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ARTIFICIAL INTELLIGENCE FOR FOOD AND HEALTH

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CONTENT

INTRODUCTION

From the ubiquitous virtual assistants in our pockets to the tailored advertisements popping up in our web browsers, Artificial Intelligence (AI) has rapidly infiltrated our daily lives and beyond. Its ability to process vast amounts of data, learn from it, and make intelligent decisions, has not only transformed the way we live, work, and connect but has also emerged as a powerful catalyst in addressing one of the most pressing challenges of our era: the transformation of the food and health landscape.

The need for more healthy, sustainable, and equitable food systems is urgent. Food and diet are major determinants of our health and well-being, influencing our susceptibility to a wide range of conditions and metabolic diseases. Poor diets are a leading risk factor of the global burden of disease. However, our understanding of food remains confined to a mere fraction of its complexity, primarily focusing on well-characterized categories of micro and macro-nutrients which represent just the tip of the iceberg. On the flip side lies the so-called "dark matter" of food, referring to the vast and complex array of molecules within food yet to be discovered, including their impacts on our bodies.

Furthermore, environmental factors and agricultural practices exert a profound influence on food systems and the composition of the food we consume, with consequences that extend to both human and planetary health. Food production and consumption are leading stressors on ecosystems compared to all other human activities, including greenhouse gas emissions linked to climate change. At the same time, food systems are critically dependent on multiple ecosystem services to thrive.

Concurrently, food security is a notable challenge in the United States and globally, with disparities existing among minority, tribal, rural, and low-income communities. Drivers of increased food insecurity, including climate, conflict, and economic shocks, disproportionately disrupt food accessibility and safety for low-income, rural, and underrepresented populations. These disparities emphasize that efforts to strengthen food systems need to foster equity. Meeting the rising demand for food with high nutritional value in sustainable and equitable ways while coping with climate change is a pressing societal challenge.

While the field of AI's application is virtually limitless, its impact in agriculture, food and health science holds the potential to bridge knowledge gaps and revolutionize the way we grow, manufacture, and consume food to deliver sustainable, nutritionally balanced, equitable, and health-enhancing food for all. AI tools present an opportunity to refine agricultural practices and enhance the discovery of functional ingredients, ultimately contributing to the development of food products that are not only healthier and more nutritious but also personalized and support the wellbeing of the planet in a changing climate.

In this paper, we provide an overview of the pivotal role played by AI in reshaping food and health systems through its application in key domains including precision agriculture, foodomics, personalized nutrition, and food safety, distribution, and quality.

THE EVOLUTION OF AI AND KEY CONCEPTS

Decades before the modern definition of AI emerged, Alan Turing, often referred to as the "father of computer science," introduced the concept in his 1950 paper, "Computing Machinery and Intelligence" [1]. Turing's work posed the fundamental question of whether machines could exhibit human-like thinking and introduced the "Turing Test," where a human examiner tries to differentiate between computer-generated and human responses. It was in 1956 during the Dartmouth Workshop led by John McCarthy and other pioneers including Nathaniel Rochester, Allen Newell, Herbert A. Simon, and Marvin Minsky that the term "Artificial Intelligence" was coined, and the field officially founded [2]. While exploring the potential of machines in emulating human cognitive processes, they developed the “Logic Theorist”, one of the earliest AI programs capable of demonstrating mathematical theorems [3]. This approach using logical reasoning marked the inception of symbolic AI and served as the cornerstone for the development of expert systems such as MYCIN; a program designed in the 70’s to diagnose bacterial infections and assist medical professionals in prescribing appropriate antibiotics [4].

As computing power and big data availability started to match expectations in AI capabilities, significant advancement in the field was made possible through the development of machine learning and deep learning algorithms enabling computers to learn from data and make predictions or decisions without being explicitly programmed. In other words, these algorithms automatically identify patterns, generalize from data, and improve their performance on specific tasks through experience [5].

Machine learning can be subdivided into three main categories including supervised (learning from labeled data), unsupervised (finding patterns in unlabeled data), and reinforcement learning (making decisions through interaction). A core feature of deep learning — a subset of machine learning — resides in the use of artificial neural networks to automatically learn and represent complex patterns and features from raw data. Inspired by the human brain's structure, these artificial neural networks consist of interconnected layers of artificial neurons particularly efficient in processing unstructured data [5], [6] with more complex versions known as deep neural networks when using multiple layers of artificial neurons [7].

The development of machine learning and deep learning algorithms constitutes a breakthrough in the evolution of modern AI leading to numerous real-world applications including automation and recommendation systems, natural language processing (NLP), and computer vision. These applications are now revolutionizing various aspects of the food industry. From precision agriculture and optimized food production to foodomics and personalized nutrition (Figure 1), let’s explore the potential of AI in creating solutions for addressing both human and planetary health challenges.

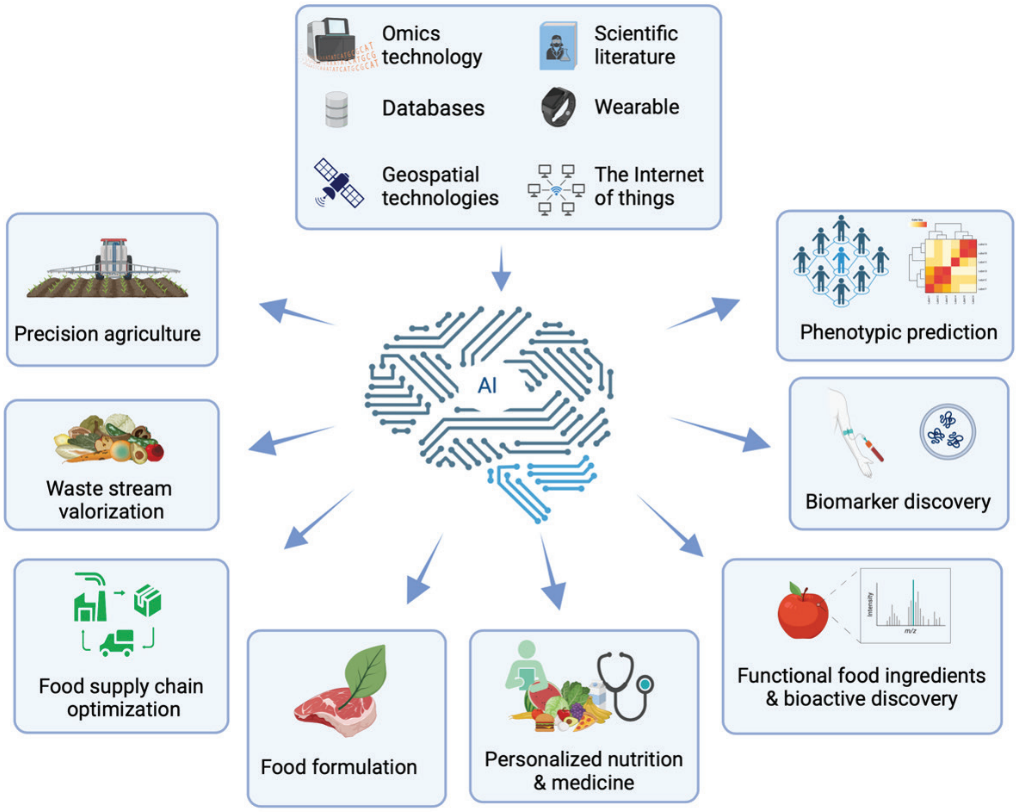

Figure 1. The integration of data collected from omic technologies, scientific literature, the Internet of things, geospatial technologies and wearable sensors can be used to train Artificial Intelligence (AI) algorithms in food and health. The outputs drive innovation to improve the food and health landscape including applied solutions in precision agriculture, optimization of food supply chain and food formulation, identification of functional food ingredients and bioactives, biomarker discovery, and phenotypic prediction for personalized nutrition and medicine.

AI IN AGRICULTURE: TOWARD A MORE SUSTAINABLE, EQUITABLE AND HEALTHIER FOOD SYSTEM

By 2050, the world must provide sustenance for 10 billion individuals, requiring an increase in global food production by approximately 60-70 percent to meet the growing demand [8], [9]. Yet our existing food system is far from being environmentally sustainable. While water, land, and biodiversity are dwindling at an alarming rate, our food supply chain is responsible for around one-quarter of the world's greenhouse gas emissions with 11 percent attributed to agriculture only [10].

In the same time, the global number of hungry individuals ranged from 691 million to 783 million in 2022, marking an increase of 180 million people experiencing severe food insecurity compared to the previous year [11]. Food insecurity manifests in various forms, including insufficient quantity, poor quality, or limited diversity of food, further exacerbated by challenges faced by the food and agricultural sector in optimizing their operations to minimize losses and costs while maximizing yields. Among other issues, these challenges encompass factors, such as low crop yields, losses due to weather events, pest and disease incidences, post-harvest losses during storage and transportation, high costs of production, low revenue generation, and uncertainties due to market dynamics [12], [13].

Once seen as a solution to bolster yield and cope with the rising food demand, conventional agriculture is now largely questioned. Its heavy reliance on synthetic fertilizers, pesticides, and monoculture cropping systems, raises major concerns about its long-term sustainability including soil erosion, water pollution, biodiversity loss, fossil fuel dependency, and accumulation of chemical residues on crops.

But that's not the only drawback. These agricultural practices developed to answer the growing demand for food often compromise the nutritional value of our diet ultimately reflecting on human health. Since the 40's, agronomic research focus primarily revolved around achieving increased yields and greater crop protein content through an over-reliance on synthetic inputs and tillage with little consideration regarding their negative effects on soil health and crop micronutrient density [14], [15]. Now it is well established in numerous crops that the reduction in soil life diversity due to these farming practices has a detrimental impact on the mineral uptake and production of phytochemicals like polyphenols, flavonoids, and anthocyanins [16]–[19] known for their antioxidant and anti-inflammatory properties [20]

With growing recognition of the environmental toll of conventional agriculture, there is an urgent need for innovative techniques and approaches that can satisfy future healthy food demands while minimizing the footprint of our agricultural system on the planet. Application of emerging technologies and AI solutions in precision agriculture, including geospatial technologies, the Internet of Things, and Big Data analysis marks a paradigm shift toward the creation of a more environmentally conscious, equitable and healthier food system. By integrating data-driven solutions and information from diverse sources such as satellite imagery, weather data, and soil analysis, AI-driven technologies offer the potential to inform strategic management decisions ultimately contributing to improved efficiency and resource optimization [21], [22].

The availability of high-resolution (spatial, spectral, and temporal) satellite images has promoted the use of remote sensing in many precision agriculture applications [23]. Leveraging advanced computer vision and sensor technologies, AI facilitates real-time monitoring of crop health. Early detection of diseases and pests allows for targeted interventions, therefore limiting the emergence of crop disease and minimizing the need for chemical treatments. A number of advanced AI practices relying on machine learning and deep learning algorithms, including computer visualization and robotics, have been designed to reduce the use of herbicides through precise and appropriate management of weeds [24],

[25]. This could be extended to the implementation of new concepts based on autonomous and intelligent robots allowing cooperation and collaborative action among unmanned vehicles, both aerial and ground, (UAVs and UGVs) to perform in-field operations in precise and time-effective ways. Such technologies capable of recognizing, manipulating, collecting, and delivering soil and plant samples required for inspection could in turn greatly increase precision and quality in farming processes [26], [27].

AI can also be used to improve prediction in weather conditions and help with data interpretation from soil sensors that monitor key indicators of soil health at unprecedented levels of precision. By continuously assessing parameters such as moisture levels, nutrient content, and microbial activity, farmers can then implement precise irrigation strategies, conserving water and preventing overuse as well as tailoring fertilizer dosages to enhance soil health and structure [26].

Although these solutions are expected to promote both the health and nutritional density of crops through more sustainable and eco-friendly farming approaches, the implementation of AI in precision agriculture faces challenges. To be successful this technological revolution must ensure data quality, interoperability, affordability, and technical literacy among end-users. In addition, issues related to infrastructure, connectivity, regulations, customization, security, and ethical considerations must be addressed. Demonstrating the economic benefits of AI and providing training and support for farmers are crucial for successful adoption. Farmer.chat, an AI assistant developed by Digitalgreen [28] is accelerating this transition by providing tailored assistance to hundreds of thousands of extension workers and training small-scale farmers across the Global South on a combination of regenerative agricultural practices and nutrition. Overall, addressing these challenges requires collaborative efforts from stakeholders, including farmers, technology developers, policymakers, and researchers, to ensure the successful integration of AI in precision agriculture and make sure these solutions can benefit the greatest number.

USING AI TO ACCELERATE INNOVATION IN FOOD FOR HEALTH

The food industry is constantly evolving, driven by changing consumer preferences, dietary trends, and the growing demand for healthier and more sustainable food options. In addition to the broader recognition of the environmental impact of our dietary choices, the surge in food-related disorders has encouraged consumers to bring essential changes in their lifestyles and diet, calling for a profound remodeling of our food system.

By offering new tools and capabilities that empower researchers, chefs, and companies to create innovative solutions for better nutrition and health, AI is becoming the driving force behind these transformations. From food formulation and safety to supply management and beyond, AI is integrating every facet of the food industry. Let's explore how these applications are expected to translate into better public health outcomes.

AI Solutions for Improved Quality Control and Food Safety

In the food industry, the development of standardized and reliable procedures for quality control to ensure the safety, high quality, and regulatory compliance of food products is crucial. The sector is actively implementing AI to establish consistent quality control measures and promote health-conscious practices in food production and distribution while managing costs.

As mentioned, AI's strength lies in its ability to process and analyze enormous datasets swiftly and accurately. One way to improve food safety is by advancing AI models that combine various datasets, such as food microbial ecology, chemometric, and physical data, to thoroughly evaluate risks throughout the entire food supply chain. machine learning -based approaches are utilized to support supplier selection, procurement, food safety inspection, risk assessment of imported food, and prevention of food fraud. Furthermore, this can be enhanced using digital twin models of food processing operations that simulate sanitation, food handling, and transport to replicate the transmission of pathogens within the food system and improve foodborne disease prevention and food waste reduction [28].

Using computer vision and smart monitoring systems AI models can be crafted to analyze data from various points in the food supply chain and optimize resource allocation with a particular focus on operations promoting food safety. Using radio-frequency identification tags, Wireless Sensor Network and Near Field Communication technology, Internet of Things traceability systems enables the creation of comprehensive databases to monitor and store product information in all stages of production, processing, distribution, and consumption. Combined with blockchain based traceability systems this allows companies to enhance consumer transparency by providing detailed information about the origin, production methods, and safety of purchased products [30], [31], [32]. This transparency is critical to building trust and confidence among consumers as it offers insights into the entire supply chain, allowing informed purchasing decisions aligned with ethical and sustainable practices.

An example application of AI food safety control systems is the deployment of AI-based Horizon Scanning Methodology. Horizon Scanning detects signs of potential food safety hazards, risks, and issues, as a monitoring technique and safety assessment approach that shifts the food control paradigm from reactionary to preventative. Mars deploys Horizon Scanning in its risk mitigation and management of aflatoxin in source determination [32], which allows for early detection and early intervention to potential contamination.

Western Growner's GreenLink® is another use-case where grower's pathogen test data for romaine lettuce including both pre-harvest and post-harvest testing is collected into a data sharing platform to train machine learning models in the risk mitigation of pathogens in leafy greens [33], a recurring vehicle of foodborne illness. In the EU's Rapid Alert System for Food and Feed (RASFF) [34]–[36], a Bayesian network model is applied to predict food fraud. Another study involves the use of extreme gradient boosting (XGBoost) machine learning algorithms to assess risk associated with the presence of Vibrio parahaemolyticus in oyster farms in Taiwan.

FDA's Mandate - An Opportunity to Modernize the Food Web

Since the promulgation of Food Safety Modernization Act (FSMA) in 2011 [37], under which the FDA was given new regulatory authority on activities related to food production, the FDA generated guidance documents, rulemakings, reports, and strategies to strengthen the food system to fulfill its mandate to better protect public health and address challenges.

As computational power increased exponentially in the last decade, technological advances enabling the deployment of AI/machine learning spearheaded FDA's new paradigm shift in food safety approaches to leverage technology and other tools in creating a safer, more digital, and traceable food system [37]. Built upon the foundational pillars of the New Era of Smarter Food Safety, FDA unveiled Four Core Elements in its Blueprint, taking steps to harness the power of AI. These Four Core Elements are:

1. Tech-Enabled Traceability
2. Smarter Tools and Approaches for Prevention and Outbreak Response
3. New Business Models
4. Retail Modernization

These elements were created to strengthen Food Safety Culture, including foodborne illness outbreak prevention, response, risk mitigation, and food safety enhancement in the food supply chain.

In the domain of Tech-Enabled Traceability, rapid tracebacks, source identification, and timely removal of contaminated products from the marketplace have significant implications for the health and safety of the consumer. Foundational advances in algorithm storage capacity, data processing/mining/display, algorithm and hardware development make possible the construction of an enhanced food traceability system with mutual private, public, and governmental stakeholder partnerships. A key outcome in the protection of public health is the reduction of time in the identification of sources of contamination associated with a recall and/or outbreak [34].

To put the criticality of health challenges of product traceability into perspective, 94 percent of all seafood consumed in the United States is imported [38]. A strong foreign importer verification program as well as a robust traceability system would allow for more rapid removal of contaminated food from the market, mitigating the risk of a foodborne illness outbreak.

As such, as part of its Core Element 1 Tech-Enabled Traceability in the Blueprint, the FDA now standardizes the concept of Key Data Elements (KDEs) and Critical Tracking Events (CTEs) and requires the maintenance of these records, a prime opportunity for the adoption of AI/ML tools in traceability efforts. As part of the adoption of AI in traceability systems, the FDA has since piloted an Imported Seafood Pilot Program [39], which is now in its third phase, deploying machine learning to screen imported seafood products to quickly identify contaminated products with illness-causing pathogens, decomposition and the presence of unapproved antibiotic residues or other hazards in the supply chain.

Revealing the Dark Matter of Food

Mostly due to limited analytical capacity, research in food science and nutrition has predominantly focused on examining the biochemical and physiological properties of a small fraction of micro and macronutrients. However, the human diet consists of a multitude of food components, themselves made of thousands of biochemicals unsuspected until now (referred to earlier as the dark matter of food), that interact in various ways, influencing metabolism and physiological responses of the body through additive, synergistic, or antagonistic effects [40].

Facilitated by the advent of foodomics — a multidisciplinary approach integrating advanced omic technologies, such as genomics, transcriptomics, proteomics, and metabolomics — our comprehension of food is rapidly evolving toward a much more holistic dimension. These techniques rely on the combination of bioinformatics and advanced analytical platforms including deep-sequencing, nuclear magnetic resonance spectroscopy (NMR), and gas chromatography and liquid chromatography coupled to mass spectrometry (GC-MS and LC-MS) through both targeted and untargeted approaches [41], [42]. Although extremely powerful in deciphering the molecular composition of food, the wealth of data generated by these techniques can be particularly complex to navigate and analyze. This is where AI applications constitute a real game changer, bringing our understanding of the intricate relationship between nutrition and health to the next level [41], [43]. By analyzing large amounts of data from food composition databases, foodomics, and nutritional and clinical studies, AI is significantly advancing the identification of new ingredients and bioactives with promising health benefits.

Traditional discovery of functional food ingredients (FFIs) utilizes bioinformatic tools employing sequence similarity searches such as BLAST (basic local alignment search tool) for virtual exploration and identification of bioactives associated with certain molecular pathways and diseases. Although this strategy has greatly advanced the characterization of FFIs, it cannot predict de novo bioactives and remains limited to previously characterized compounds. Instead, AI-guided strategies using deep learning approaches such as deep neural network and designed upon pre-defined health benefits are expected to facilitate the prediction of novel bioactives at an unprecedented rate [44]. In peptidomics for example, such AI-powered benefit-driven FFI discovery approaches were recently taken from concept to pre-clinically proven solutions including the characterization of novel anti-diabetic peptides to mitigate Type 2 diabetes mellitus [45], [46] and anti-inflammatory peptides to address chronic low-grade inflammation [47]–[50].

These approaches empower AI to uncover patterns and interaction between specific ingredients and explore molecular profiles of food at unprecedented levels of detail leading to the creation of a much more robust and comprehensive food database (ei; FoodAtlas, FoodB, PTFI).

Using Food Photos to Capture What People Eat

More people around the globe carry cell phones with photo-capture capability. With advances in AI and computer vision, it is increasingly possible to capture what people eat with those cell phones. Energy and macronutrient content are accurately quantified from food photos [52], [53] and work is ongoing to capture diets at an ingredient-level [54]

(PMID: 38068830) such that foods and ingredients can then be mapped to other databases in the food system. The use of food photos in future crowd-sourced observational trials—think how many people carry cell phones—could be used to track food consumption, map to the thousands of molecules in those foods, and connect those molecules with participant health. Food photos which have been distilled down to ingredients and amounts can also be linked to food purchasing and commodity databases for economic modelling and reduction of food insecurity. Finally, capturing what people eat can also be used to inform other parts of the food ecosystem such as food supply chains and food safety.

Toward the Next Generation of Plant-Based Food Products

With growing recognition of the ethical, environmental and health concerns related to the consumption of animal-based food products [51] there is an undeniable rise in the consumer demand for plant-based alternatives as illustrated by the variety of meat and milk substitutes now available on the market [52].

Although incentives to shift toward healthier and more sustainable food options are strong, the negative sensory perception associated with plant-based alternatives remains an important barrier hindering complete consumer adherence to these products [53], [54]. Indeed taste, texture and appearance are significant drivers in consumers choices and replicating the sensorial experience and mouthfeel of animal-based products in plant-based substitutes have been a major challenge to overcome for the food industry.

In addition, the nutritional value of plant-based diets has been a controversial topic in recent years. An important aspect driving the debate is the quality of plant protein intake in terms of digestibility and amino acid composition — in particular the essential amino acids that cannot be synthetized by the human body and need to be acquired from food. Some studies reported that plant proteins often exhibit low quality, poor digestibility, and found an undesired low levels in essential amino acids (in particular lysine and methionine) in vegetarians compared to omnivores [55], [56].

To some extent these differences in bioavailability also apply to certain micronutrients and vitamins including calcium, iron, and vitamin B12 and D present only at low levels in plant-based diets [53]. Moreover, some plant compounds such as phytate and oxalate, often referred to as antinutrients can further enhance this disparity as illustrated by their role in the inhibition of mineral absorption [57].

Nonetheless it should be noted that depending on both processing techniques and the food matrix, many of these so-called antinutrients can also mediate cardioprotective, neuroprotective and antioxidants properties. Overall, when well-balanced, plant-based diet can have a beneficial impact on the incidence of chronic diseases and gut health [58]. This not only highlights the importance of food formulation in harnessing the full potential of plant bioactives in manufactured plant-based products but also opens the way to novel metabolic engineering and breeding strategies of plants with higher content in bioactives compound [59].

Groundbreaking foodtech companies are leveraging AI to explore the vast and untapped repertoire of edible plants to formulate plant-based recipes mimicking the full sensory attributes of animal-based foods while providing enhanced nutritional value and health benefits. The Chilean foodtech NotCo, for example, employs a machine learning algorithm named Giuseppe that analyzes the molecular compositions of food and suggests novel combinations from a pool of 300,000 plant ingredients to emulate distinct products like hamburgers, chicken, and milk. Meati Foods, a startup producing meat alternatives from mycelium (“mushroom root”) is partnering with PIPA LLC, an AI company specialized in nutrition and life sciences to explore the extensive range of health benefits of its products. On a similar trend through its collaboration with the machine learning -driven platform Benchling, the plant-based cheese maker Climax Foods is ramping up its ingredient discovery and streamlining its formulation process to accelerate the launch of healthier and more realistic animal-free cheese options onto the market.

AI in Personalized Health and Nutrition

Presuming that a single optimal diet would fit every person's needs is clearly unrealistic when we consider the diverse biological makeup of humans. Our genetics, metabolism, physiological status, gut microbiome, lifestyle, and environment, to name a few, deeply influence our nutritional requirements [64], [65], [66]. Through a better understanding of the inter-individual variability inherent to these factors, omic technologies hold the potential to transform our approach to nutrition and public health by facilitating the emergence of personalized dietary recommendations and medical practices [67]. Although these approaches are extremely valuable, our limited comprehension of the dynamic interaction between nutrition, metabolism, and health outcomes have hindered their translation and application.

Here as well, AI is making a major contribution. Using integrated data-driven approaches, predictive computational models can be trained to reflect phenotypic response to nutrition and changes resulting from the interaction between genotypic and nutrient-derived metabolic factors [64]. Data mining and extraction from electronic health records that capture human diversity, can significantly improve the design of personalized diets and recommendation based on patient singularities [60]. The development of wearable and mobile sensor technology is expected to provide accurate, non-invasive, and real-time insights on critical parameters including, physical activity, blood glucose levels and other metabolic biomarkers upon food intake to improve precision nutrition [65]. To further enhance tailoring, this could be paired with emerging AI powered applications using computer vision being developed to provide portion size, calorie count and macronutrient breakdown estimates of a meal from a photo.

AI4FoodDB, a public database that centralizes food images, wearable sensors, validated questionnaires and biological samples from obese patients following nutritional weight loss intervention , outlines the efficacy of digital data collection methods and AI-powered technology in mitigating food-related chronic diseases. In a case study monitoring 100 overweight and obese participants for one month, this approach showed a significant reduction of glycated hemoglobin levels, body weight and waist/hip ratio after dietary intervention accompanied by healthier lifestyle changes such as lower meat consumption and higher levels of physical activity [66].

Machine learning algorithms using a random forest model and out-of-bag estimation have also been developed to analyze the effect of dietary intake on the human gut microbiome from fecal bacteria and metabolites [71]. Through the identification of biomarkers that can help predict the influence of food components on health and disease onset, such application is expected to further enhance the development of gut microbe-targeted therapies and improve clinical outcomes in chronic diseases including Irritable bowel syndrome , depression, anxiety and Type 2 diabetes mellitus [68], [72], [73].

Database mapping and machine learning are also being used to connect diet, food composition, and health outcomes in observational trials. For example, the ingredientization of diet in a human cohort and subsequent mapping of those ingredients to the Davis Food Glyocopedia 1.0 [74], demonstrated that specific dietary monosaccharides are associated with specific gut microbes, implying that we may one day be able to tailor diet to manipulate gut microbes [75]. Exploring diet, lifestyle factors, and bone mineral density (BMD) in the same cohort using machine learning revealed that BMD in postmenopausal women is associated with fecal pH; higher BMD occurred in those with lower pH, an indicator of increased microbial fermentation of dietary fiber in the colon [76]. As more comprehensive food composition databases become available, specific molecules associated with desired health outcomes can be identified, and then used to inform food formulation.

On the consumer end, many food recommender systems and applications such as Deepfood, PERSON, and Nutrinet can help people explore nutrition patterns and maintain a healthy diet through the use of deep convolutional neural network models based on food recognition, dietary assessment or individual's genetics [70]–[73].

As the field of personalized nutrition keeps expanding, the question of data protection needs to be carefully examined to ensure personal information privacy and security, particularly when health records are concerned. Moreover, dietary and lifestyle choices are influenced by a broad range of socioeconomic factors including income, education, social networks, and environment which can, in turn, significantly impact both large-scale adoption of these new technologies and their long-term efficacy in terms of health outcomes.

CONCLUSION

Since its inception, technological advancements in computing, hardware developments and processing performance have revolutionized AI technologies, leading to a considerable expansion of its field of application. We now have tools to learn from the best - Mother Nature - and create foods with unprecedented health benefits that are affordable, sustainable, and satisfying. Similar to how we revolutionized human well-being in the early 20th century by discovering the micronutrients that make up only 1 percent of our food, we can achieve a much deeper transformative change by uncovering the molecular composition of the remaining 99 percent.

From seed to fork, the creation of more robust and complex deep learning models offers exciting opportunities to reshape the entire food industry by transforming the way we produce, consume, and experience food. With the adoption of AI-powered innovations, crop breeding strategies can be streamlined to create more resilient and nutritious crop varieties that can help address climate change and food security challenges. Also, as we progress towards a more sustainable food system, developing a digital atlas to map essential material flows enables the identification of valuable resources that are presently being wasted. Ultimately, through the curation of the right data sets we can move beyond traditional food labeling and empower consumers to make informed decisions simply by capturing a photo with their phone.

Although the potential of AI driven approaches is immense, this transformation does not come without challenges and risks. The acquisition of reliable big data for deep learning training requires time and effort, and still relies largely on human judgment making its automation difficult. Though AI has machine precision, it isn't immune to human error. When fed with biased datasets, erroneous decisions and conclusions can be made, which can in turn impede trust building and hinder consumer adoption. In addition, ensuring privacy and security of sensitive information while maintaining transparency in the methods used for data selection can be extremely challenging to achieve.

Nonetheless, AI technology offers an opportunity to deconstruct and learn from low-quality datasets, resulting in more robust experimental approaches and improved data reliability. Additionally, by making complex data more accessible and interpretable, the development of better data visualization tools is critical in enhancing comprehension, communication, and decision-making in AI-driven technology. To achieve this technological revolution, fostering an engaged computer science community to help develop the necessary data and algorithms is key.

As we can anticipate the next generation of AI to be increasingly performant, what was previously considered from the realm of science fiction is becoming more and more tangible. With developers working toward the creation of strong AI or Artificial General Intelligence expected to autonomously perform virtually any task — or even potentially reach self-awareness and surpass human mind — close scrutiny of the risk-benefit balance provided by such technologies is fundamental. Although it is imperative to implement safeguards to prevent misuse and ensure that profitability, societal well-being, and planetary health all possess aligned incentives, the rapid evolution of AI systems is expected to play a pivotal role in the creation of a healthier and more sustainable future.

CONTRIBUTORS

Antoine Abrieux
Strategic Research Associate, Innovation Institute for Food and Health

Selena Ahmed
Global Director, Periodic Table of Food Initiative, American Heart Association

Dana Armstrong
Talent Development Coordinator, Innovation Institute for Food and Health

Mary Avilla
Program Manager, Innovation Institute for Food and Health

Hanna Bartram
Education and Public Engagement Coordinator, AI Institute for Next Generation Food Systems

Steve Brown
Associate Director, AI Institute for Next Generation Food Systems

John de la Parra
Director, Global Food Portfolio, The Rockefeller Foundation

Mason Earles
Co-PI and Lead of Agricultural Production Cluster, AI Institute for Next Generation Food Systems

Kim Fisher
Director of Programs, Innovation Institute for Food and Health

Rikin Gandhi
Chief Executive Officer, Digital green

Mariana Barboza Gardner
Research Program Manager, Innovation Institute for Food and Health

Tana Hernandez Barrueta
Science Communication Fellow, Innovation Institute for Food and Health

Rene Herrera
Program Assistant, Innovation Institute for Food and Health

Veronica Keys
Program Assistant, Innovation Institute for Food and Health

Danielle G. Lemay
USDA ARS Research Scientist & UC Davis Associate Adjunct Professor, Deptartment of Nutrition; Nutrition Lead, AI Institute for Next Generation Food Systems

CONTRIBUTORS

Christie Waisum Ng
Program Assistant, AI Institute for Next Generation Food Systems

Marissa Pickard
Lead Community Coordinator, Innovation Institute for Food and Health

Justin B. Siegel
Associate Professor of Chemistry, Biochemistry & Molecular Medicine, UC Davis | Faculty Director, Innovation Institute for Food and Health

Arielle Soomi Yoo
Biomedical Engineering PhD Student, AI Institute for Next Generation Food Systems

Roy Steiner
Senior Vice President for the Food Initiative, The Rockefeller Foundation

Ilias Tagkopoulos
Professor of Computer Science, UC Davis | Faculty Director and Principal Investigator, AI Institute for Next Generation Food Systems

Visakan Vairavamoorthy
Project Coordinator, Innovation Institute for Food and Health

Ginger Welsh
Marketing and Communications Coordinator, AI Institute for Next Generation Food Systems

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