessments, replacing traditional, time-consuming methods often relying on memory and interviews. However, the system faces limitations, such as variability in food composition databases, which can lead to inconsistencies in nutrient estimates and challenges in handling various food types with differing nutritional profiles. Further validation and refinements are needed to improve the system's accuracy and reliability across diverse populations and dietary needs.

In summary, current research in nutrition surveillance has made significant strides in integrating artificial intelligence, machine learning, and image recognition technologies to improve dietary assessments and personalized nutrition. Studies have demonstrated the potential of AI-based systems to provide more accurate and timely nutritional evaluations compared to traditional methods. However, despite advancements in segmentation techniques, nutrient estimation, and menu planning, limitations persist in the variability of food composition databases, the need for extensive manual data input, and the handling of complex medical conditions or diverse populations. These challenges highlight the importance of developing more robust and adaptable systems. The proposed study aims to address these limitations by leveraging the capabilities of the OpenAI API to create a more intelligent and user-friendly nutrition surveillance system. By integrating natural language processing and advanced machine learning algorithms, this system seeks to provide accurate, real-time dietary guidance, streamline data collection, and enhance the overall functionality of existing nutrition surveillance tools.

3. Materials and methods

The intelligent nutrition surveillance system developed in this research integrates various advanced technologies, with the OpenAI API serving as the core component. The system architecture is built around a combination of artificial intelligence techniques, including natural language processing (NLP), machine learning, and image recognition. These technologies provide personalized dietary recommendations based on user data, ensuring the system can efficiently process, analyze, and present nutritional information in real time. Figure 1 presents the system's architecture.

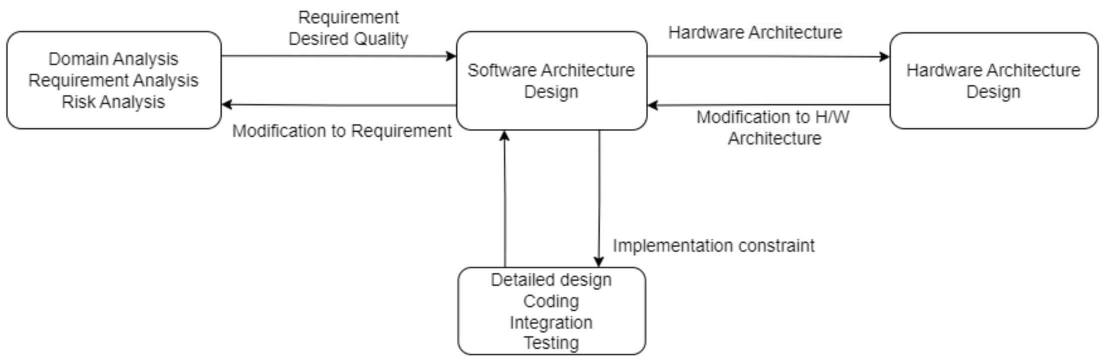

Figure 1: System's architecture

The system relies heavily on the OpenAI API to generate tailored dietary advice. User inputs, such as age, gender, weight, height, and dietary preferences, are collected through a user-friendly interface developed using C# and the Windows Presentation Foundation platform. These inputs are processed by the OpenAI model, which generates personalized meal plans and nutritional recommendations. MongoDB Atlas, a cloud-based NoSQL database, securely stores and manages user data, allowing for scalability and high system availability. The database stores demographic information, user dietary preferences, and meal history, ensuring personalized recommendations are based on accurate and comprehensive data.

The system also incorporates a food image analysis component, allowing users to upload photos of their meals. These images are analyzed using convolutional neural networks (CNNs) for food identification and segmentation. The CNN model segments the food items from the image, identifies the types of food, and estimates portion sizes. These segmented food items are then cross-referenced with a food composition database to calculate the nutritional content, including calories and macronutrient breakdowns. This data is stored in the user's profile for future reference and further refinement of recommendations.

OpenAI API integration allows the system to provide real-time responses to user queries, offering personalized dietary suggestions. When a user submits a query, the system formulates a request in JSON format, which includes relevant user data and dietary goals. This request is sent to the OpenAI API, which processes the input and generates a text-based recommendation or meal plan. The system then formats this response and presents it to the user in an intuitive and accessible manner through the interface. The model's ability to understand and process natural language enables it to provide contextually relevant advice, even for complex dietary questions.

Image recognition technology is employed for nutrient estimation to enhance the system's utility. The system can provide an accurate breakdown of the user's nutrient intake by analyzing the volume and type of food in a meal. The food recognition model is trained on a large dataset of labelled food images to ensure high accuracy. It uses image segmentation techniques to divide the meal into individual food items, which are then analyzed for nutritional content. This process allows users to receive real-time feedback on their nutrient intake, making the system a valuable tool for continuous dietary monitoring.

Figure 2 presents the classes diagram.

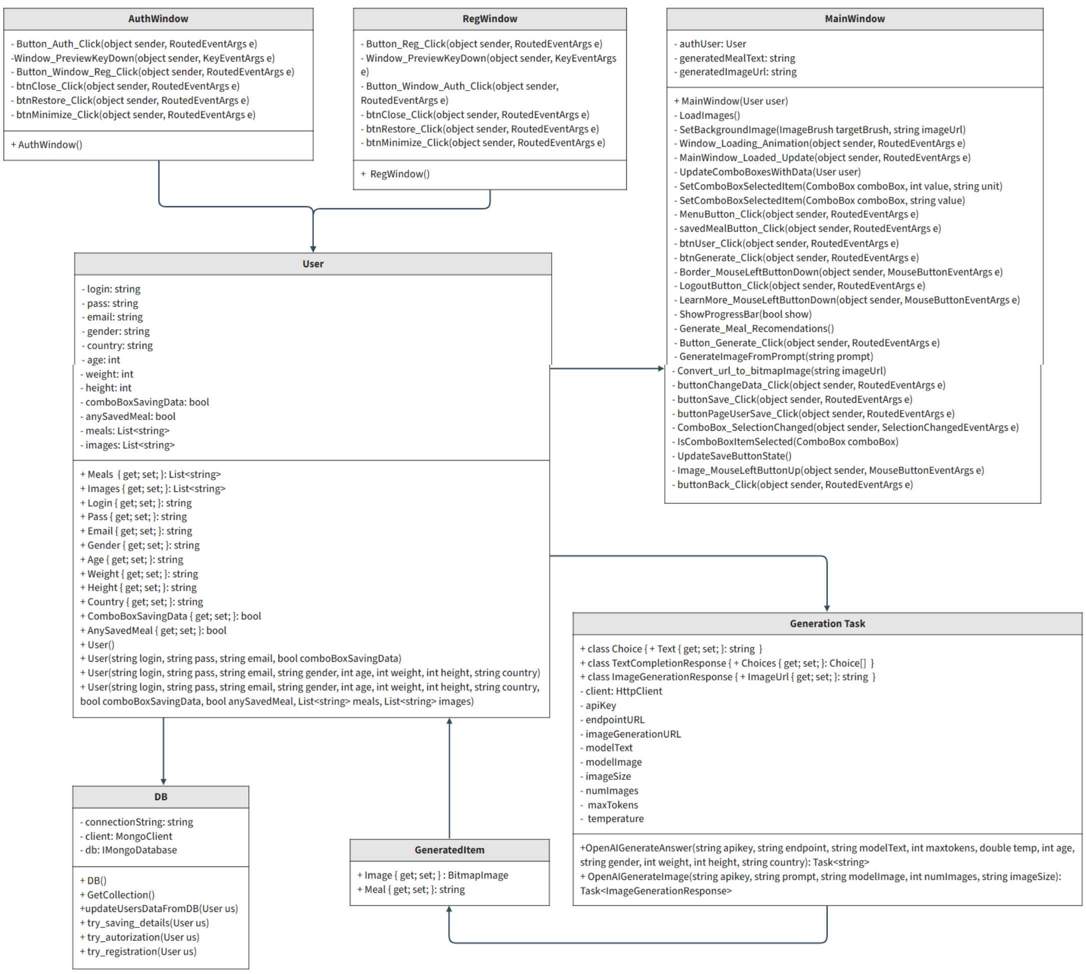

Figure 2: The class diagram

The system's AI models, particularly the GPT model from OpenAI and the CNN for image analysis, are fine-tuned to improve accuracy and performance in the context of nutrition. The GPT model is adapted to respond with accurate dietary advice by training it on a diverse range of nutritional literature and dietary guidelines. Similarly, the food image recognition model undergoes optimization to handle diverse food types and complex meals, improving the precision of portion size and nutrient estimation.

Extensive testing and validation were conducted to ensure the system's reliability and accuracy. The system's performance was tested in various conditions, including high user demand, to ensure it could provide quick and accurate responses. The accuracy of the nutritional recommendations was evaluated by comparing them with established nutritional standards and expert dietary advice. Additionally, dietitians and healthcare professionals provided feedback on the system's interface and functionality, which was used to refine the user experience further and improve the accuracy of the generated recommendations.

This study's methodology establishes a robust framework for an intelligent, AI-powered nutrition surveillance system that can provide personalized dietary guidance and continuous monitoring, leveraging the capabilities of OpenAI's advanced models.

4. Use cases

Tables 1-5 presents the use cases of the system.

Table 1
Use case "Authorization"

Parameter	Value
Actors	Guest
Goal	The application needs to be opened
Main flow	1. The user reaches the authentication page. 2. The user enters a username and password. 3. The system checks the username and password. If the username or password is incorrect, the alternative flow A1 is executed. If the user enters correct data, the alternative flow A2 is executed. The use case is then completed.
Result	The guest logs into the system as an authenticated user.
Alternative flow 1	"Username or password is incorrect" 1. The system notifies the user about incorrect data. 2. The system prompts the user to re-enter the data. 3. The use case is completed.
Alternative flow 2	"Correct data" 1. The system notifies the user of successful authentication. 2. The system redirects the user to the main page. 3. The use case is completed.
Postcondition	The user is redirected to the main page of the application.

Table 2
Use case "Registration"

Parameter	Value
Actors	Guest
Goal	Register
Main flow	1. The user reaches the authentication page. 2. The user clicks on the "Sign up" button. 3. The user enters a username, a new email, and a password and confirms the password. 4. The system checks whether the entered data is correct. If it is, alternative flow A1 is executed; if it is incorrect, flow A2 is executed.

	5. After completing alternative flow A1, the system checks if the entered email is unique. If it is, alternative flow A3 is executed; if a user with the same email or username already exists, alternative flow A2 is executed.
Result	The guest is registered in the system as a new user.
Alternative flow 1	"The entered data is correct." 1. The system begins checking if the user already exists. 2. The use case is completed.
Alternative flow 2	"The entered data is incorrect." 1. The system notifies the user about the incorrect data. 2. The system prompts the user to re-enter the data. 3. The use case is completed.
Alternative flow 3	"No users with the same email or username found in the system." 1. The system notifies the user of successful registration. 2. The system redirects the user to the authentication page. 3. The use case is completed.
Postcondition	The user is redirected to the authentication page.

Table 3
Use case "Adding and updating the information of user"

Parameter	Value
Actors	User
Goal	Upload file
Precondition	The user must be registered in the web application.
Main flow	1. Click on the "Your details" button. 2. Fill in the data. 3. After completing the data entry, click the "Save" button. 4. The use case is completed.
Result	The user's data is uploaded to the database. The system notifies the user of the successful data saving.
Alternative flow 1	"The user did not select one or more required fields" 1. The user receives an error message. 2. The unfilled fields are highlighted in red. 3. The system prompts the user to re-enter the data. 4. The use case is completed.
Postcondition	The user's data is updated on the screen.

Table 4
Use case "Menu generation for healthy diet for the week"

Parameter	Value
Actors	User
Goal	Menu generation
Precondition	The user must be registered.
Main flow	1. The user navigates to the generation page by clicking the appropriate button. 2. The user selects their details if they have not already entered them on the "Your details" page. 3. The user clicks the "Generate" button. 4. If any data is missing, alternative flow A1 is executed. If all data is complete, the generation process begins. 5. Once the generation is complete, the user is presented with the generated healthy diet menu, and an image corresponding to the menu is generated and set as the background.

	6. At the end, the user has the option to regenerate the menu (return to step 5), change the data (return to step 2), or save the menu to favorites (alternative flow A2 is executed). 7. The use case is completed.
Result	The menu is added to the user's favourites.
Alternative flow 1	"Some data is missing" 1. The user receives an error message. 2. The system prompts the user to re-enter the missing data. 3. The use case is completed.
Alternative flow 2	"Saving the menu to favorites" 1. The system notifies the user that the data was successfully saved. 2. The use case is completed.
Postcondition	The generation page reopens.

Table 5
Use case "Viiew favorite menus"

Parameter	Value
Actors	User
Goal	View favorite menu
Precondition	The user must be registered.
Main flow	1. The user navigates to the favorites page by clicking the appropriate button. 2. A grid of generated images corresponding to the saved menus is displayed on the page. 3. By clicking on an image, the text of the menu is opened. 4. The use case is completed.

5. Results

The intelligent nutrition surveillance system successfully provided personalized dietary recommendations and effectively managed user data. The system's performance was assessed based on the quality of personalized recommendations, the accuracy of food recognition, and user feedback.

The OpenAI API demonstrated robust performance in generating meal plans tailored to individual user profiles. The generated recommendations adhered closely to standard dietary guidelines and were well-suited to user-specific inputs such as age, weight, and health goals. The personalization component was highly effective, offering relevant suggestions for users aiming for weight loss, muscle gain, or balanced nutrition. Validation against established nutritional practices showed that the system provided nutritionally sound meal plans, confirming the effectiveness of AI in personalized dietary planning. Figure 3 presents the system's generation page.

In the food image recognition component, CNNs identified simple food items and estimated their portion sizes well. The model achieved high accuracy when dealing with individual food items, making it reliable for common meals. However, it faced challenges when presented with mixed or complex dishes, where segmentation became less reliable. This limitation reduced the precision of nutrient estimation for meals containing multiple ingredients. The overall accuracy of the image recognition was satisfactory, but the need for improvement in handling complex meals was evident. Figure 4 presents the generated menu.

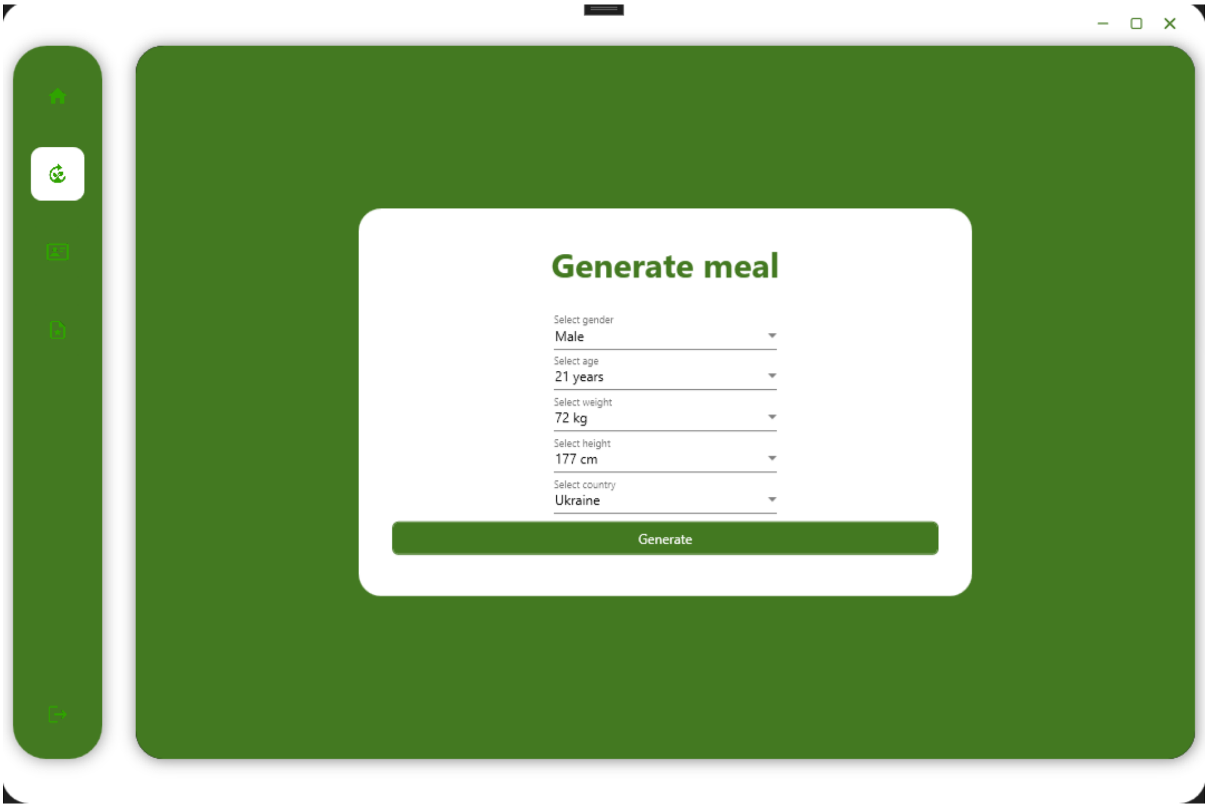

Figure 3: System's generation page

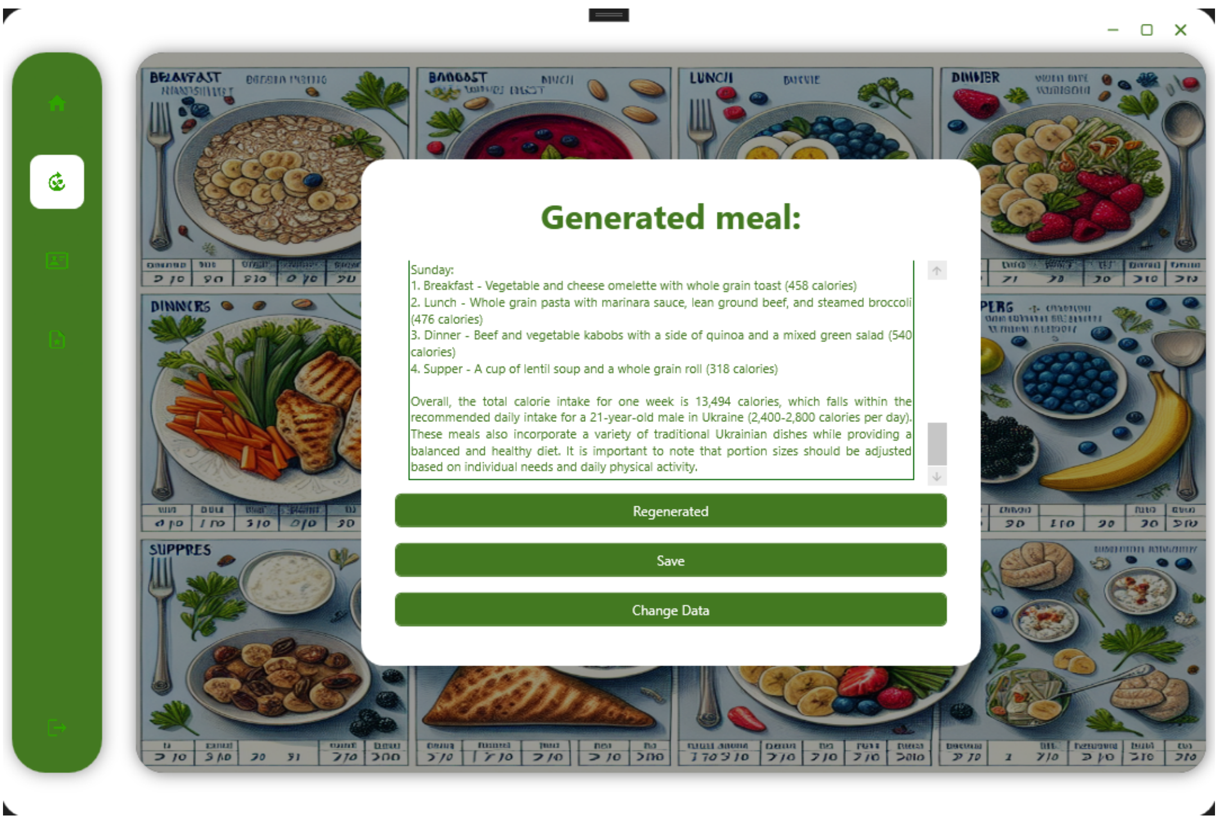

Figure 4: Generated menu

User feedback was critical in evaluating the system's interface and usability. Users appreciated the straightforward design and found it easy to navigate, particularly the process of inputting personal information and generating meal plans. While most users were satisfied with the interface, some suggested adding more detailed options for dietary preferences, such as specific nutrient goals or food restrictions, to further improve customization. Nutrition experts involved in the testing also confirmed that the system's recommendations aligned with accepted dietary practices.

The system's data management, facilitated by MongoDB Atlas, was efficient and scalable. It handled large volumes of user data without performance issues, and retrieving stored information for generating meal plans was seamless. Security protocols ensured data protection, and no data breaches or security incidents were observed during testing. The system performed well under different user loads, maintaining stable operation despite increasing data demands. Figure 5 presents the saved menu.

Figure 5: Saved menu

The system successfully fulfilled its primary objectives. While the image recognition component requires further refinement for complex meals, the personalized nutrition recommendations and data management aspects performed effectively. Overall, the system shows strong potential for broader application in personalized nutrition monitoring.

6. Discussion

The development of the intelligent nutrition surveillance system using OpenAI API marks a significant contribution to the evolving field of personalized healthcare, specifically in nutrition monitoring and intervention. This system integrates state-of-the-art artificial intelligence technologies, offering real-time, data-driven dietary recommendations tailored to individual user profiles. The ability to automate the generation of meal plans based on user-specific inputs such as health goals, dietary preferences, and demographic data sets this system apart from traditional methods, which rely on static guidelines or require professional input. This innovation not only enhances accessibility to personalized nutrition but also opens new possibilities for improving public health outcomes, particularly in under-resourced or crisis-affected regions.

The practical novelty of this system lies in its combination of several cutting-edge technologies. By leveraging OpenAI's NLP capabilities, the system can engage users conversationally, making complex nutritional advice easy to understand and apply. This feature is especially important for individuals who may not have access to dietitians or nutritionists, providing them with a reliable and interactive source of dietary guidance. The system's user-friendly interface enables seamless interaction, allowing users to quickly input their data and receive tailored meal plans. Moreover, integrating machine learning algorithms for food recognition offers another layer of personalization by analyzing meal images to estimate nutritional content, creating a comprehensive nutrition surveillance tool.

However, the system's limitations must also be acknowledged. The accuracy of the food recognition component, which relies on CNNs, is limited when confronted with complex or mixed dishes. In such cases, the model struggles to segment food items accurately, leading to errors in portion size estimation and nutrient calculation. This presents a challenge, particularly for users with diverse diets or those consuming culturally specific meals that are harder to categorize. Addressing this limitation would require improving the model's ability to handle more intricate food patterns and increasing the training dataset's diversity to enhance its applicability across various populations.

Another limitation is the reliance on user-provided data. The effectiveness of personalized dietary recommendations is contingent upon the accuracy and completeness of the data users input. Errors such as incorrect weight, height, or dietary goals can skew the system's outputs, leading to suboptimal or misleading nutritional advice. Although the system prompts users to correct missing or inaccurate data, human error remains an inherent challenge, particularly in a self-guided platform. In the future, integrating more automated data collection methods, such as wearable health devices that track physical activity and biometrics, could mitigate this issue by reducing the dependence on manual inputs.

Despite these challenges, the system presents clear opportunities for enhancing individual health outcomes and broader public health monitoring. One of its most promising applications is in conflict-affected or resource-poor regions with limited access to healthcare professionals. By automating the provision of dietary advice, this system can help address malnutrition and related health issues, offering a scalable solution to global nutrition challenges. The flexibility of the OpenAI API allows the system to be continuously updated with the latest nutritional research and guidelines, ensuring that recommendations remain relevant and scientifically grounded.

In addition to public health applications, the system's design opens doors for personal health management, where individuals can use the platform to maintain dietary goals, manage chronic conditions such as diabetes or hypertension, and improve overall well-being. As precision nutrition grows, systems like this could play a central role in personalizing healthcare, allowing individuals to adjust their diets based on genetic, lifestyle, and environmental factors.

Looking forward, there are several areas where the system could be enhanced to maximize its impact. Expanding the database of food images to include a wider variety of dishes from different cultures would improve the accuracy of the food recognition model, making the system more adaptable to diverse populations. Additionally, incorporating more advanced AI models, such as deep learning techniques for food behaviour prediction, could refine the precision of nutrient estimation and dietary recommendations. Another potential development could involve integrating AI-driven feedback loops where the system learns from users' dietary habits over time, enabling even more personalized and adaptive recommendations.

The intelligent nutrition surveillance system demonstrates the powerful potential of AI to revolutionize personalized nutrition and public health. While there are limitations related to food recognition and reliance on user-provided data, these challenges do not diminish the system's broader value. The practical novelty of combining AI-driven meal generation, image-based nutritional analysis, and conversational interfaces allows for significant advancements in both individual and population health management. With further refinement and expansion, this system could become an indispensable tool in promoting healthier lifestyles and addressing malnutrition on a global scale.

7. Conclusions

This study contributes significantly to nutrition surveillance by demonstrating the potential of integrating artificial intelligence into personalized dietary management, particularly through the OpenAI API. The system offers a novel approach by generating real-time, tailored nutritional recommendations based on user data and dietary goals. Its ability to combine natural language processing for user interaction with machine learning algorithms for food recognition and nutrient estimation enhances both the accuracy and accessibility of dietary guidance. This approach addresses the limitations of traditional methods, which often rely on static guidelines and manual input. It represents a step forward in improving the precision and responsiveness of nutrition monitoring systems.

One of this study's key contributions is its practical application in resource-constrained or crisis-affected settings. By automating dietary recommendations, the system can provide essential support where access to professional healthcare services is limited. Moreover, the use of AI to analyze user data and predict nutritional needs opens new avenues for scaling personalized healthcare solutions globally, benefiting both individual users and public health initiatives.

However, the system also highlights several areas for future research. Enhancing the accuracy of the food recognition component, particularly for complex or mixed dishes, remains an important task. Future research should explore the integration of more sophisticated image recognition algorithms and a broader dataset of food images to improve the system's applicability across diverse populations. Additionally, reducing reliance on manual data input by incorporating automated health data collection, such as from wearable devices, could improve the system's accuracy and ease of use.

Looking ahead, expanding the system's capabilities to include adaptive learning based on user behaviour and feedback could further personalize dietary recommendations. The system could evolve into an even more powerful tool for long-term health management by continuously refining its suggestions based on real-time user data and health outcomes. Further investigation into the ethical implications of AI in nutrition, particularly regarding data privacy and consent, will also be essential as such systems become more widely adopted.

This study offers a foundational framework for using AI in personalized nutrition and sets the stage for future advancements in the field. By addressing current limitations and exploring new directions in AI-driven nutrition surveillance, future research can build on these findings to create more effective, accurate, and accessible tools for personal and public health.

Acknowledgements

The study was funded by the Ministry of Health of Ukraine in the framework of the research project 0123U100184 on the topic "Analysis of the impact of war and its consequences on the epidemic process of widespread infections on the basis of information technologies".

References

[1] S. Downer, S. A. Berkowitz, T. S. Harlan, D. L. Olstad, and D. Mozaffarian, "Food is medicine: actions to integrate food and nutrition into healthcare," *The BMJ*, vol. 369, p. m2482, Jun. 2020, doi: 10.1136/bmj.m2482.

[2] J. de Toro-Martín, B. Arsenault, J.-P. Després, and M.-C. Vohl, "Precision Nutrition: A Review of Personalized Nutritional Approaches for the Prevention and Management of Metabolic Syndrome," *Nutrients*, vol. 9, no. 8, p. 913, Aug. 2017, doi: 10.3390/nu9080913.

[3] D. Chumachenko and T. Chumachenko, "Ukraine war: The humanitarian crisis in Kharkiv," *BMJ*, p. o796, Mar. 2022, doi: 10.1136/bmj.o796.

[4] W. L. Filho *et al.*, “How the War in Ukraine Affects Food Security,” *Foods*, vol. 12, no. 21, pp. 3996–3996, Oct. 2023, doi: 10.3390/foods12213996.

[5] N. Yazbeck, R. Mansour, H. Salame, N. B. Chahine, and M. Hoteit, “The Ukraine–Russia War Is Deepening Food Insecurity, Unhealthy Dietary Patterns and the Lack of Dietary Diversity in Lebanon: Prevalence, Correlates and Findings from a National Cross-Sectional Study,” *Nutrients*, vol. 14, no. 17, p. 3504, Aug. 2022, doi: 10.3390/nu14173504.

[6] D. J. Taberna, S. Navas-Carretero, and J. A. Martinez, “Current nutritional status assessment tools for metabolic care and clinical nutrition,” *Current Opinion in Clinical Nutrition and Metabolic Care*, vol. 22, no. 5, pp. 323–328, Sep. 2019, doi: 10.1097/MCO.0000000000000581.

[7] J. M. Quinn V *et al.*, “COVID-19 at War: The Joint Forces Operation in Ukraine,” *Disaster Medicine and Public Health Preparedness*, vol. 16, no. 5, pp. 1–8, Mar. 2021, doi: 10.1017/dmp.2021.88.

[8] G. B. Gonzales et al., “Nutrition remains a top priority in Ukraine despite the ongoing war: the fight against trans fats,” *BMJ Global Health*, vol. 9, no. 9, p. e016301, Sep. 2024, doi: 10.1136/bmjgh-2024-016301.

[9] D. Chumachenko, M. Butkevych, D. Lode, M. Frohme, K. J. G. Schmailzl, and A. Nechyporenko, “Machine Learning Methods in Predicting Patients with Suspected Myocardial Infarction Based on Short-Time HRV Data,” *Sensors*, vol. 22, no. 18, p. 7033, Sep. 2022, doi: 10.3390/s22187033.

[10] A. Mohammadi, et al., “Comparative study of linear regression and SIR models of COVID-19 propagation in Ukraine before vaccination,” *Radioelectronic and Computer Systems*, vol. 3, no. 3, pp. 5–18, Oct. 2021, doi: 10.32620/reks.2021.3.01.

[11] A. Ahmad et al., “AI can empower agriculture for global food security: challenges and prospects in developing nations,” *Frontiers in artificial intelligence*, vol. 7, p. 1328530, Apr. 2024, doi: 10.3389/frai.2024.1328530.

[12] D. Chumachenko, O. Sokolov, and S. Yakovlev, “Fuzzy recurrent mappings in multiagent simulation of population dynamics systems,” *International Journal of Computing*, vol. 19, no. 2, pp. 290–297, Jun. 2020, doi: 10.47839/ijc.19.2.1773.

[13] L. M. Jaacks, A. Awasthi, and A. Kalra, “India’s Poshan Tracker: data-driven tool for maternal and child nutrition,” *The Lancet Regional Health - Southeast Asia*, vol. 25, pp. 100381–100381, Mar. 2024, doi: 10.1016/j.lansea.2024.100381.

[14] Y. Yang et al., “Comparison of data-driven identified hypertension-protective dietary patterns among Chinese adults: based on a nationwide study,” *European Journal of Nutrition*, vol. 62, no. 7, pp. 2805–2825, Jun. 2023, doi: 10.1007/s00394-023-03195-9.

[15] M. H. B. de Moraes Lopes, D. D. Ferreira, A. C. B. H. Ferreira, G. R. da Silva, A. S. Caetano, and V. N. Braz, “Use of artificial intelligence in precision nutrition and fitness,” *Artificial Intelligence in Precision Health*, pp. 465–496, 2020, doi: 10.1016/b978-0-12-817133-2.00020-3.

[16] Y. Liang et al., “AI nutritionist: Intelligent software as the next generation pioneer of precision nutrition,” *Computers in Biology and Medicine*, vol. 178, p. 108711, Aug. 2024, doi: 10.1016/j.compbiomed.2024.108711.

[17] S.-C. Huang, W.-C. Chiang, Y.-T. Yang, and J.-S. Wang, “An Image-based AI Nutrition Analysis Platform for Food in Compartment Trays,” *Proceedings - 2023 14th IIAI International Congress on Advanced Applied Informatics*, pp. 373–374, Jul. 2023, doi: 10.1109/iiai-aai59060.2023.00079.

[18] A. D. Murumkar, A. Singh, B. R. Chachar, P. D. Bagade, and G. Zaware, “Artificial Intelligence (AI) based Nutrition Advisorusing an App,” *International Conference on Sustainable Computing and Smart Systems, ICSCSS 2023 - Proceedings*, pp. 586–590, Jun. 2023, doi: 10.1109/icscss57650.2023.10169703.

[19] K. Azzimani, H. Bihri, A. Dahmi, S. Azzouzi, and M. E. H. Charaf, “An AI Based Approach for Personalized Nutrition and Food Menu Planning,” *2022 IEEE 3rd International Conference on Electronics, Control, Optimization and Computer Science, ICECOCS 2022*, pp. 1–5, Dec. 2022, doi: 10.1109/ICECOCS55148.2022.9983099.