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Article · September 2024

DOI: 10.59298/RIJPP/2024/322225

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https://rijournals.com/public-health-and-pharmacy/

RESEARCH INVENTION JOURNAL OF PUBLIC HEALTH AND PHARMACY 3(2): 22-25, 2024

RIJPP Publications ISSN ONLINE: 1115-8689

ISSN PRINT 1597-8559

https://doi.org/10.59298/RIJPP/2024/322225

The Role of Artificial Intelligence in Personalized Nutrition

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ABSTRACT

Personalised nutrition uses individual data to optimise dietary recommendations for better health results. The rapid growth of artificial intelligence (AI) provides an innovative solution to the issues of this industry. AI can process massive and complicated datasets, such as genetic, phenotypic, and behavioural data, to generate highly personalised nutrition recommendations. Machine learning methods, ranging from grouping and prediction to deep learning, allow for the discovery of food patterns, health effects, and individualised nutritional requirements. This study investigates the use of AI in personalised nutrition, including existing applications and future perspectives needed to overcome problems such as data interoperability, ethical considerations, and model interpretability.

Keywords: Artificial Intelligence (AI), MPersonalized Nutrition, Precision Nutrition, Machine Learning, Genomics.

INTRODUCTION

Recent years have seen a surge of interest in personalized nutrition, fueled by various scientific and technological advances, as well as trends in the food and pharmacological industries. Consumers and healthcare professionals alike are increasingly aware of how diet and nutrition can determine a person's health and are seeking ways to optimize dietary choices for healthy living and disease prevention. Technologies such as big data, the Internet of Things, and wearable sensors provide tools for improved personalized data collection, while advances in biotechnology increasingly allow the development of personalized nutrition solutions [1, 2]. At the same time, artificial intelligence and more specifically machine learning have achieved groundbreaking successes in various application domains, with deep learning used for image recognition and reinforcement learning revolutionizing areas such as machine control and gaming in the last decade. While many of these applications center around general-purpose or industrial problems, we argue that the success of AI can also be leveraged to solve domain-specific challenges nutrition faces today. This is especially important in the case of personalized nutrition where recommendations should consider individual variance. It isn't just about the macro- and micronutrient intake, which current technology could already address, but also about ingredient and recipe contributions to food organoleptic properties that matter to consumers [3, 4].

FUNDAMENTALS OF PERSONALIZED NUTRITION

Personalized nutrition is an interdisciplinary field that involves the use of data related to individuals to develop specific recommendations with the express purpose of helping people make meaningful behavior and lifestyle changes. Personalized nutrition is viewed as an approach, or a multi-faceted process, rather than as an endpoint in itself. Personalized nutrition involves an iterative process that moves individuals between four realizations: 1) prediction of the metabolic composition of an individual's diet by machine learning; 2) recommendation of best-fit diet based on an individual's health and genetics; 3) measurement of both the outcome of the diet and feedback; and 4) integration of individualized nutritional and microbiome data with expert domain knowledge. Nutritional health, regulatory mechanisms, and social interactions all play substantial and interacting roles in determining human health and variation between different individuals [5, 6]. Personalized nutrition research is, however, still in its infancy. Many scientists, nutritionists, and public health professionals, specializing in not only human diet and nutrition but also agriculture, food science, dietary supplements, microbiome, bioinformatics, mathematical modeling, and personalized health and behavior, are starting to use new technologies to integrate nutrition with health. At present, personalized nutrition is enabled by direct involvement of consumers and can be facilitated by data analysis techniques including artificial intelligence, machine learning, and data mining that process aggregated data for health benefits. These data sources contain information with different dimensions and from different levels such as lifestyle, genomics, variables related to health metrics such as glucose, cholesterol levels, and chronic diseases, and specific indicators of behaviors and emotions such as stress, sleep, and physical activity [1, 7].

FUNDAMENTALS OF ARTIFICIAL INTELLIGENCE

Vastly considered synonymous with actual intelligence, the term "intelligence" refers to the ability of learning, understanding, and knowing. Moreover, artificial intelligence is an area in computer science that studies the creation of machines that think and function like humans. Informally, intelligent devices display an understanding capability that can be performed by a human. The theory and development of computer systems capable of performing tasks that require human intelligence are implemented in the conception, construction, and improvement of robots and algorithmic programs. While AI may offer numerous benefits to all sectors, nutrition science is scarcely integrating technologies, including AI. Artificial intelligence methods and interventions are powerful tools for nutrition researchers and practitioners. AI allows for better outcomes in specific applications due to the storage and analysis of massive and complex datasets and its ability to recognize patterns and associations [8, 9]. In applications of machine learning, it is often the case that human intelligence is extended rather than replaced, as learning algorithms alter themselves to better assign data categories of interest. In the field of personalized nutrition, it is not entirely practical to assign a certified nutritionist to each person being considered because it would be both costly and time-consuming, reducing people's adherence to the prescription health plan whenever incorporated into a clinical trial. As the quantity of people involved and trial period raise, the construction of health plans needs to become more efficient. Therefore, with AI, machines become capable of learning and performing human intelligence tasks, and here, AI has the potential to become a powerful assistant to nutrition practitioners [10, 11].

INTEGRATION OF ARTIFICIAL INTELLIGENCE IN PERSONALIZED NUTRITION

In precision nutrition, artificial intelligence algorithms use special genetic and phenotypic data to create specific cells that express an individual's response to certain nutrients. Usually, this data is coupled with big data sources to identify food chemical components and additives and analyze their interactions that may influence health and performance. Artificial intelligence can help in treating people with specific nutrient requirements such as athletes and soldiers and improve food taste and catering within specific food production systems. Precision nutrition, which is an important extension of personalized nutrition, uses individual-specific information to create personalized nutrition recommendations. Using tools such as artificial intelligence, precision nutrition recommendations focus on food types, portion sizes, and diet patterns to enhance health, prevent, and treat existing medical conditions. Precision nutrition often combines genetic and phenotypic information with big data and analysis of interactions between food and beverage nutrients, non-nutrient components, and the individual during the pre- and post-meal consumption phases [12, 13].

DATA COLLECTION AND ANALYSIS

Dietary collection and metadata extraction are essential to provide personalized data for precise dietary intake. However, traditional approaches for dietary assessment are based on self-reporting, which is subject to misreporting, under-reporting, and other biases. To prevent deviations from as-built datasets, such as extra salt added after rote intake interviews but unavailable prior to analysis, other available dietary data augmentation approaches are required. Nevertheless, insufficient labeled datasets hamper research. Users' dietary data can be extended using algorithms and sensors, allowing them to have permanent access to sound advice. Among current self-reporting approaches, FFQs and food diaries are time-consuming and reach temporal saturation during the interview process. However, the problems of food intake interviews can be addressed. The performance of retrospection technologies, such as smartphone food logs and food photography, is affected by recall, memory, record periods, privacy concerns, and installation and usage constraints, which limit their use. Efforts should focus on implementing more advanced fuzzy logic algorithms and rule-based systems, together with image recognition and deep learning technologies, for automatic metadata extraction. Furthermore, statistical methods will be used to assess the soundness and degree of under-reporting of the derived datasets in real time. Future data collection should integrate cost-effective and convenient approaches and auxiliary dietary intake data sources to overcome the current problems with dietary consumption [14, 15].

MACHINE LEARNING ALGORITHMS FOR PERSONALIZED NUTRITION

Machine learning algorithms for personalized nutrition can generally be split into four classes: clustering, prediction, classification, and deep learning. Clustering is used to form groups of individuals that share similar dietary intake or metabolic profiles. This class of reproducibility is not impacted by biological differences across individuals, which is a major point in personalized nutrition. K-means and hierarchical clustering are common algorithms used in this class. These algorithms first assign each individual to a particular group with an assumption of similarity and then use averages or some centers of the data points to update the group until convergence. The second class is prediction, which aims to predict key health outcomes or phenotypes of interest given dietary data, anthropometric, and genetic data. Ordinary least squares, support vector machines, and elastic net are some common tools that have been used for prediction analysis. This class is most useful to investigate the relationship between food intake and phenotypes of interest [16, 8]. The third class is classification of individuals based on health status, which involves using dietary, genetic, or microbiome data or a combination of these to determine groups of healthy and diseased individuals. Logistic regression, random forest, and support vector machines are some common tools that belong to this category. The fourth class of algorithms, deep learning, includes recurrent neural networks, convolutional neural networks, and generative adversarial networks. Deep learning has become a promising field for many bioinformatics problems due to its strong representation power and has also shown some initial success in food assessments. However, deep learning methods in personalized nutrition are still in their early stages and warrant further exploration [6, 1].

CHALLENGES AND FUTURE DIRECTIONS

- There is a need to perform more RCTs for the development of robust DRI and AI methods.
- AI and DRI rely heavily on genotype, phenotype, and medical data, meaning that the interoperability of all electronic health records of patients is of critical importance for both clinical trials and AI.
- More interpretable AI models, methods, and algorithms are critically important for nutritionists to understand the root causes for dietary suggestions AI produces and accept them to provide patients with the best individually suited diets.
- The granular data of all types across multiple scales of the human body and main data such as a wide spectrum of foods, and their forms, combined with spatio-temporal and individual-level validation instructions are of paramount importance. These data types will enable the correction of DRI and subsequent training for AI models with a greater number of facts, which in turn might contribute to better performance on real data.
- Several ethical, legal, and human rights issues should be resolved before the wide implementation of AI because changes that are currently implemented and proposed are woefully inadequate.
- The need to balance the mentality required before the use of more biomarker-driven dietary planning programs while remembering that for those with differing educational levels, both food access and food preparation for perceived palatability are medicinally important. Proper balance where fewer constraints are equally clinically efficacious will assist the public in a more personally responsible direction.
- A wider discussion of what are appropriate nutrition strategies for problems and an assessment of methods that are helpful to assess diets to be prescribed for these issues.
- This wider application should be part of the body of studies before the application of nutrition strategies in the field of obesity and type 2 diabetes occurs [17, 18].

CONCLUSION

The potential for improving health and wellness through the integration of artificial intelligence with personalised nutrition is substantial. With the use of artificial intelligence (AI), personalised nutrition can advance to offer more precise, effective, and customised nutritional recommendations based on personal information including genetics, phenotypic features, and lifestyle choices. However, issues with data quality, ethics, and the interpretability of AI models must be resolved if AI is to fulfill its full potential in this domain. To enable the general adoption of personalised nutrition as a norm in preventive healthcare and chronic disease management, future research should concentrate on developing AI algorithms, enhancing data integration, and overcoming ethical concerns.

REFERENCES

1. Kirk D, Catal C, Tekinerdogan B. Precision nutrition: A systematic literature review. Computers in Biology and Medicine. 2021 Jun 1;133:104365.
2. Samieri C, Yassine HN, Melo van Lent D, Lefèvre-Arbogast S, van de Rest O, Bowman GL, Scarmeas N. Personalized nutrition for dementia prevention. Alzheimer's & Dementia. 2022 Jul;18(7):1424-37. researchgate.net
3. Camaréna S. Artificial intelligence in the design of the transitions to sustainable food systems. Journal of Cleaner Production. 2020 Oct 20;271:122574.
4. Arefin S, Kipkoech G. Using AI and Precision Nutrition to Support Brain Health during Aging. Advances in Aging Research. 2024 Aug 19;13(5):85-106.
5. Bush CL, Blumberg JB, El-Sohemy A, Minich DM, Ordovás JM, Reed DG, Behm VA. Toward the definition of personalized nutrition: a proposal by the American Nutrition Association. Journal of the American College of Nutrition. 2020 Jan 2;39(1):5-15. tandfonline.com
6. Berry SE, Valdes AM, Drew DA, Asnicar F, Mazidi M, Wolf J, Capdevila J, Hadjigeorgiou G, Davies R, Al Khatib H, Bonnett C. Human postprandial responses to food and potential for precision nutrition. Nature medicine. 2020 Jun 1;26(6):964-73. nih.gov
7. Rogers PC, Barr RD. The relevance of nutrition to pediatric oncology: A cancer control perspective. Pediatric Blood & Cancer. 2020 Jun;67:e28213.
8. Kirk D, Kok E, Tufano M, Tekinerdogan B, Feskens EJ, Camps G. Machine learning in nutrition research. Advances in Nutrition. 2022 Nov 1;13(6):2573-89. sciencedirect.com
9. Chew HS, Ang WH, Lau Y. The potential of artificial intelligence in enhancing adult weight loss: a scoping review. Public health nutrition. 2021 Jun;24(8):1993-2020.
10. Qarajeh A, Tangpanithandee S, Thongprayoon C, Suppadungsuk S, Krisanapan P, Aiumtrakul N, Garcia Valencia OA, Miao J, Qureshi F, Cheungpasitporn W. AI-Powered Renal Diet Support: Performance of ChatGPT, Bard AI, and Bing Chat. Clinics and Practice. 2023 Oct;13(5):1160-72. mdpi.com
11. Jain A, Way D, Gupta V, Gao Y, de Oliveira Marinho G, Hartford J, Sayres R, Kanada K, Eng C, Nagpal K, DeSalvo KB. Development and assessment of an artificial intelligence–based tool for skin condition diagnosis by primary care physicians and nurse practitioners in teledermatology practices. JAMA network open. 2021 Apr 1;4(4):e217249-. jamanetwork.com
12. Connell J, Toma R, Ho C, Shen N, Moura P, Cai Y, Tanton D, Banavar G, Vuyisich M. Evidence-based precision nutrition improves clinical outcomes by analyzing human and microbial molecular data with artificial intelligence. Biorxiv. 2021 Apr 26:2021-04. biorxiv.org
13. Sak J, Suchodolska M. Artificial intelligence in nutrients science research: a review. Nutrients. 2021 Jan 22;13(2):322.
14. Schruff-Lim EM, Van Loo EJ, van Kleef E, van Trijp HC. Turning FOP nutrition labels into action: A systematic review of label+ interventions. Food Policy. 2023 Oct 1;120:102479. sciencedirect.com
15. Zhang J. Innovative food recommendation systems: a machine learning approach. 2023. brunel.ac.uk
16. Panagoulias DP, Sotiropoulos DN, Tsihrintzis GA. Biomarker-based deep learning for personalized nutrition. In2021 IEEE 33rd International Conference on Tools with Artificial Intelligence (ICTAI) 2021 Nov 1 (pp. 306-313). IEEE. researchgate.net
17. Saxena S, Jena B, Gupta N, Das S, Sarmah D, Bhattacharya P, Nath T, Paul S, Fouda MM, Kalra M, Saba L. Role of artificial intelligence in radiogenomics for cancers in the era of precision medicine. Cancers. 2022 Jun 9;14(12):2860. mdpi.com
18. Brancato V, Esposito G, Coppola L, Cavaliere C, Mirabelli P, Scapicchio C, Borgheresi R, Neri E, Salvatore M, Aiello M. Standardizing digital biobanks: integrating imaging, genomic, and clinical data for precision medicine. Journal of Translational Medicine. 2024 Feb 5;22(1):136. springer.com

CITE AS: Ngugi Mwaura J. (2024). The Role of Artificial Intelligence in Personalized Nutrition. RESEARCH INVENTION JOURNAL OF PUBLIC HEALTH AND PHARMACY 3(2):22-25. https://doi.org/10.59298/RIJPP/2024/322225