

Biological Forum – An International Journal

16(9): 124-132(2024)

ISSN No. (Print): 0975-1130 ISSN No. (Online): 2249-3239

Al Innovations in Nutrition: A Critical Analysis

Midhila Mahendran*, Karthika B., Manoj Kumar Verma and Krishnaja U. Department of Community Science, College of Agriculture Vellayani, Trivandrum (Kerala), India.

(Corresponding author: Midhila Mahendran*) (Received: 27 June 2024; Revised: 26 July 2024; Accepted: 11 August 2024; Published: 14 September 2024) (Published by Research Trend)

ABSTRACT: Artificial Intelligence (AI) can be defined as the theory and development of computer systems capable of performing tasks that typically require human intelligence, including visual perception, speech recognition, decision-making, and language translation. The primary objective of AI development is to create machines or software that can simulate human activities and reasoning, such as image recognition, language comprehension, problem-solving, and decision-making through learning from errors. AI is rapidly advancing and offers significant opportunities for progress and applications across various healthcare fields. In nutrition research, AI's ability to extract, structure, and analyze extensive data from social media platforms is enhancing our understanding of dietary behaviours and perceptions. Additionally, AI-powered tools can aid in tracking dietary intake, providing feedback, and encouraging healthier food choices, though their adoption in clinical nutrition brings ethical and regulatory concerns, such as data privacy and potential bias. This article aims to review the current applications of AI in nutrition science research, exploring its growing impact on medical diagnostics, risk prediction, and therapeutic support.

Keywords: Artificial Intelligence (AI), Optimal diet, Gut microbiome, Mobile health (mHealth) applications, Step Tracker, Image analysis.

INTRODUCTION

Assuming a single perfect diet could meet everyone's needs is unrealistic given the vast diversity in human biology. Our genetics, metabolism, physiological condition, gut microbiome, lifestyle, and environment all play significant roles in shaping our nutritional requirements (Verma et al., 2018). Nutrition may contribute to assisting individuals with such conditions. With the technology currently at our disposal, we suggest implementing a recommendation system for their daily lifestyle (WHO, 2018). At first, computer scientist John McCarthy developed "artificial intelligence" in 1955 (Adams et al., 2020). The term Artificial intelligence (AI) describes the "cognitive" functions of computers and machines. In the 50-year history of AI, this field has made remarkable achievements that play very important roles in both research and industrial applications. The latest wave of AI started in 2012 and was facilitated by the success of novel computation models like deep learning neural network models (Krizhevsky et al., 2012). The idea of 'one size fits all' is swiftly becoming outdated in the field of nutritional science. AI's ability to process extensive datasets ranging from genetic information to personal lifestyle habitsis driving a transformation towards highly customized dietary advice. This personalized approach not only addresses unique nutritional requirements but also aligns with individual health objectives and tastes. By leveraging advanced algorithms and analytics, detailed nutrition

recommendations are now more finely tuned to each person's specific needs. This evolution represents a significant shift from generalized dietary guidelines to a more bespoke nutrition strategy. As AI continues to advance, the precision of dietary suggestions is becoming increasingly sophisticated, ensuring they are more relevant to each person's unique profile. This shift towards individualized nutrition holds promise for more effective and engaging health interventions. Ultimately, this tailored approach is poised to revolutionize how we understand and manage our dietary health (Sharma and Gaur 2024). The 2018 Global Nutrition Report showed that a nutritional conflict caused by an extreme lack or excess of nutrition is a worldwide nutritional security problem (Fanzo et al., 2018). In this era, there is sufficient research evidence to suggest that nutritional imbalance is the main risk factor leading to cardiovascular disease, diabetes, and colorectal cancer. Consequently, the principle of dietary balance emphasizes the variety and thoughtful combination of foods, emerging as a key strategy for contemporary individuals seeking to enhance their health and quality of life (Cao et al., 2021). Artificial Intelligence (AI) in personalized nutrition and food development presents a compelling narrative, one that might reshape our approach to health and wellness. The AI applications in the field of nutrition and dietetics are a fairly new and important field. Different apps related to nutrition are offered to the use of individuals. The importance of individual nutrition has also triggered the increase in

Mahendran et al.,

artificial intelligence apps (Matusheski et al., 2021). It is extremely important to explain the practices in this field with scientific evidence (Adams et al., 2020; Rozga et al., 2020). It is thought that different apps such as food preferences and dietary intake can play an important role in health promotion (Matusheski et al., 2021). Artificial intelligence is used in science and engineering to expand upon human intelligence by building intelligent machines and intelligent computer programs (Joshi et al., 2024). At present, with the new round of scientific and technological revolution and the in-depth evolution of industrial transformation, a new generation of cutting-edge technologies and equipment based on artificial intelligence is constantly infiltrating and integrating into the field of food nutrition, and driving the global food nutrition industry to develop rapidly in the direction of personalization, precision, and intelligence (Miyazawa et al., 2022).

MATERIAL AND METHODS

This review focused on articles from the year 2000 to 2024. The selection was influenced by the current rapid advancement in AI technology. Searches were conducted across eight major databases: PubMed, Web of Science, EBSCO, Agricola, Scopus, IEEE Explore, Google Scholar, and Cochrane. The review covered studies where AI was directly applied to nutritional science. It also incorporated research utilizing AI to assess dietary needs and enhance lifestyle. Investigations centered on AI's application in managing human nutrition were included. However, studies involving animals were not considered. Research published in non-English languages was excluded from the review. Only articles that met these criteria were analyzed. The focus was on AI's impact on human dietary practices and health. The review aimed to gather relevant and high-quality evidence within these parameters. References were meticulously examined to determine their relevance. Relevant excerpts were transferred to Word documents for further examination. These documents were organized under designated subheadings to ensure clarity. The initial screening involved assessing titles and abstracts for relevance. This was followed by a thorough review of the full text. During this stage, studies were assessed for their methodological quality. Only those meeting established quality standards were incorporated into the final review. Data extracted from each study included author names and publication years. The review also documented each study's objectives and subject matter. The features, results, and constraints of the studies were meticulously documented. The type of AI used in each study was noted. The specific area of nutrition to which AI was applied was identified. A total of 250 articles were initially retrieved. Out of these, 22 articles met the inclusion criteria. These 22 articles were included in the final review article

RESULTS AND DISCUSSION

Our evaluation highlights that Artificial Intelligence (AI) is essential in the domain of nutrition, with a major focus on dietary evaluation. AI systems are adept at

analyzing and interpreting complex dietary information to deliver personalized dietary assessments. Although it is less emphasized, AI also aids in predicting malnutrition by identifying individuals at risk based on their eating habits and health data. Moreover, AI supports lifestyle modifications by recommending individualized dietary adjustments and behavioral changes. Its use extends to overseeing and managing diet-related health conditions, providing actionable insights to enhance health outcomes. While dietary evaluation remains the core function. AI's capability to foresee malnutrition and guide lifestyle changes is gaining traction. Additionally, AI-powered tools facilitate the early detection of diet-related health issues, enabling timely interventions. The integration of AI in nutrition research is advancing, with ongoing improvements enhancing its effectiveness. Despite its wide-ranging applications, the focus on managing dietrelated conditions through AI is still developing. Overall, AI's contributions to nutrition are diverse, with a primary emphasis on dietary evaluation and expanding roles in other aspects.

Application of AI in Dietary Assessment. Traditional methods of dietary evaluation mainly rely on selfreported data or structured interviews carried out under the guidance of dietitians. These approaches, however, can be subjective, prone to inaccuracies, and require significant time investment. Artificial Intelligence (AI) is addressing these issues by transforming the process of dietary assessment. AI provides innovative solutions that enhance the accuracy and efficiency of evaluating dietary habits. By leveraging advanced algorithms, AI reduces the subjectivity inherent in traditional methods. It also minimizes the potential for errors and accelerates the assessment process. AI tools offer more precise and objective insights into dietary patterns. Consequently, these technologies streamline the evaluation process, making it less time-consuming. The integration of AI into dietary assessment represents a significant advancement over conventional practices.

Food image databases, food image segmentation, food classification, and food volume estimation are components of image analysis that can be integrated into dietary assessment systems within mobile health (mHealth) applications. These systems utilize smartphone cameras to capture images, offering a convenient method for users of all ages to take photos, particularly of food items. This technology enables continuous and real-time recording of health data. By employing advanced image analysis techniques, these systems can categorize and assess food types and quantities with greater precision. Food image databases store a wide range of food images for reference and comparison. Food image segmentation breaks down images into distinct components to identify and analyze specific items. Food classification assigns categories to different foods based on their visual attributes. Food volume estimation measures the quantity of food captured in images. Together, these features support detailed and accurate dietary tracking. Users can easily capture and record their meals using their smartphones. This approach provides a seamless way to monitor dietary intake and health metrics. The integration of

these technologies facilitates real-time health data collection. It also offers an accessible solution for ongoing dietary management. As a result, individuals can maintain a comprehensive record of their nutritional habits. This innovative method enhances the effectiveness and convenience of dietary assessment (Konstantakopoulos *et al.*, 2023; Konstantakopoulos *et al.*, 2024).

Overall, the AI-powered Nutrition Assistant and Step Tracker created in this project could greatly enhance individuals' capacity to sustain a well-balanced diet and lifestyle. By active delivering tailored recommendations, real-time monitoring, and datainformed insights, this technology offers significant benefits. It marks a noteworthy advancement in the realm of digital health and wellness solutions. Users are empowered to make knowledgeable choices and reach their dietary and fitness objectives. This tool provides customized advice based on individual needs and preferences. It enables ongoing tracking of dietary intake and physical activity. The data-driven approach allows for more precise adjustments to personal health strategies. The integration of these features supports improved adherence to nutrition and exercise plans. This innovation contributes meaningfully to personal health management. It also helps users stay engaged and motivated by providing real-time feedback. The application of AI in this context signifies a major leap forward in health technology. By leveraging advanced algorithms, it offers more accurate and actionable information. The AI-powered system enhances the overall user experience in managing wellness. It represents a substantial development in personalized health solutions. In essence, it equips users with the tools to better achieve their health and fitness aspirations (Shakthivel et al., 2024).

Natural language processing (NLP) is a revolutionary development in food tracking and dietary evaluation. This technology has the potential to redefine how people record their food consumption by translating textual descriptions into meaningful nutritional information. NLP algorithms can scrutinize and understand food-related text, pinpointing particular food items, portion sizes, and even preparation methods mentioned in descriptions or restaurant menus. This automated system not only alleviates the effort required from users who might find manual food logging cumbersome but also greatly improves the precision of the dietary data gathered (Bond *et al.*, 2023)

Unique dietary guidance, powered by artificial intelligence (AI), introduces ainnovative approach to nutrition by leveraging individual data to formulate customized diet plans. These suggestions are based on a thorough evaluation of variables such as a person's age, sex, activity level, genetic composition, dietary history, and specific health goals or preferences. AI algorithms analyze this information to create highly personalized nutritional strategies that enhance nutrient intake, assist in weight management, address nutritional deficiencies, and accommodate dietary restrictions or desires. Whether aiming for weight reduction, muscle enhancement, chronic condition management, or overall wellness, AI provides tailored recommendations to meet these objectives.

Assessment of food and nutrient intake by using AI. The 24-hour food recall, food diary, and three-day food weighed survey are widely recognized methods for evaluating an individual's food and nutrient intake. These approaches are time-consuming and demand trained professionals to conduct interviews and gather data. They largely depend on the individual's recollection of their dietary intake (Sharma et al., 2020). The precision of the data is often limited. particularly when the individual is elderly or suffers from conditions that impair memory, such as dementia or Alzheimer's disease. In these situations, ensuring proper nutrition and accurately assessing food and nutrient intake becomes challenging, as nutritional adequacy is crucial for maintaining well-being and mitigating functional decline associated with aging and disease (WHO, 2021). Dependable and precise data on food and nutrient intake are crucial for designing and evaluating therapeutic menus for patients receiving medical care. Previous research has indicated that the accuracy of data collected using traditional methods may be compromised due to incorrect estimations of food intake (Martin et al., 2009). Moreover, the data does not provide any legitimacy and validity of the menu consumed. The facial recognition or vision-based system designed to identify food items and portion sizes aims to address this issue. Previously, the method of facial recognition was employed in specialized user interfaces for mobile phones and adapted for the advancement of food identification and portion estimation (Zhu et al., 2010).



Fig. 1. Process flow of design of AI for Food and Nutrient intake.

AI and nutrient evaluation of diet. Accurate dietary assessment and food and nutrient intake information may lead to healthier diets and better clinical outcomes. This is particularly important for providing nutritional care to those with obesity and diet-related non-communicable diseases. In such cases, precise evaluation of food and nutrient intake enables glycqemic and lipidemic control. Miscalculations in carbohydrate intake and counting can affect the dose fixing of insulin (Brazeau *et al.*, 2013).

Machine learning techniques, employing random forest models and out-of-bag estimation, have been created to assess the impact of dietary intake on the human gut

Mahendran et al.,

microbiome by analyzing fecal bacteria and metabolites. These advanced algorithms facilitate a detailed understanding of how diet influences gut health through comprehensive data analysis (Shinn et al., 2020). By identifying biomarkers that predict how food components affect health and disease onset, such applications are anticipated to advance the development of targeted therapies for gut microbiota. This approach aims to enhance clinical outcomes for chronic conditions like irritable bowel syndrome, depression, anxiety, and type 2 diabetes mellitus (Li et al., 2022).

AI-driven risk prediction models are now capable of identifying individuals who are at risk of developing diet-related health problems. Self-monitoring dietary habits has been streamlined with AI-powered tools, and precision nutrition has become increasingly tailored to individual needs. Additionally, AI-based image analysis techniques have been trialed for evaluating nutrient intake in hospitalized patients (Tahir and Loo 2021), estimating protein content of supplement powders (Dalakleidi et al., 2022), fully automating calorie intake estimation (Wang et al., 2022), estimating carbohydrate content of foods for diabetics and estimating children's fruit and vegetable consumption (Boushey et al., 2017). This technology holds considerable promise for various applications within the field of nutrition.

Research is exploring the effectiveness of AI-driven dietary assessment tools for self-monitoring food intake. Studies show that self-monitoring is linked to successful weight loss. AI improves the accuracy and efficiency of tracking dietary habits. It provides realtime feedback, personalized recommendations, and helps identify food consumption trends. This advancement in AI offers potential for more effective weight management and healthier eating behaviors. (Burke et al., 2011) but people often underestimate dietary intake (especially energy) particularly those with obesity (Subar et al., 2015). Digital image dietary assessment has been shown to reduce under reporting (Ege et al., 2018). Technology-supported selfmonitoring may improve dietary changes, adherence, and anthopometric outcomes compared to other methods (Wang et al., 2022). Findings from the burgeoning field of AI-assisted dietary assessment suggest potential to estimate portion size, carbohydrate content, and calorie content of foods (Kaur et al., 2023). Every method of dietary assessment has its drawbacks. For instance, a single 24-hour recall only captures the food consumed on one atypical day and may not accurately represent an individual's usual intake. To obtain a more reliable estimate of typical dietary patterns, multiple 24-hour recalls or food records are necessary. Relying on just one day's data can lead to an incomplete picture of overall eating habits. Collecting data over several days helps to account for daily variations in diet. This approach provides a more comprehensive view of an individual's usual intake. Thus, using multiple recalls or records improves the accuracy of dietary assessments. Overall, this method helps in better understanding dietary habits and intake distributions (Yang et al, 2019). One limitation of food records is that they can cause awareness bias (Garden et al., 2018). FFQs can lead Mahendran et al., Biological Forum – An International Journal 16(9): 124-132(2024)

to over reporting of average dietary intakes and can rely on the participant's ability to accurately recall portion sizes and frequencies, similar to 24-hour recalls. Also, the FFQ may be interrupted; therefore, its ability to stay focused can be challenging for indices (Gause, 2024). For these reasons, new dietary assessment methods are needed for the well-being of individuals and researchers. AI shows promise to meet the critical need for accurate, low-burden dietary assessment. AI-based digital image methods can reduce the burden when they require fewer tools (e.g. smartphone instead of a heavy scale).

A critical review of this array of techniques is needed, particularly as these types of technologies become increasingly deployed for use by the public. For instance, in some countries, smartphones are already on the market equipped with camera technology purported to provide feedback about the calorie content of foods (Doulah et al., 2019). The objective of this study was to conduct a systematic review of the literature comparing fully automated AI-based methods of dietary assessment from digital images to human assessors and to ground truth. The advantages of AI-powered image recognition over traditional methods like manual food diaries and 24-hour recalls are significant. Firstly, it reduces the burden on participants by eliminating the need for meticulous record-keeping and memory-based reporting. Users can simply snap pictures of their meals, making the process more convenient and less prone to recall bias. Secondly, AI can provide real-time feedback and nutritional analysis, empowering individuals to make informed dietary choices instantly. Additionally, AI-driven dietary assessment offers the potential for personalized recommendations, catering to an individual's specific nutritional needs and goals. Overall, AI-powered image recognition represents a transformative shift in the field of dietary assessment, promising greater accuracy, efficiency, and userfriendliness, while minimizing the limitations associated with traditional methods.

Dietary assessment with multimodal CHATGPT. The rise of AI foundation models has introduced a fresh viewpoint. However, AI techniques face difficulties in effectively generalizing across various food types, dietary habits, and cultural contexts. As a result, AI applications in the nutrition sector often exhibit narrow specialization. This limitation affects their overall effectiveness and accuracy. Consequently, these models may struggle to provide comprehensive dietary insights. Thus, there's a need for further development to enhance their adaptability and precision in diverse dietary scenarios. Recently, the emergence of multimodal foundation models such as GPT-4V powering the latest ChatGPT has exhibited alarming potential across a wide range of tasks (e.g., Scene understanding and image captioning) in numerous research domains. These models have demonstrated remarkable generalist intelligence and accuracy, capable of processing various data modalities (Lo et al., 2024). GPT-4V can leverage surrounding objects as scale references to deduce the portion sizes of food items, further enhancing its accuracy in translating food weight into nutritional content. GPT-4V, which powers the latest 127

generation of ChatGPT, for dietary assessment. Previously, GPT-4V has demonstrated impressive capabilities in understanding visual content and responding to queries with a wide spectrum of knowledge and a high degree of natural language proficiency (Open AI, 2023). GPT-4V demonstrates satisfactory performance in identifying food items, achieving an improved accuracy of 87.5% when language prompts regarding the food's origin are provided. Adeptness in estimating portion sizes is remarkable, with the ability to utilize the scale of nearby objects as a reference. GPT-4V's ability to convert the weight of food items into their nutritional components shows a high level of accuracy, correlating closely with the nutritional data from the USDA National Nutrient Database1. This highlights GPT4V's potential for effective cross-referencing and accurate interpretation within the context of nutritional science (Lo et al., 2024).

	Language Promot	Language Prompt
Insop Prompt	Recognise the fact <u>hyper</u> in the provided images, both before and after consumption. Use surrounding objects as references for approximating <u>ordering stars</u> . Provide a reasonable estimate in grams for the amount of each food category consumed. Please note that these food items are from Ghana and Kerya.	Calculate the <u>nutritional content</u> , including carbohydrates, protein, fat, and calories, for a 300g rifed fish, 25g of banku, 75g of tomato sauce and 20g of onion slices. Please present the results in the following format: Carbohydrates: [g], Protein: [g], Fat [g], Calories: [kcal].
	GPT-4V	GPT-4V
	To approximate the position size, If use the cap and the plate as references, assuming the plate is of administration grant and which is approximately <u>(10):2 plate in strategies</u> (using a splicits as a sales, we can make the biologing estimates: Food stern 1 (Fried Faith): Initial portion approximately 400g; Positions on the splicit of the sales of the splicit of the proton approximately 300g; Position consumed approximately 250g; Position consumed approximately 75g; Position consumed approximately 75g; Position consumed approximately 75g; Position consumed approximately 25g; Position consumed approximately 25g; Position consumed approximately 25g; Position consumed approximately 25g;	For 303g of final flah, the nutlitional content include log of cataloyidates, 78g of protein, 33g of fat, and 606 kcal of calorise. For 250g of banks, it contains 120g of carabidythesis, 43g of protein, 10g of fat, and 527.5 ktal of calorise. For 75g of formatic searce, it provides 3g of carabidythesis, 0.75g of protein, 0.225g of fat, and 15 kcal of calorise. For 20g of onion silices, there are 1.8g of carabidythates, 0.22g of protein, 0.22g of fat, and 8 kcal of calorise.

Role of AI in food selection. Currently, the term deep artificial intelligence refers to the classic artificial neural network (ANN) with more perceptron layers. ANN is a supervised learning model inspired by the biological neural networks of our nervous system. It is a mathematical model that describes an input/output relationship. This model can be trained based on human experience (training data), and the well-trained model can subsequently be applied to new inputs (test data) for practical applications. Here is a simple example from the 2015 Nature review paper (LeCun et al., 2015): the success of deep learning has brought up many new food-related research and applications. These will be introduced in this SIB. However, it is worthwhile to mention that current AI models are considered "narrow AI" since each model can only focus on a specific targeted task during training. Therefore, researchers still need to choose specific AI models for different food-related applications and prepare corresponding datasets to train each respective model according to the required task. Large-scale Image recognition is one of the most important applications of deep learning and relies on a large image dataset for supervised network training. Food-101 (Bossard et al., 2014) is the largest public dataset for food image classification. It consists of 101,000 images of the top 101 food categories from 'foodspotting.com' as shown in Fig. 2(a). Japanese researchers released two food detection datasets UECFOOD-100 (Matsuda *et al.*, 2012) and UECFOOD-256 (Kawano and Yanai 2015) for detecting the location of food in images and predicting the categories of foods. UECFOOD-100 contains 9,060 images Fig. 1. A typical workflow diagram of training a supervised learning model (such as ANN), the training process needs to manually prepare input and output pairs, and the well-trained model can be directly applied to the new data. 3 of the most popular 100 classes of Japanese foods as. UECFOOD-256 further added international foods of various countries with 256 categories. It includes 60,000 images of 60 food categories and 78,000 bounding-box labelled sample images which can be used for training the network to accurately detect the position of specific food in the camera field of view. It can further benefit for potential robotic operations for fully automated warehouses and grocery stores (Cai et al., 2019). With these known categories of food, the nutrient content of that food can be estimated based on the food and nutrient database released by USDA Food and Nutrient Database for Dietary Studies. Using equipment like 3D cameras and smartphones, the accuracy of nutrient content estimation is expected to rise soon. With this goal in mind, (Meyers et al., 2015) reported the development of an automated mobile vision food diary system called Im2Calories. This app uses an RGB depth image of food to estimate the volume of food and its respective calories. This helps users monitor and control their dietary behaviors. Amazon Go and Amazon Fresh also try to integrate various AI techniques to push the development of advanced shopping technologies.

Advanced learning is a potential and powerful chemometrics tool for qualitative spectroscopic analysis. Spectroscopy, especially near or short infrared spectroscopy (with wavelength range 780- 2500nm), is a powerful tool in food analysis that can assess chemical bond vibrations of food constitutes. As a consequence of the physics of diffuse transmittance and reflectance and the complexity of the spectra, spectroscopy analysis is normally carried out using multivariate mathematics models (Osborne, 2006). Researchers explored the feasibility of CNN to predict the content value using some public and self-collected spectroscopy datasets. Compared to large image datasets in other fields, these spectroscopy datasets are relatively small.

Nutrigenomics and personalised nutrition. Artificial intelligence (AI) in bioinformatics provides effective tools and techniques for collecting, organizing, and analyzing extensive biological datasets, such as genetic, nutritional, and additional pertinent information (Lecroq et al., 2014). Originally, the field of nutrigenomics exclusively focused on research into how nutrients and bioactive foods influence an individual's gene expression. Today, this definition has expanded to encompass studies on nutritional elements that safeguard the genome (Ronteltap et al., 2008).

The use of AI allows for the development of unique meal plans based on a person's genetic makeup. This means that dietary modification can be adjusted to built healthy outcomes, accounting for how specific genes affect nutrient metabolism and overall well-being. This bespoke method signifies a significant advancement 128

Mahendran et al.,

over the traditional one-size-fits-all dietary advice. It provides individualised dietary suggestions by evaluating a person's genetic profile and the genetic differences associated with nutrient metabolism. To develop customized nutrition plans, bioinformatics and can integrate genetic information, dietary evaluations, lifestyle elements, and health data. (Detopoulou et al., 2023).

AI and predictive modelling of diseases. In nutrition science, artificial intelligence plays a critical role in predictive modelling for disease prevention. The included research illustrates the development of forecasting models that employ machine learning methods to identify trends associated with disease risk. These studies showcase how predictive algorithms analyze data to uncover correlations with potential health issues. By leveraging advanced computational techniques, these models reveal patterns that could indicate susceptibility to various conditions. Overall, the research highlights the growing use of AI in predicting health risks based on identified patterns (Theodore et al., 2024). In their discussion of the potential of artificial intelligence (AI) in clinical nutrition, Singer et al. (2024) concentrate on the ways in which AI can improve screening and assessment, identify cancer patients who are malnourished and forecast clinical events in intensive care, as well as the ethical issues and constraints surrounding AI in clinical nutrition. Deep learning with a five-fold crossvalidation demonstrated better prediction accuracy in the study than the current statistical analysis techniques of decision trees and logistic regression (Kim et al., 2021). Through machine learning techniques, Bhat and Ansari (2021) were able to predict diabetes and suggest appropriate diets for patients with the disease. The authors stress the value of data analysis in healthcare and provide a model for predicting diabetes and suggesting a diet.

AI in food recognition and tracking. Advances in computer vision and image analysis have made it possible to identify and classify food items from images automatically. The included studies provide a useful tool for dietary assessment by showing how deep learning models can be applied to analyze food images (Theodore et al., 2024). A part of the food computing domain Techniques for estimating food nutrition have surfaced as viable substitutes. The majority of current techniques estimate food's nutrition by using its external representation (Wang et al., 2022). In a studythe viability of applying deep learning techniques to the near-infrared hyperspectral imaging method of identifying the protein content of a given food is investigated (Li et al., 2023). In order to enhance the efficiency of deep learning-based food segmentation, A sequential transfer learning technique utilises hierarchical clustering. In order to track dietary intake, the ability to segment foods in the meals served to Danish schoolchildren was also tested (Siemon et al., 2021). Their work offers a thorough framework for the automatic nutritional evaluation of Chinese tray meals, addressing the difficulties in applying deep learning techniques for nutrition estimation and tray meal detection to automatically classify food images for Mahendran et al., Biological Forum – An International Journal 16(9): 124-132(2024)

nutritional assessment, deep learning algorithms and machine learning techniques were formulated. Their suggested method divides food into classes based on health by dividing it into segments using a support vector machine (SVM) and a deep learning convolutional neural network (CNN) (Sripada et al., 2023).

Challenges and limitations of ai-based nutrition. There are several limitations to utilizing artificial intelligence in Nutrition science. A major issue in using AI for nutrition is the quality and accessibility of data. Numerous studies reviewed encountered challenges related to the completeness, accuracy, and standardization of dietary and health data (Theodore et al., 2024). Tackling these issues is essential to guarantee the reliability and application of AI models in nutritional research. Additionally, algorithmic bias represents a significant concern when developing and implementing AI models in this field (Mitchell et al., 2021). Several studies have highlighted the limitations of AI models' lack of comprehensibility. As these models grow more complex, understanding the reasoning behind their predictions becomes more difficult. This drawback is especially concerning in clinical and healthcare settings, where extremetrasparency is crucial for building trust and enabling informed decision-making (Panagoulias et al., 2021). Privacy issues surrounding the collection and sharing of personal health data and the ethical use of AI to influence dietary behaviors demand careful attention. Previous research has highlighted the necessity for transparent and ethical guidelines to direct the creation and application of AI technologies (Mitchell et al., 2021).

Effective collaboration between data scientists. nutritionists, healthcare professionals, and policymakers as challenge. Interdisciplinary emerged а communication can help bridge the gap between technical advancements in AI and practical implementation in nutrition science and public health (Mitchell et al., 2021).

Ethical Concerns Regarding AI-Based Nutrition. AIbased nutrition promises to provide personalized dietary recommendations, improve dietary tracking, and enhance overall health outcomes. However, the adoption of AI in this field also raises significant ethical concerns that need to be carefully considered and addressed. The general concerns that are related to the ethical aspects of artificial intelligence as proposed by The Association for the Advancement of Artificial Intelligence are that AI should contribute positively to society and human well-being. It should prioritize not harm and uphold honesty and trustworthiness among AI professionals. Fairness and non-discrimination are essential principles for those involved in AI. Respect for the efforts involved in creating new ideas, inventions, and computing artifacts is crucial. Additionally, AI practitioners must prioritize protecting privacy and confidentiality (AAAI, 2021). The ethical concern of AI-based nutrition is further analyzed concerning nutrition.

Numerous patient-focused communication methods, such as motivational interviewing, are employed to 129

modify dietary habits. However, implementing these techniques via technology presents challenges (Côté and Lamarche 2022). Furthermore, there's a risk of overestimating the effectiveness of promising technological solutions, potentially leading to unforeseen issues (WHO, 2021).

It is also crucial to take into account the privacy of individuals' personal information. Collecting and analyzing sensitive patient data requires strict measures to keep them secure and confidential (WHO, 2021). Another concern is unauthorized access and misuse of electronic medical records, which can lead to privacy breaches (Keshta and Odeh 2021). There might be a potential chance of bias that could be present in AI model training due to various factors such as missing data, participant numbers, misclassification, measurement inaccuracies, and social inequalities (Gianfrancesco, 2018).

Rather than uncritically accepting the outcomes produced by an AI algorithm, medical professionals should make final decisions after thoroughly evaluating the clinical context and other pertinent information. The aforementioned threshold value should also be adjusted appropriately to fit the clinical scenario. Consequently, although high-performance AI might take over certain tasks in specific, controlled conditions, it is not an autonomous tool capable of replacing a medical professional. Its role is limited to offering proficient assistance and information to healthcare providers (Park *et al.*, 2021).

While technology is rapidly evolving, legislation, which takes ethical and political factors into account, progresses at a much slower pace. As a result, "if policies are not developed to steer technological advancements, then technology will shape policy instead" (Detopoulou *et al.*, 2023).

CONCLUSIONS

In conclusion, the future of AI in nutrition holds great promise, presenting a myriad of opportunities for advancements that span personalized health solutions to global food security initiatives. AI's capability to analyze vast datasets, including genetic information, biomarkers, dietary habits, and health records, allows for the creation of highly personalized dietary recommendations tailored to individual needs such as age, gender, health conditions, and personal preferences. This personalized approach has the potential to revolutionize how we approach nutrition, shifting from generalized guidelines to targeted interventions that optimize health outcomes.

Furthermore, AI can play a crucial role in enhancing food safety by predicting and detecting contaminants, spoilage, and pathogens in food supply chains. It can also improve food quality through advanced quality control mechanisms and ensure compliance with nutritional labeling standards. Beyond individual health and safety, AI-driven insights can inform public policy and interventions aimed at addressing global nutrition challenges like food insecurity and malnutrition.

However, realizing the full potential of AI in nutrition requires continued research and development to refine algorithms, improve accuracy, and expand the scope of applications. Ethical considerations surrounding data privacy, consent, and algorithmic bias must also be addressed to ensure responsible deployment and equitable access to AI-driven nutrition solutions worldwide.

FUTURE SCOPE

The synergy between AI and nutrition promises groundbreaking advancements across diverse fields, from personalized dietary recommendations to enhancing food safety and sustainability.

• AI analyzes extensive data, including genetics, biomarkers, diet, and health records, to offer personalized dietary recommendations through machine learning, tailored to individual needs such as age, gender, health conditions, and preferences.

• AI-powered tools can accurately analyze the nutrient content of foods from images or spectroscopic data, improving the accuracy of food labeling.

• AI can analyze behavioral patterns and environmental factors influencing dietary choices. This information can be used to develop interventions and applications that promote healthy eating habits and improve adherence to dietary guidelines

• AI accelerates research in nutrition by processing and interpreting large datasets, identifying patterns, and generating

Hypotheses for further investigation. AI-powered virtual assistants can provide personalized dietary advice, answer nutrition-related questions, and offer real-time support for users seeking to improve their diet and lifestyle.

Acknowledgement. I extend my sincere thanks to Dr. Krishnaja U (Major Advisor) for giving me proper guidance throughout the course of my study. I also sincerely thank my co-authors for their immense support.

Conflict of Interest. None.

REFERENCES

- AAAI (2021). AAAI Ethics and Diversity AAAI. https://aaai.org/about-aaai/ethics-and-diversity/.
- Adams, S. H., Anthony, J. C., Carvajal, R., Chae, L., Khoo, C. S. H., Latulippe, M. E., Matusheski, N. V., McClung, H. L., Rozga, M., Schmid, C. H. and Wopereis, S. (2020). Perspective: guiding principles for the implementation of personalized nutrition approaches that benefit health and function. *Advances in nutrition*, 11(1), 25-34.
- Artificial Intelligence (AI) (2023). Definition of Artificial Intelligence in English by Oxford Dictionaries; Oxford Dictionaries: Oxford, UK.
- Bhat, S. S. and Ansari, G. A. (2021). Predictions of diabetes and diet recommendation system for diabetic patients using machine learning techniques. In 2021 2nd International Conference for Emerging Technology (INCET), 1-5.
- Bond, A., Mccay, K., and Lal, S. (2023). Artificial intelligence & clinical nutrition: What the future might have in store. *Clinical Nutrition ESPEN*, 57, 542–549.
- Bossard, L., Guillaumin, M. and Van Gool, L. (2014). Food-101–mining discriminative components with random forests. *Springer International Publishing*, 7(13), 446-461.

- Boushey, C. J., Spoden, M., Zhu, F. M., Delp, E. J. and Kerr, D. A. (2017). New mobile methods for dietary assessment: review of image-assisted and image-based dietary assessment methods. Proceedings of the Nutrition Society, 76(3), 283-294.
- Brazeau, A.S., Mircescu, H., Desjardins, K., Leroux, C., Strychar, I., Ekoé, J.M. and Rabasa-Lhoret, R. (2013). Carbohydrate counting accuracy and blood glucose variability in adults with type 1 diabetes. Diabetes research and clinical practice, 99(1), 19-23.
- Burke, L. E., Wang, J. and Sevick, M. A. (2011). Selfmonitoring in weight loss: a systematic review of the literature. Journal of American Dietetic Association, 111(1), 92–102.
- Cai, Q., Li, J., Li, H. and Weng, Y. (2019). BTBUFood-60: Dataset for object detection in food field. In 2019 IEEE International conference on big data and smart computing, (BigComp), 1-4.
- Cao, E., Watt, M. J., Nowell, C. J., Quach, T., Simpson, J. S., De Melo Ferreira, V., Agarwal, S., Chu, H., Srivastava, A., Anderson, D. and Gracia, G. (2021). Mesenteric lymphatic dysfunction promotes insulin resistance and represents a potential treatment target in obesity. Nature Metabolism, 3(9), 1175-1188.
- Côté, M. and Lamarche, B. (2022). Artificial intelligence in nutrition research: perspectives on current and future applications. Applied Physiology, Nutrition, and Metabolism, 47(1), 1-8.
- Dalakleidi, K. V., Papadelli, M., Kapolos, I. and Papadimitriou, K. (2022). Applying image-based food-recognition systems on dietary assessment: a systematic review. Advances in Nutrition, 13(6), 2590-2619.
- Detopoulou, P., Voulgaridou, G., Moschos, P., Levidi, D., Anastasiou, T., Dedes, V., Diplari, E.M., Fourfouri, N., Giaginis, C., Panoutsopoulos, G. I. and Papadopoulou, S. K. (2023). Artificial intelligence, nutrition, and ethical issues: A mini-review. Clinical Nutrition Open Science, 50, 46-56.
- Doulah, A., McCrory, M. A. and Higgins, J. A. (2019). A systematic review of technology-driven methodologies for estimation of energy intake. IEEE Access, 7, 49653-49668.
- Ege, T. and Yanai, K. (2018). Image-based food calorie estimation using recipe information. IEICE TRANSACTIONS on Information and Systems, 101(5), 1333-1341
- Fanzo, J., Hawkes, C., Udomkesmalee, E., Afshin, A., Allemandi, L., Assery, O., Baker, P., Battersby, J., Bhutta, Z., Chen, K. and Corvalan, C. (2018). Global Nutrition Report: Shining a light to spur action on nutrition, 88149.
- Garden, L., Clark, H., Whybrow, S. and Stubbs, R. J. (2018). Is misreporting of dietary intake by weighed food records or 24-hour recalls food specific ? European journal of clinical nutrition, 72(7), 1026-1034.
- Gause, A. (2024). Examining the Feasibility and Implementation of a New Dietary Intake Documentation Method in a Hospital Setting, Journal of Academy of Nutrition and Dietetics, 118(2), 301-307.
- Gianfrancesco, M. A., Tamang, S., Yazdany, J. and Schmajuk, G. (2018). Potential biases in machine learning algorithms using electronic health record data. JAMA Internal Medicine, 178(11), 1544-1547.
- Joshi, S., Bisht, B., Kumar, V., Singh, N., Jameel Pasha, S.B., Singh, N. and Kumar, S. (2024). Artificial intelligence assisted food science and nutrition perspective for smart nutrition research and healthcare. Systems. Microbiology and Biomanufacturing, 4(1), 86-101.

- Kaur, R., Kumar, R. and Gupta, M. (2023). Deep neural network for food image classification and nutrient identification: A systematic review. Reviews in Endocrine and Metabolic Disorders, 24(4), 633-653.
- Kawano, Y. and Yanai, K. (2015). Automatic expansion of a food image dataset leveraging existing categories with domain adaptation. Springer International Publishing, 13(3), 3-17.
- Keshta, I. and Odeh, A. (2021). Security and privacy of electronic health records: Concerns and challenges. Egyptian Informatics Journal, 22(2), 177-183.
- Kim, H., Lim, D. H. and Kim, Y. (2021). Classification and prediction on the effects of nutritional intake on overweight/obesity, dyslipidemia, hypertension and type 2 diabetes mellitus using deep learning model: 4-7th Korea national health and nutrition examination survey. International Journal of Environmental Research and Public Health, 18(11), 5597.
- Konstantakopoulos, F. S., Georga, E. I. and Fotiadis, D. I. (2024). A review of Image-Based Food Recognition and Volume Estimation Artificial Intelligence Systems. IEEE Reviews in Biomedical Engineering, 17, 136-152.
- Konstantakopoulos, F. S., Georga, E. I. and Fotiadis, D. I. (2023). An automated image-based dietary assessment system for mediterranean foods. IEEE Open Journal of Engineering in Medicine and Biology, 4, 45-54.
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems. Communications of ACM, 60(6), 84-90.
- Lecrog, T. and Soualmia, L. F. (2014). Managing large-scale genomic datasets and translation into clinical practice. Yearbook of Medical Informatics, 23(01), 212-214.
- LeCun, Y., Bengio, Y. and Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.
- Li, P., Luo, H., Ji, B. and Nielsen, J. (2022). Machine learning data integration in human for gut microbiome. *Microbial Cell Factories*, 21(1), 241.
- Lo, F. P., Qiu, J., Wang, Z., Chen, J., Xiao, B., Yuan, W., Giannarou, S., Frost, G. and Lo, B. (2024). Dietary Assessment with Multimodal Chat GPT: A Systematic Analysis. Journal of Biomedical and Health Informatic, 16(5), 158-163.
- Martin, C. K., Kaya, S. and Gunturk, B. K. (2009). September. Quantification of food intake using food image analysis. In 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 6869-6872.
- Matsuda, Y., Hoashi, H. and Yanai, K. (2012). Recognition of multiple-food images by detecting candidate regions. In 2012 IEEE international conference on multimedia and expo, 25-30.
- Matusheski, N. V., Caffrey, A., Christensen, L., Mezgec, S., Surendran, S., Hjorth, M. F., McNulty, H., Pentieva, K., Roager, H. M., Seljak, B. K. and Vimaleswaran, K. S. (2021). Diets, nutrients, genes and the microbiome: recent advances in personalised nutrition. British Journal of Nutrition, 126(10), 1489-1497
- Meyers, A., Johnston, N., Rathod, V., Korattikara, A., Gorban, A., Silberman, N., Guadarrama, S., Papandreou, G., Huang, J. and Murphy, K. P. (2015). Im2Calories: towards an automated mobile vision food diary. In Proceedings of the IEEE international conference on computer vision, 1233-1241.
- Mitchell, E., M. Heitkemper, E., Burgermaster, M., E. Levine, M., Miao, Y., L. Hwang, M., M. Desai, P., Cassells, A., N. Tobin, J., G. Tabak, E. and J. Albers, D. (2021). 131

Mahendran et al.,

From reflection to action: combining machine learning with expert knowledge for nutrition goal recommendations. In Proceedings of the 2021 CHI conference on human factors in computing systems, 1-17.

- Miyazawa, T., Hiratsuka, Y., Toda, M., Hatakeyama, N., Ozawa, H., Abe, C., Cheng, T.Y., Matsushima, Y., Miyawaki, Y., Ashida, K. and Iimura, J. (2022). Artificial intelligence in food science and nutrition: a narrative review. *Nutrition Reviews*, 80(12), 2288-2300.
- World Health Organization (2018). Non-communicable Diseases Country Profiles.
- Open AI. Gpt-4v(ision) system card (2023).
- Osborne, B.G., (2006). Near infrared spectroscopy in food analysis. Encyclopedia of analytical chemistry: applications, theory and instrumentation, 1658-1678.
- Panagoulias, D. P., Sotiropoulos, D. N. and Tsihrintzis, G. A. (2021). Nutritional biomarkers and machine learning for personalized nutrition applications and health optimization. *Intelligent Decision Technologies*, 15(4), 645-653.
- Park, S. H., Choi, J. and Byeon, J. S. (2021). Key principles of clinical validation, device approval, and insurance coverage decisions of artificial intelligence. *Korean journal of radiology*, 22(3), 442.
- Ronteltap, A., Van Trijp, J. C. M. and Renes, R. J. (2008). Consumer acceptance of nutrigenomics-based personalised nutrition. *British Journal of Nutrition*, 101(1), 132-144.
- Rozga, M., Latulippe, M. E. and Steiber, A. (2020). Advancements in personalized nutrition technologies: guiding principles for registered dietitian nutritionists. *Journal of the Academy of Nutrition and Dietetics*, 120(6), 1074-1085.
- Sharma, S. K. and Gaur, S. (2024). Optimizing Nutritional Outcomes: The Role of AI in Personalized Diet Planning. *International Journal for Research Publication and Seminar*, 15(2), 107-116.
- Sharma, V., Sharma, V., Khan, A., Wassmer, D. J., Schoenholtz, M. D., Hontecillas, R., Bassaganya-Riera, J., Zand, R. and Abedi, V. (2020). Malnutrition, health and the role of machine learning in clinical setting. *Frontiers in nutrition*, 7, 44.
- Shinn, L.M., Li, Y., Mansharamani, A., Auvil, L.S., Welge, M. E., Bushell, C., Khan, N. A., Charron, C. S., Novotny, J. A., Baer, D. J. and Zhu, R. (2021). Fecal bacteria as biomarkers for predicting food intake in healthy adults. *The Journal of nutrition*, 151(2), 423-433.
- Sakthivel N. K., Subasree S., Kumbhar S. K., Hasan J., Murugura G. and Shabin S. J. (2024). AI-Powered Nutrition Assistant and Step Tracker. *International Journal of Engineering Research and Technology*, 13(4), 50-54.

- Siemon, M. S., Shihavuddin, A. S. M. and Ravn-Haren, G. (2021). Sequential transfer learning based on hierarchical clustering for improved performance in deep learning based food segmentation. *Scientific Reports*, 11(1), 813.
- Singer, P., Robinson, E. and Raphaeli, O. (2024). The future of artificial intelligence in clinical nutrition. *Current Opinion in Clinical Nutrition & Metabolic Care*, 27(2), 200-206.
- Sripada, N. K., Challa, S. C. and Kothakonda, S. (2023). Al-Driven Nutritional Assessment Improving Diets with Machine Learning and Deep Learning for Food Image Classification. In 2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS), 138-144.
- Subar, A. F., Freedman, L. S., Tooze, J. A., Kirkpatrick, S. I., Boushey, C., Neuhouser, M. L., Thompson, F. E., Potischman, N., Guenther, P. M., Tarasuk, V. and Reedy, J. (2015). Addressing current criticism regarding the value of self-report dietary data. *The Journal of nutrition*, 145(12), 2639-2645.
- Tahir, G. A. and Loo, C. K. (2021). December. A comprehensive survey of image-based food recognition and volume estimation methods for dietary assessment. *Healthcare*, *9*(12), 1676.
- Theodore Armand, T. P., Nfor, K. A., Kim, J. I. and Kim, H. C. (2024). Applications of Artificial Intelligence, Machine Learning, and Deep Learning in Nutrition: A Systematic Review. *Nutrients*, 16(7), 1073.
- Verma, M., Hontecillas, R., Tubau-Juni, N., Abedi, V. and Bassaganya-Riera, J. (2018). Challenges in personalized nutrition and health. *Frontiers in Nutrition*, 5, 117.
- Wang, W., Min, W., Li, T., Dong, X., Li, H. and Jiang, S. (2022). A review on vision-based analysis for automatic dietary assessment. *Trends in Food Science* & *Technology*, 122, 223-237.
- WHO (2021). Ethics and governance of artificial intelligence for health. World Health Organization. health and function" Advances in Nutrition, 11(1), 25-34.
- World Health Organization. Nutrition topics: Nutrition for Older persons (WHO). (2021). https://www.who.int/nutrition/topics/ageing/en/ viewed on 11-02-2021
- Yang, Y., Jia, W., Bucher, T., Zhang, H. and Sun, M. (2019). Image-based food portion size estimation using a smartphone without a fiducial marker. *Public health nutrition*, 22(7), 1180-1192.
- Zhu, F., Bosch, M., Woo, I., Kim, S., Boushey, C. J., Ebert, D. S. and Delp, E. J. (2010). The use of mobile devices in aiding dietary assessment and evaluation. *IEEE Journal of selected topics in signal processing*, 4(4), 756-766.

How to cite this article: Midhila Mahendran, Karthika B., Manoj Kumar Verma and Krishnaja U. (2024). AI Innovations in Nutrition: A Critical Analysis. *Biological Forum – An International Journal, 16*(9): 124-132.