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Artificial intelligence in nutrition research: perspectives on current and future applications

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TITLE

Artificial intelligence in nutrition research: perspectives on current and future applications

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Abstract

Artificial intelligence (AI) is a rapidly evolving area that offers unparalleled opportunities of progress and applications in many healthcare fields. In this review, we provide an overview of the main and latest applications of AI in nutrition research and identify gaps to address to potentialize this emerging field. AI algorithms may help better understand and predict the complex and non-linear interactions between nutrition-related data and health outcomes, particularly when large amounts of data need to be structured and integrated, such as in metabolomics. AI-based approaches, including image recognition, may also improve dietary assessment by maximizing efficiency and addressing systematic and random errors associated with self-reported measurements of dietary intakes. Finally, AI applications can extract, structure and analyze large amounts of data from social media platforms to better understand dietary behaviours and perceptions among the population. In summary, AI-based approaches will likely improve and advance nutrition research as well as help explore new applications. However, further research is needed to identify areas where AI does deliver added value compared to traditional approaches, and other areas where AI is simply not likely to advance the field.

Novelty Bullets

- Artificial intelligence offers unparalleled opportunities of progress and applications in nutrition.
- There remains gaps to address to potentialize this emerging field.

Résumé

L'intelligence artificielle (IA) est un domaine qui évolue rapidement et qui offre des possibilités de progrès inégalées dans de nombreux domaines de la santé. Cette courte revue propose un aperçu des principales applications de l'IA pour la recherche en nutrition et identifie les lacunes dans ce domaine émergent. L'IA permet d'une part de mieux comprendre les interactions complexes et non linéaires entre les données nutritionnelles et le risque de maladies, en particulier dans un contexte de données massives, comme dans le domaine de la métabolomique.

L'IA, incluant les approches basées sur la reconnaissance d'images, promet également d'améliorer l'évaluation des apports alimentaires en maximisant l'efficacité et en atténuant les erreurs systématiques et aléatoires associées aux questionnaires alimentaires auto-administrés. Enfin, l'IA permet de recueillir, structurer et analyser de grandes quantités de données tirées des plateformes de médias sociaux afin de mieux comprendre les comportements et les perceptions alimentaires au sein de diverses populations. En résumé, les approches basées sur l'IA sont susceptibles d'améliorer et de faire progresser la recherche en nutrition. Cependant, davantage d'études sont nécessaires afin d'identifier les domaines où l'IA apporte une valeur ajoutée réelle par rapport aux approches traditionnelles et d'autres domaines où ce n'est pas le cas.

Keywords

Artificial intelligence, machine learning, algorithms, nutrition, prediction, dietary assessment, metabolomics, social media

Introduction

Artificial intelligence (AI) is a rapidly evolving field that has offered unparalleled opportunities of progress in many healthcare fields, like precision medicine, radiology, genetics and molecular medicine (Davenport and Kalakota, 2019, Mintz and Brodie, 2019, Hamet and Tremblay, 2017). AI has the advantage of harnessing voluminous datasets, such as Electronic Health Records, omics data and longitudinal data from large cohorts (Goldstein et al., 2016, Mehta and Devarakonda, 2018, van der Ploeg et al., 2014, Wiens and Shenoy, 2018). Nutrition research is among the healthcare fields that are increasingly benefiting from these new computational techniques, notably because of the important amount and complexity of data generated in this field. Among others, AI-based methods have enhanced health outcome prediction in the context of various dietary exposures and have contributed to the improvement and development of dietary assessment tools (Morgenstern et al., 2021). AI-based methods are used in several “omics”-related nutrition research as well as in processing and analyzing social media information. This article provides a brief overview of such current and future applications of AI in nutrition research and addresses research gaps. The main AI techniques discussed in this review are machine learning (ML), deep learning (DL) and natural language processing (NLP).

Machine learning

The field of ML, which is considered an important area of AI, shares several similarities with traditional statistical. However, while traditional statistical methods are generally more focused on inference due to its probabilistic nature, ML is more oriented towards prediction and classification by using learning algorithms trained in large datasets (Bzdok et al., 2018). Another difference between both approaches is that traditional statistical models are developed based on *a*

priori knowledge of associations among a set of variables while ML algorithms assume that the data is not generated by any particular mechanism (Lavigne et al., 2019). ML can also deal in a much more efficient way with very large and complex datasets than traditional statistics. Popular ML techniques include supervised learning and unsupervised learning.

Supervised learning algorithms are provided with the labeled output results so they can *learn* from the data to find relationships among variables and improve predictions (Alloghani, 2020, Lavigne et al., 2019). Predictive performances such as accuracy of various algorithms can then be compared when new data points are presented. Supervised learning algorithms require a lot of data to adequately train and test the algorithms. Main applications of supervised learning are for prediction purposes, such as regression or classification. Popular supervised learning algorithms discussed in this review include decision trees (DT), random forests (RF), support vector machines (SVM) and k-nearest neighbour (KNN). DT make predictions by learning a set of decision rules based on the structure of the data (Song and Lu, 2015). Following a flow-like (or tree) structure, each node of a decision tree represents an input variable, each branch represents a decision rule, and each leaf represents a prediction or classification result (Song and Lu, 2015). RF is a more sophisticated classification algorithm that replicates (or bootstraps) samples of the data to generate a multitude of decision trees and determines a predicted class by averaging the estimated prediction of each tree (Zhang and Ma, 2012). SVM sort data into two or more classes of the outcome of interest using multi-dimensional hyperplanes derived from linear, polynomial, radial basis or sigmoid functions (Howley and Madden, 2005). KNN is an algorithm that assumes that close (or neighbor) data points in a complex dataset share similar features

(Cunningham and Delany, 2020). Therefore, a new data point is classified according to the similarities of a predetermined number of closest points in the dataset.

In unsupervised learning, no labels are provided to the algorithms. These algorithms rather search for natural or hidden patterns and relations within the data (Alloghani, 2020, Lavigne et al., 2019). Algorithms cannot formally be compared, as model performance cannot be measured. Therefore, unsupervised learning is mostly useful in exploratory analyses. Main applications of unsupervised learning include clustering, feature extraction and visualization. An example of unsupervised learning includes the k-means clustering, which finds a fixed number (k) of clusters that group similar data points together to identify underlying patterns (Likas et al., 2003).

Deep learning

DL is a subsection of ML that processes several data types and structures multiple times before achieving the output of interest. The main DL algorithms used are artificial neural networks with multiple hidden layers (convolutional neural networks, recurrent neural networks, etc.), which aim to imitate the human brain (Dongare et al., 2012). In other words, the extra depth, compared to traditional ML algorithms, allows carrying out more complex tasks. Broadly, an input dataset is fed to a first layer of multiple algorithms. The outputs (prediction, classification) of the first layer are then fed to a second layer of algorithms. This can be repeated multiple times to reach a final output, such as for example a predicted health status. Main applications of DL algorithms include NLP, information retrieval and image recognition (Deng, 2014).

Natural language processing

Natural language processing (NLP) aims to achieve human-like language processing (Liddy, 2001). It is applied among others for speech recognition, text analysis and translation. More specifically, NLP can analyze written or spoken texts to paraphrase, translate, answer questions or identify context or meaning (Liddy, 2001). It is particularly useful to extract and structure information from social media, medical files or articles from blogs, among others (Lavigne et al., 2019).

Diet-related health outcome prediction

ML is particularly powerful to analyse multi-dimensional data and to uncover nonlinear relationships and interactions among variables of interest, with the potential to achieve a more in-depth, accurate and sophisticated prediction of diet-related health outcomes (Morgenstern et al., 2021). For example, processing of dietary patterns or nutrient and food intake data using RF, SVM and KNN algorithms have been shown to predict malnutrition among children under five as well as early risk factors of developing overweight/obesity later in life among prematurely born children (Talukder and Ahammed, 2020, Fu et al., 2020). In some instances, ML algorithms have outperformed traditional predictive and classification statistical models. For example, KNN and RF algorithms outperformed standard statistical models to predict long-term cardiometabolic risk based on dietary patterns (Panaretos et al., 2018). Similarly, “feeding” nutrition-related data to RF algorithms improved cardiovascular mortality risk prediction compared to standard Cox models (Rigdon and Basu, 2019). Another study compared logistic regression with ML algorithms, including a neural network, DT, SVM and KNN, to predict the risk of depression using US and

South Korean population-based data (Oh et al., 2019). The neural network identified participants with depression with the highest accuracy among the ML algorithms and performed significantly better than logistic regression in the South Korean dataset. A large proportion of ML applications in nutrition is oriented towards prediction purposes, because ML alone cannot be used for inferential purposes (Hernán et al., 2019). However, ML can assist in better processing data by analyzing a larger number of variables with more complex relationships and don't require restrictive assumptions (Schuler and Rose, 2017). Studies have demonstrated that nonparametric methods, like ML algorithms, can be used along with doubly robust estimation techniques such as targeted maximum likelihood estimation (TMLE) for estimating causal effects (Schuler and Rose, 2017, Naimi and Balzer, 2018). For example, TMLE paired with the Super Learner ML algorithm has revealed protective associations between diets high in fruits and vegetables and the risk of adverse pregnancy outcomes that logistic regression models did not reveal (Bodnar et al., 2020). The Super Learner is an ML algorithm that uses cross-validation to first estimate the performance of multiple preselected classification or regression models and then uses the optimal weighted combination of these models to make a prediction (Naimi and Balzer, 2018). It must be noted that these studies concern more traditional and less complex statistical models, i.e., simpler, linear models. Other, more complex, statistical models, like cubic splines, may take in account non-linear associations and perform equally or better than ML algorithms and thus should also be compared to ML algorithms.

Other AI techniques, like unsupervised ML, can also be used to investigate the intricate associations between diet and health. For example, k-means clustering algorithms were used to identify risk factors for low muscle mass based on nutritional and health-related factors among

men and women (Kwon et al., 2020). The algorithm generated five clusters for men and women separately based on age, total energy, carbohydrate ratio, protein ratio, fat ratio, smoking habits, alcohol consumption, physical activity and number of chronic diseases, yielding similar characteristics among each cluster. Logistic regression was then used to analyze the associations between each of the nine variables and low muscle mass index, hence identifying risk factors within each cluster. For example, key characteristics of two clusters associated with an increased risk of low muscle mass among men were old age, low energy intake, high carbohydrate intake, low protein and fat intake, low alcohol consumption, less physical activity and a high number of chronic diseases. Clustering algorithms may therefore help identify phenotypes or risk factors related to distinct exposure-disease relationships and overcome some of the limitations of conventionally used models, such as better representing complex data structures (Kwon et al., 2020).

Finally, AI-based approaches are particularly powerful when applied to the field of precision nutrition, as summarized in a recent systematic literature review (Kirk et al., 2021). For example, a study demonstrated that a boosted DT-based algorithm integrating data from blood samples, dietary intake, anthropometry, physical activity and gut microbiota composition was superior to traditional glucose monitoring approaches in predicting postprandial glycemic responses to real-life meals (Zeevi et al., 2015). Data also showed that individualized dietary interventions based on these predictions significantly improved postprandial glucose management through consistent alterations to the gut microbiota (Zeevi et al., 2015). Berry *et al.* (Berry et al., 2020) demonstrated promising applications of RF regression models to predict the postprandial triglyceride, glucose and C-peptide response to food intake based on meal composition, habitual diet, meal context,

anthropometry, genetics, microbiome and clinical and biochemical parameters. Hall *et al.* (Hall et al., 2018) used an unsupervised clustering algorithm to identify different types of patterns of elevations in postprandial glucose response, “glucotypes”. The temporal profiles of blood glucose responses of 57 participants with different diagnoses for diabetes were clustered into three “glucotypes” representing low, moderate and severe variability in glycemic responses. Further research may allow a more accurate identification of patients among whom high glucose variability influences the risk of developing diabetes or cardiovascular diseases. Using information from Single Nucleotide Polymorphisms (SNPs) related to type 2 diabetes as well as sex, BMI and age among a sample of 677 healthy or diabetic participants, Lopez *et al.* (Lopez et al., 2018) have shown that a RF algorithm performed better than logistic regression for classifying the diabetes status. Other studies in precision nutrition focused on predicting body weight or risk of obesity. Ramyaa *et al.* (Ramyaa et al., 2019) have used supervised regression algorithms, including SVM, neural networks and KNN, as well as unsupervised algorithms, including k-means clustering, to predict weight or body mass index using self-reported dietary intake and physical activity data. For instance, a KNN algorithm could predict body weight with a mean approximate error of 6.98 kg. When performing k-means clustering and then using KNN to predict body weight within the cluster, the algorithm performed better with a mean approximate error of 1.1 kg. Similarly, Babajide *et al.* (Babajide et al., 2020) tested different ML algorithms, including SVM, RF and ANN, to predict body weight at the end of 10-week dietary intervention program based on anthropometry, body composition, metabolic rate and dietary intake data. The RF model performed best with the lowest error rate and highest R-square value of 96%. Curbelo Montanez *et al.* (Curbelo Montañez et al., 2017) have used a RF-based feature selection algorithm to identify the most relevant SNPs and a SVM classifier to identify genetic variants predicting susceptibility

to obesity. The SVM classifier performed better than logistic regression when using the obesity-associated SNPs identified by the RF-based algorithm.

In sum, it is being increasingly recognized that traditional predictive models may fall short in deciphering the complex interactions and nonlinear associations between diet-related data and health outcomes. AI-based approaches, particularly ML algorithms, show great potential in this field because of their capacity to better capture such complexity in predictive medicine.

Dietary assessment

Assessing dietary intake in research using self-reported methods such as 24-hour recalls, food diaries and food frequency questionnaires is highly challenging because such methods are time-consuming, subjective and prone to nontrivial systematic and random errors (Zhao et al., 2020). Morgenstern *et al.* (Morgenstern et al., 2021) have provided a thorough overview on how ML can help address challenges in nutritional epidemiology, with particular focus on measurement errors, statistical power, increasing precision and validity and reducing bias.

Non image-based tools

The measurement of dietary intakes and behaviors using non image-based tools may also be enhanced through the use of novel ML-based approaches. For example, a voice-based mobile nutrition monitoring system that uses NLP techniques has been developed to monitor dietary intake (Hezarjaribi et al., 2018). Once NLP techniques convert spoken words to text, an algorithm links food names to a nutrition database to estimate calorie intake. This monitoring system estimated

calorie intake with an accuracy of 92.2%. Kalantarian *et al.* (Kalantarian and Sarrafzadeh, 2015) used a smartwatch microphone combined with a RF algorithm to identify chews and swallows. Authors report good classification performance between food items, talking and ambient noise, with a F-measure of 94.5%, a common metric used in ML. Heydarian *et al.* (Heydarian et al., 2019) have summarized the current evidence on the use of upper limb-mounted motion sensors for passive and objective assessment of certain eating behaviours. DT, RF, SVM and DL algorithms can be used to differentiate between eating activities (e.g., chewing, swallowing) and non-eating activities (e.g., walking, writing, talking on the phone, brushing teeth). In another study, Mertes *et al.* (Mertes et al., 2020) used a plate with weight sensors and a bite detection algorithm based on a RF classifier to assess eating. Out of 836 bites, the algorithm detected 602 bites, yielding an accuracy of 74%. Other studies have focused on developing algorithms that improve the accuracy of food intake measurements using data derived from existing self-reported instruments. For example, applying DT-based approaches to the UK National Diet and Nutrition Survey, Rosso and Giabbenalli (Rosso and Giabbanelli, 2018) have shown that public health dietary surveys can be simplified while improving accuracy in predicting adherence to five key dietary recommendations. Authors concluded that the use of simplified surveys to monitor public health nutrition is cost-effective while possibly attenuating biases as participation burden is reduced. Chin *et al.* (Chin et al., 2019) have demonstrated the feasibility of using ML algorithms to substantially decrease time required to estimate nutrient intakes that are not automatically outputted in a web-based 24-hour recall, by combining 24-hour recall data with information from food and nutrient databases. Finally, applying ML algorithms to dietary intake data from the Global Burden of Disease study, Schmidhuber *et al.* (Schmidhuber et al., 2018) have developed predictive models that estimate the consumption of each nutrient based on their national availability, with an accuracy greater than

80%. Such data is invaluable to address the nutritional needs of specific populations in the context of particular food systems.

Image-based tools

Development of new dietary assessment methods based on automated food image recognition and analysis is a fast-evolving field of research. Indeed, an increasing number of food image databases, algorithms for food recognition and classification models are being developed and validated for use on multiple devices for food intake monitoring (Bruno et al., 2017). For example, the Snap-n-eat is a food recognition application based on a SVM classifier that estimates energy, food and nutrient intake using images taken directly with the user's smartphone, without additional intervention by the research team (Zhang et al., 2015). Similarly, the Keenoa food recognition application, which is linked to the Canadian Nutrient File (2015), generates a nutrient analysis that is sent directly to a dietician when a patient or participant in research takes a picture of their meal, thus facilitating the monitoring of dietary habits by a dietician or a research team (Ji et al., 2020). The use of artificial neural networks (ANN), particularly convolutional neural networks (CNN), are also prominent in food recognition algorithms (Bruno et al., 2017). Merchant and Pande (Merchant and Pande, 2019) have developed a smartphone application based on a CNN for food recognition to provide nutritional assessment and suggest food recipes to diabetic patients. The algorithm recognized food with an accuracy of 70%. Fang *et al.* (Fang et al., 2019) have developed a CNN to estimate total energy intake based on a single image of a meal, yielding predictions with an average error of 209 kilocalories. Since such algorithms are training-based, capturing more images with distinct food types and sizes will help generate more accurate predictions. Another study has shown that a trained ANN can reconstruct a 3D point cloud of a single food image taken

in depth on a smartphone and predict its volume with an accuracy of up to 93% (Lo et al., 2018). Other studies have developed CNN algorithms to recognize foods and drinks among voluminous datasets of images. For example, CNN algorithms were able to recognize 11 food groups among thousands of images with an accuracy of up to 82% (Gözde Özsert and Özyildirim, 2017). Quite similarly, Jia *et al.* (Jia et al., 2019) have developed a CNN algorithm that differentiates food items from non-food items with an accuracy of 86.4% using images passively taken by a wearable camera among free-living individuals and Liu *et al.* (Liu et al., 2016) developed CNN algorithms trained using food images taken by smartphones that recognized different foods with an accuracy of up to 77%.

The performance of ML algorithms to recognize and identify food on images is improving rapidly due to the voluminous and increasing number of food image datasets available (Tahir and Chu, 2021). Indeed, the training-based nature of ML algorithms implies that the use of more images of distinct food types and sizes will inevitably improve their performance. Popular food datasets used to develop such algorithms include the Food-101 dataset (11 categories, 101 000 images (Bossard et al., 2014)), the Food-5k (2 categories, 5000 images (Singla et al., 2016)), the Food-11 (11 categories, 16 643 images (Singla et al., 2016)), the UEC-FOOD-100 (100 categories, 14 361 images (Matsuda et al., 2012)) and the UEC-FOOD-256 (256 categories, 25 088 images (Kawano and Yanai, 2015)). Other studies are developing databases by extracting images from publicly available data, like Mezgec *et al.* (Mezgec and Korousic Seljak, 2017), who generated a dataset of 225 953 images of food and drinks from the Internet, or Rich *et al.* (Rich et al., 2016) who generated a dataset with 808 864 food-related images from Instagram.

These examples are just a glimpse at the numerous AI applications that exist for collecting nutritional data and assessing food intake (Kirk et al., 2021, Lo et al., 2020, Tahir and Chu, 2021). Multiple ML, NLP and DL algorithms are being developed to assess food intake more accurately, relying more on objectively recorded food intake and behaviours, thus potentially attenuating biases known to be associated with self-reported dietary intake data as well as decreasing participation burden (Zhao et al., 2020, Morgenstern et al., 2021). However, conventional dietary assessment tools and AI-based tools are to date complementary methods because most new AI-based tools cannot yet fully replace conventional tools (Zhao et al., 2020, Morgenstern et al., 2021).

Nutritional metabolomics and biomarkers

Principal component analysis, multivariate data analysis and partial least squares discriminant analysis are among the most common models used to analyze metabolomics data. However, AI and related algorithms and methods, like ANN, RF and SVM are particularly well-tailored to decipher the nonlinear nature of complex associations found in large nutritional metabolomics datasets. More specifically, AI techniques combined with metabolomics are used to identify biomarkers of foods or nutrients. For example, Shinn *et al.* (Shinn et al., 2021) have developed a RF algorithm to identify fecal bacteria biomarkers of 6 specific foods. The overall classification accuracy of the 6 foods was 70% using 22 fecal bacteria biomarkers. KNN, SVM and RF algorithms have been developed to predict total antioxidant properties of food matrices based on datasets of flavonoid food content, which may ultimately reveal new roles of these bioactive molecules on health and disease (Guardado Yordi et al., 2019). In the sports nutrition realm, ML has been employed to investigate the impact of nutrient intake on biomarkers of hydration in

cyclists (Munoz et al., 2020). Since multicollinearity between variables can increase errors in traditional statistical modelling, thus augmenting the chance of observing null associations, researchers used k-means clustering to first identify clusters representing one or more nutrients that may serve as mediators of body water status in cyclists.

AI-based methods applied to large metabolomics datasets may help identify biomarkers of health outcomes. For instance, SVM, a supervised ML algorithm, and Random Walks, an unsupervised ML algorithm, were developed to predict anti-cancer molecules within different foods (Veselkov et al., 2019). The researchers were able to show that specific plant-based foods contained molecules with anti-cancer properties that were similar to those seen with existing cancer drugs on molecular networks. The relationship between food addiction and the brain-gut-microbiome axis has been explored using metabolomics and brain imaging among female participants with obesity (Dong et al., 2020). Researchers were able to accurately classify participants according to criteria related to food addiction using a RF algorithm that processed fecal metabolites and brain imaging data. Algorithms like RF, SVM and ANN have also been used to process mass spectrometry-based metabolomics, through selection and processing of peaks, normalizing, imputing and interpreting data, for biomarker detection, classification or regression (Liebal et al., 2020).

Finally, AI-related approaches are widely used to facilitate analysis and interpretation of multiple omics datasets (Khorraminezhad et al., 2020, Liebal et al., 2020, Mendez et al., 2020). For example, Perakakis *et al.* (Perakakis et al., 2019) applied SVM, KNN and RF algorithms to metabolomics, lipidomics and glycomics data to predict non-alcoholic steatohepatitis (NASH)

and non-alcoholic fatty liver (NAFL). The SVM algorithm classified healthy, NASH or NAFL participants with an accuracy of 90%. Hence, there is no doubt that advanced AI-based methods are revolutionizing our capacity to take advantage of the multidimensional nature of datasets available in the nutritional “omics” fields.

Social media content analysis

In social media lies exceptional amounts of data for health research, including a breadth of nutrition-related information to which large segments of the population are exposed and influenced by. AI-based applications, like NLP and ML, can gather, structure and analyze information from a variety of social media platforms to monitor and better understand nutritional behaviours and perceptions among populations of interest. For example, models have been developed to analyze the textual and image content of social media, like Twitter and Reddit, to assess content and perceptions regarding weight loss, emotional eating, diet, diabetes, obesity or exercise (Karami et al., 2018, Hwang et al., 2020, Liu and Yin, 2020, Shaw and Karami, 2017). For example, NLP topic modeling and clustering algorithms have been used to process and analyze posts on *r/loseit*, an online community built around weight management and weight loss (Liu and Yin, 2020). More classical linear regression models were then used to investigate associations between the content of the posts and the user’s weight loss. Another study trained ML classification algorithms, including DT, SVM, and KNN, to detect emotional eating posts in the *r/loseit* community (Hwang et al., 2020). NLP was then used to categorize the emotional eating posts in four main topics: addressing feelings, sharing physical changes, sharing or asking for dietary information and sharing dietary strategies (Hwang et al., 2020). Karami *et al.* (Karami et al., 2018) analyzed 4.5 million Twitter posts mentioning obesity (51.7%), diet (23.7%), exercise (16.6%) or diabetes (8%)

and identified related topics and correlations. For instance, sub-topics for obesity, apart from diet, exercise and diabetes, included Alzheimer, cancer and children. Sub-topics for diet, apart from obesity, exercise and diabetes, included vegetarian, pregnancy, celebrities, weight loss, religious and mental health. Strong correlations existed between topics related to exercise and obesity, while notable correlations were found between topics related to diet and obesity as well as diabetes and obesity.

AI-based methods are also being developed to better understand the spatial pattern of nutrition-related information found in social media. For example, NLP and geocoding of social media posts have provided information on the real-time distribution of nutritional behaviours, habits and health outcomes, which may help in turn identify populations at risk (Ghosh and Guha, 2013, Nguyen et al., 2016, Shah et al., 2019, De Choudhury et al., 2016, Cesare et al., 2019, Widener and Li, 2014). Such information may be proven to be of great value from a public health perspective. For instance, NLP and ML algorithms have been developed to collect and analyze data from Twitter to assess Canadian's health and nutritional habits (Shah et al., 2019). Using NLP to analyze social media content has the advantage of being less time consuming than traditional dietary assessment methods and allow quick access to information and data collected in real time (Shah et al., 2019). The developed model classified food and non-food posts with an accuracy of 93% and provided information such as approximate caloric ratio (caloric intake vs energy expenditure) of Twitter posts per province as well as foods and activities most tweeted about per province in Canada. Another study estimated the quality of available foods in different geographical locations using data from 3 million food-related posts shared on Instagram to better understand healthy food availability (De Choudhury et al., 2016). Notably, Instagram posts made by people located in food

deserts were higher in fat, cholesterol and sugar intake and lower in protein and fiber. Nguyen *et al.* (Nguyen et al., 2016) used geotagged Twitter posts to create a neighbourhood database with indicators of well-being and health behaviours, to better understand the effects of neighbourhood on health. For example, the study found that social and economic disadvantage, high urbanicity and a higher density of fast-food restaurants was associated with lower happiness and fewer healthy behaviours. A study also used an NLP framework to geolocate social media posts to map out availability of healthy and unhealthy foods (Widener and Li, 2014). They demonstrated among others that there was a higher number of unhealthy food-related Twitter posts in disadvantaged areas with low access to healthy food stores.

In sum, social media has the potential to contribute to time-dependent and geospatial surveillance of physical activity, dietary habits and a multitude of other topics. Such information, along with more conventional data on dietary habits, may eventually become an integral part of the evidence considered to craft public health policy and initiatives.

Research gaps

Studies have shown that AI-based approaches do not always outperform conventionally used classification and prediction models. For example, many studies have reported no advantage of using AI in disease and health outcome prediction compared to using traditional statistical models (Christodoulou et al., 2019, Gravesteijn et al., 2020, Lynam et al., 2020, Nusinovici et al., 2020, Kuhle et al., 2018). For outcome variables that can be measured with less signal to noise ratio, like survival rate or readmission rate in hospitals, ML algorithms have been shown to perform better than traditional statistical models (Feng et al., 2019, Mortazavi et al., 2016). However, for outcome variables that have more signal to noise ratio, such as predicting risk of major chronic diseases,

depression or prognosticating traumatic brain injury, ML algorithms have not always outperformed conventionally used models (Nusinovici et al., 2020, Gravesteyn et al., 2020, Oh et al., 2019). ML algorithms may also have little to no impact on improving performance when applied to smaller sample sizes and/or used with a small number of variables, because the advantage of added model complexity is not necessary in these cases. Finally, there are other examples where ML algorithms did not outperform traditional statistical models. For example, in a study that compared classification performance of eight different linear and ML approaches on ten clinical metabolomics datasets, linear classification models performed similarly to ML algorithms, like SVM and ANN, in most datasets, because the outcome was linearly separable (Mendez et al., 2019b). Therefore, classification performance depends not only highly on the structure and the amount of data, but also on the need for more complex algorithms (Mendez et al., 2019b). The contradictions regarding the best models for disease and health outcome prediction suggests that AI-based modeling should always be compared to traditional statistical models to identify for which types of variables and for which outcomes traditional statistical models or AI algorithms are better suited (Goldstein et al., 2016, Liebal et al., 2020). This is particularly the case in nutrition where there is only a paucity of studies having compared AI-based and traditional approaches. Another limitation is the fact that datasets, which are necessary to improve performance of AI algorithms, are not always available. As indicated above, voluminous datasets are available for image and social media analysis, as well as in metabolomics analysis. However, the same cannot be said for precision nutrition and other nutrition-related disease and health prediction, which may rely on smaller sample sizes with fewer variables. Generating voluminous datasets for precision nutrition and nutrition-related predictions is inevitable to improve performance of algorithms. Also, the challenge of interpretability of the output from AI algorithms

remains a significant limitation in many instances, including when trying to identify sets of metabolites that predict a given outcome in nutritional metabolomics studies (Mendez et al., 2019a, Mendez et al., 2020, Sen et al., 2021), as interpretability relates to the understanding of the model's design, i.e., how the model works, and explainability relates to the understanding of what the model is saying, i.e., being able to understand and explain its prediction output (Marcinkevics and Vogt, 2020). Like interpretability, explainability is also a limitation of AI, especially in the realm of health where legal, medical and ethical issues must be considered (Amann et al., 2020). Inherent interpretability and explainability must be a priority beyond performance and error rates, especially for algorithms labeled as "black-box models". Therefore, one must adopt a critical stance towards AI when developing and validating algorithms for specific data structures and outcome variables. Such posture applies fully to the nutrition research field.

While AI-based dietary assessment tools may address certain challenges and limitations associated with the use of conventional dietary assessment instruments such as 24-hour recalls, food diaries and FFQ, they are not exempt of important limitations. While AI-based dietary assessment tools may be less subjective to biases associated to self-reported data, this is not always the case as reactive biases remain when participants knowingly wear a sensor or take pictures of their meals (Zhao et al., 2020). For example, Ji *et al.* (Ji et al., 2020) demonstrated that participants using an AI-based dietary assessment smartphone application alone under-reported food intakes compared to when a dietician could adjust the participants intake on the application. Food image analysis is also limited in its capacity to determine the nutrient content of certain foods, such as the fat percentage of dairy products. Identifying hidden or mixed foods and precisely estimating nutrients and calories from food images have also been mentioned as important challenges when using AI-

based tools (Bruno et al., 2017). Hence, AI-based dietary assessment tools cannot currently address all the challenges and limitations inherent to traditional tools. Using AI for dietary assessment is promising, but more research is needed to improve and validate algorithms (Zhao et al., 2020). Therefore, it may be more appropriate and even recommended for the time being at least to combine AI-based and traditional tools to improve dietary assessment and the quality of dietary intake data (Zhao et al., 2020).

Finally, many limitations and ethical concerns exist regarding the use of AI for social media analysis. Social media information comes in large amounts and concerns a wide variety of topics. However, this information can be incomplete, incorrect or biased and algorithms have inherent limitations in this regard (Lanfranchi et al., 2017, Matheny et al., 2020). For example, people may post about what they eat in a different location from where they live, creating a geographical bias (Shah et al., 2019). Also, algorithms may not always be developed to identify food words or posts that were used in a metaphorical way (Shah et al., 2019, Widener and Li, 2014). The type and number of posts can also be affected by other factors, like seasons, special events or new social media trends (Shah et al., 2019, Widener and Li, 2014). More importantly, social media data is inevitably biased because of missing information concerning people who do not use the social media of interest, with notable underrepresentation of minority and low socioeconomic groups (Lanfranchi et al., 2017, Widener and Li, 2014, Hwang et al., 2020, Matheny et al., 2020, Safdar et al., 2020). This is an important concern from a public health nutrition perspective, where we wish to identify populations at risk. There have also been ethical and regulation concerns related to the use of AI to extract and use social media data. Many users may be unaware that their information is used for research because of a misunderstanding of what “publicly available data”

means (Kern et al., 2016). Therefore, meticulousness is necessary to avoid training algorithms with strongly biased and inequitable data and results should always be interpreted with nuance. It may be of more interest to use social media as a tool for *taking the pulse*, for more time-dependent monitoring and for comparison purposes with other public health datasets rather than using it as the only data source (Widener and Li, 2014).

Conclusion

Has AI revolutionized nutrition research? Not quite yet. Application of AI-based methods may contribute to improving predictive models of diet and disease outcomes, to better collecting, processing and understanding complex nutrition-related data, and to better monitoring of a population's nutritional status. However, several limitations and concerns regarding the use of AI in nutrition research emphasize the importance of further research to develop and identify the algorithms best suited to nutrition data. The remaining gaps between the promises and the true enhancements of research through AI reinforces the importance of deploying AI-based approaches with caution and realism, with emphasis on legal and regulatory issues as well as on prioritization of equity, inclusion, and a human rights lens for this work while addressing implicit and explicit biases (Matheny et al., 2020).

Competing interests

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TITLE

Artificial intelligence in nutrition research: perspectives on current and future applications

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Abstract

Artificial intelligence (AI) is a rapidly evolving area that offers unparalleled opportunities of progress and applications in many healthcare fields. In this review, we provide an overview of the main and latest applications of AI in nutrition research and identify gaps to address to potentialize this emerging field. AI algorithms may help better understand and predict the complex and non-linear interactions between nutrition-related data and health outcomes, particularly when large amounts of data need to be structured and integrated, such as in metabolomics. AI-based approaches, including image recognition, may also improve dietary assessment by maximizing efficiency and addressing systematic and random errors associated with self-reported measurements of dietary intakes. Finally, AI applications can extract, structure and analyze large amounts of data from social media platforms to better understand dietary behaviours and perceptions among the population. In summary, AI-based approaches will likely improve and advance nutrition research as well as help explore new applications. However, further research is needed to identify areas where AI does deliver added value compared to traditional approaches, and other areas where AI is simply not likely to advance the field.

Novelty Bullets

- Artificial intelligence offers unparalleled opportunities of progress and applications in nutrition.
 - There remains gaps to address to potentialize this emerging field.
- ~~Artificial intelligence (AI) is a rapidly evolving area that offers unparalleled opportunities of progress and applications in many healthcare fields. In this review, we provide an overview of the main and latest applications of AI in nutrition research and identify gaps to address to potentialize this emerging field. AI algorithms may help better understand and predict the complex and non-linear interactions between nutrition-related data and health outcomes, particularly when large amounts of data need to be structured and integrated, such as in metabolomics. AI-based approaches, including image recognition, may also improve dietary assessment by maximizing efficiency and addressing systematic and random errors associated with self-reported measurements of dietary~~

intakes. Finally, AI applications can extract, structure and analyze large amounts of data from social media platforms to better understand dietary behaviours and perceptions among the population. In summary, AI-based approaches will likely improve and advance nutrition research as well as help explore new applications. However, further research is needed to identify areas where AI does deliver added value compared to traditional approaches, and other areas where AI is simply not likely to advance the field.

Résumé

L'intelligence artificielle (IA) est un domaine qui évolue rapidement et qui offre des possibilités de progrès inégalées dans de nombreux domaines de la santé. Cette courte revue propose un aperçu des principales applications de l'IA pour la recherche en nutrition et identifie les lacunes dans ce domaine émergent. L'IA permet d'une part de mieux comprendre les interactions complexes et non linéaires entre les données nutritionnelles et le risque de maladies, en particulier dans un contexte de données massives, comme dans le domaine de la métabolomique. L'IA, incluant les approches basées sur la reconnaissance d'images, promet également d'améliorer l'évaluation des apports alimentaires en maximisant l'efficacité et en atténuant les erreurs systématiques et aléatoires associées aux questionnaires alimentaires auto-administrés. Enfin, l'IA permet de recueillir, structurer et analyser de grandes quantités de données tirées des plateformes de médias sociaux afin de mieux comprendre les comportements et les perceptions alimentaires au sein de diverses populations. En résumé, les approches basées sur l'IA sont susceptibles d'améliorer et de faire progresser la recherche en nutrition. Cependant, davantage d'études sont nécessaires afin d'identifier les domaines où l'IA apporte une valeur ajoutée réelle par rapport aux approches traditionnelles et d'autres domaines où ce n'est pas le cas.

74

75 **Keywords**

76 Artificial intelligence, machine learning, algorithms, nutrition, prediction, dietary assessment,
77 metabolomics, social media

Draft

Introduction

Artificial intelligence (AI) is a rapidly evolving field that has offered unparalleled opportunities of progress in many healthcare fields, like precision medicine, radiology, genetics and molecular medicine (Davenport and Kalakota, 2019, Mintz and Brodie, 2019, Hamet and Tremblay, 2017). AI has the advantage of harnessing voluminous datasets, such as Electronic Health Records, omics data and longitudinal data from large cohorts (Goldstein et al., 2016, Mehta and Devarakonda, 2018, van der Ploeg et al., 2014, Wiens and Shenoy, 2018). Nutrition research is among the healthcare fields that are increasingly benefiting from these new computational techniques, notably because of the important amount and complexity of data generated in this field. Among others, AI-based methods have enhanced health outcome prediction in the context of various dietary exposures and have contributed to the improvement and development of dietary assessment tools (Morgenstern et al., 2021). AI-based methods are used in several “omics”-related nutrition research as well as in processing and analyzing social media information. This article provides a brief overview of such current and future applications of AI in nutrition research and addresses research gaps. The main AI techniques discussed in this review are machine learning (ML), deep learning (DL) and natural language processing (NLP).

Machine learning

The field of ML, which is considered an important area of AI, shares several similarities with traditional statistical. However, while traditional statistical methods are generally more focused on inference due to its probabilistic nature, ML is more oriented towards prediction and classification by using learning algorithms trained in large datasets (Bzdok et al., 2018). Another difference between both approaches is that traditional statistical models are developed based on *a*

priori knowledge of associations among a set of variables while ML algorithms assume that the data is not generated by any particular mechanism (Lavigne et al., 2019). ML can also deal in a much more efficient way with very large and complex datasets than traditional statistics. Popular ML techniques include supervised learning and unsupervised learning.

Supervised learning algorithms are provided with the labeled output results so they can *learn* from the data to find relationships among variables and improve predictions (Alloghani, 2020, Lavigne et al., 2019). Predictive performances such as accuracy of various algorithms can then be compared when new data points are presented. Supervised learning algorithms require a lot of data to adequately train and test the algorithms. Main applications of supervised learning are for prediction purposes, such as regression or classification. Popular supervised learning algorithms discussed in this review include decision trees (DT), random forests (RF), support vector machines (SVM) and k-nearest neighbour (KNN). DT make predictions by learning a set of decision rules based on the structure of the data (Song and Lu, 2015). Following a flow-like (or tree) structure, each node of a decision tree represents an input variable, each branch represents a decision rule, and each leaf represents a prediction or classification result (Song and Lu, 2015). RF is a more sophisticated classification algorithm that replicates (or bootstraps) samples of the data to generate a multitude of decision trees and determines a predicted class by averaging the estimated prediction of each tree (Zhang and Ma, 2012). SVM sort data into two or more classes of the outcome of interest using multi-dimensional hyperplanes derived from linear, polynomial, radial basis or sigmoid functions (Howley and Madden, 2005). KNN is an algorithm that assumes that close (or neighbor) data points in a complex dataset share similar features

(Cunningham and Delany, 2020). Therefore, a new data point is classified according to the similarities of a predetermined number of closest points in the dataset.

In unsupervised learning, no labels are provided to the algorithms. These algorithms rather search for natural or hidden patterns and relations within the data (Alloghani, 2020, Lavigne et al., 2019). Algorithms cannot formally be compared, as model performance cannot be measured. Therefore, unsupervised learning is mostly useful in exploratory analyses. Main applications of unsupervised learning include clustering, feature extraction and visualization. An example of unsupervised learning includes the k-means clustering, which finds a fixed number (k) of clusters that group similar data points together to identify underlying patterns (Likas et al., 2003).

Deep learning

DL is a subsection of ML that processes several data types and structures multiple times before achieving the output of interest. The main DL algorithms used are artificial neural networks with multiple hidden layers (convolutional neural networks, recurrent neural networks, etc.), which aim to imitate the human brain (Dongare et al., 2012). In other words, the extra depth, compared to traditional ML algorithms, allows carrying out more complex tasks. Broadly, an input dataset is fed to a first layer of multiple algorithms. The outputs (prediction, classification) of the first layer are then fed to a second layer of algorithms. This can be repeated multiple times to reach a final output, such as for example a predicted health status. Main applications of DL algorithms include NLP, information retrieval and image recognition (Deng, 2014).

146 *Natural language processing*

147 Natural language processing (NLP) aims to achieve human-like language processing (Liddy,
148 2001). It is applied among others for speech recognition, text analysis and translation. More
149 specifically, NLP can analyze written or spoken texts to paraphrase, translate, answer questions
150 or identify context or meaning (Liddy, 2001). It is particularly useful to extract and structure
151 information from social media, medical files or articles from blogs, among others (Lavigne et al.,
152 2019).

153

154 **Diet-related health outcome prediction**

155 ML is particularly powerful to analyse multi-dimensional data and to uncover nonlinear
156 relationships and interactions among variables of interest, with the potential to achieve a more in-
157 depth, accurate and sophisticated prediction of diet-related health outcomes (Morgenstern et al.,
158 2021). For example, processing of dietary patterns or nutrient and food intake data using RF, SVM
159 and KNN algorithms have been shown to predict malnutrition among children under five as well
160 as early risk factors of developing overweight/obesity later in life among prematurely born children
161 (Talukder and Ahammed, 2020, Fu et al., 2020). In some instances, ML algorithms have
162 outperformed traditional predictive and classification statistical models. For example, KNN and
163 RF algorithms outperformed standard statistical models to predict long-term cardiometabolic risk
164 based on dietary patterns (Panaretos et al., 2018). Similarly, “feeding” nutrition-related data to RF
165 algorithms improved cardiovascular mortality risk prediction compared to standard Cox models
166 (Rigdon and Basu, 2019). Another study compared logistic regression with ML algorithms,
167 including a neural network, DT, SVM and KNN, to predict the risk of depression using US and

South Korean population-based data (Oh et al., 2019). The neural network identified participants with depression with the highest accuracy among the ML algorithms and performed significantly better than logistic regression in the South Korean dataset. A large proportion of ML applications in nutrition is oriented towards prediction purposes, because ML alone cannot be used for inferential purposes (Hernán et al., 2019). However, ML can assist in better processing data by analyzing a larger number of variables with more complex relationships and don't require restrictive assumptions (Schuler and Rose, 2017). Studies have demonstrated that nonparametric methods, like ML algorithms, can be used along with doubly robust estimation techniques such as targeted maximum likelihood estimation (TMLE) for estimating causal effects (Schuler and Rose, 2017, Naimi and Balzer, 2018). For example, TMLE paired with the Super Learner ML algorithm has revealed protective associations between diets high in fruits and vegetables and the risk of adverse pregnancy outcomes that logistic regression models did not reveal (Bodnar et al., 2020). The Super Learner is an ML algorithm that uses cross-validation to first estimate the performance of multiple preselected classification or regression models and then uses the optimal weighted combination of these models to make a prediction (Naimi and Balzer, 2018). It must be noted that these studies concern more traditional and less complex statistical models, i.e., simpler, linear models. Other, more complex, statistical models, like cubic splines, may take in account non-linear associations and perform equally or better than ML algorithms and thus should also be compared to ML algorithms.

Other AI techniques, like unsupervised ML, can also be used to investigate the intricate associations between diet and health. For example, k-means clustering algorithms were used to identify risk factors for low muscle mass based on nutritional and health-related factors among

men and women (Kwon et al., 2020). The algorithm generated five clusters for men and women separately based on age, total energy, carbohydrate ratio, protein ratio, fat ratio, smoking habits, alcohol consumption, physical activity and number of chronic diseases, yielding similar characteristics among each cluster. Logistic regression was then used to analyze the associations between each of the nine variables and low muscle mass index, hence identifying risk factors within each cluster. For example, key characteristics of two clusters associated with an increased risk of low muscle mass among men were old age, low energy intake, high carbohydrate intake, low protein and fat intake, low alcohol consumption, less physical activity and a high number of chronic diseases. Clustering algorithms may therefore help identify phenotypes or risk factors related to distinct exposure-disease relationships and overcome some of the limitations of conventionally used models, such as better representing complex data structures (Kwon et al., 2020).

Finally, AI-based approaches are particularly powerful when applied to the field of precision nutrition, as summarized in a recent systematic literature review (Kirk et al., 2021). For example, a study demonstrated that a boosted DT-based algorithm integrating data from blood samples, dietary intake, anthropometry, physical activity and gut microbiota composition was superior to traditional glucose monitoring approaches in predicting postprandial glycemic responses to real-life meals (Zeevi et al., 2015). Data also showed that individualized dietary interventions based on these predictions significantly improved postprandial glucose management through consistent alterations to the gut microbiota (Zeevi et al., 2015). Berry *et al.* (Berry et al., 2020) demonstrated promising applications of RF regression models to predict the postprandial triglyceride, glucose and C-peptide response to food intake based on meal composition, habitual diet, meal context,

anthropometry, genetics, microbiome and clinical and biochemical parameters. Hall *et al.* (Hall et al., 2018) used an unsupervised clustering algorithm to identify different types of patterns of elevations in postprandial glucose response, “glucotypes”. The temporal profiles of blood glucose responses of 57 participants with different diagnoses for diabetes were clustered into three “glucotypes” representing low, moderate and severe variability in glycemic responses. Further research may allow a more accurate identification of patients among whom high glucose variability influences the risk of developing diabetes or cardiovascular diseases. Using information from 96 Single Nucleotide Polymorphisms (SNPs) related to type 2 diabetes as well as sex, BMI and age among a sample of 677 healthy or diabetic participants, Lopez *et al.* (Lopez et al., 2018) have shown that a RF algorithm performed better than logistic regression for classifying the diabetes status. Other studies in precision nutrition focused on predicting body weight or risk of obesity. Ramyaa *et al.* (Ramyaa et al., 2019) have used supervised regression algorithms, including SVM, neural networks and KNN, as well as unsupervised algorithms, including k-means clustering, to predict weight or body mass index using self-reported dietary intake and physical activity data. For instance, a KNN algorithm could predict body weight with a mean approximate error of 6.98 kg. When performing k-means clustering and then using KNN to predict body weight within the cluster, the algorithm performed better with a mean approximate error of 1.1 kg. Similarly, Babajide *et al.* (Babajide et al., 2020) tested different ML algorithms, including SVM, RF and ANN, to predict body weight at the end of 10-week dietary intervention program based on anthropometry, body composition, metabolic rate and dietary intake data. The RF model performed best with the lowest error rate and highest R-square value of 96%. Curbelo Montanez *et al.* (Curbelo Montañez et al., 2017) have used a RF-based feature selection algorithm to identify the most relevant SNPs and a SVM classifier to identify genetic variants predicting susceptibility

to obesity. The SVM classifier performed better than logistic regression when using the obesity-associated SNPs identified by the RF-based algorithm.

In sum, it is being increasingly recognized that traditional predictive models may fall short in deciphering the complex interactions and nonlinear associations between diet-related data and health outcomes. AI-based approaches, particularly ML algorithms, show great potential in this field because of their capacity to better capture such complexity in predictive medicine.

Dietary assessment

Assessing dietary intake in research using self-reported methods such as 24-hour recalls, food diaries and food frequency questionnaires is highly challenging because such methods are time-consuming, subjective and prone to nontrivial systematic and random errors (Zhao et al., 2020). Morgenstern *et al.* (Morgenstern et al., 2021) have provided a thorough overview on how ML can help address challenges in nutritional epidemiology, with particular focus on measurement errors, statistical power, increasing precision and validity and reducing bias.

Non image-based tools

The measurement of dietary intakes and behaviors using non image-based tools may also be enhanced through the use of novel ML-based approaches. For example, a voice-based mobile nutrition monitoring system that uses NLP techniques has been developed to monitor dietary intake (Hezarjaribi et al., 2018). Once NLP techniques convert spoken words to text, an algorithm links food names to a nutrition database to estimate calorie intake. This monitoring system estimated

calorie intake with an accuracy of 92.2%. Kalantarian *et al.* (Kalantarian and Sarrafzadeh, 2015) used a smartwatch microphone combined with a RF algorithm to identify chews and swallows. Authors report good classification performance between food items, talking and ambient noise, with a F-measure of 94.5%, a common metric used in ML. Heydarian *et al.* (Heydarian et al., 2019) have summarized the current evidence on the use of upper limb-mounted motion sensors for passive and objective assessment of certain eating behaviours. DT, RF, SVM and DL algorithms can be used to differentiate between eating activities (e.g., chewing, swallowing) and non-eating activities (e.g., walking, writing, talking on the phone, brushing teeth). In another study, Mertes *et al.* (Mertes et al., 2020) used a plate with weight sensors and a bite detection algorithm based on a RF classifier to assess eating. Out of 836 bites, the algorithm detected 602 bites, yielding an accuracy of 74%. Other studies have focused on developing algorithms that improve the accuracy of food intake measurements using data derived from existing self-reported instruments. For example, applying DT-based approaches to the UK National Diet and Nutrition Survey, Rosso and Giabbenalli (Rosso and Giabbanelli, 2018) have shown that public health dietary surveys can be simplified while improving accuracy in predicting adherence to five key dietary recommendations. Authors concluded that the use of simplified surveys to monitor public health nutrition is cost-effective while possibly attenuating biases as participation burden is reduced. Chin *et al.* (Chin et al., 2019) have demonstrated the feasibility of using ML algorithms to substantially decrease time required to estimate nutrient intakes that are not automatically outputted in a web-based 24-hour recall, by combining 24-hour recall data with information from food and nutrient databases. Finally, applying ML algorithms to dietary intake data from the Global Burden of Disease study, Schmidhuber *et al.* (Schmidhuber et al., 2018) have developed predictive models that estimate the consumption of each nutrient based on their national availability, with an accuracy greater than

80%. Such data is invaluable to address the nutritional needs of specific populations in the context of particular food systems.

Image-based tools

Development of new dietary assessment methods based on automated food image recognition and analysis is a fast-evolving field of research. Indeed, an increasing number of food image databases, algorithms for food recognition and classification models are being developed and validated for use on multiple devices for food intake monitoring (Bruno et al., 2017). For example, the Snap-n-eat is a food recognition application based on a SVM classifier that estimates energy, food and nutrient intake using images taken directly with the user's smartphone, without additional intervention by the research team (Zhang et al., 2015). Similarly, the Keenoa food recognition application, which is linked to the Canadian Nutrient File (2015), generates a nutrient analysis that is sent directly to a dietician when a patient or participant in research takes a picture of their meal, thus facilitating the monitoring of dietary habits by a dietician or a research team (Ji et al., 2020). The use of artificial neural networks (ANN), particularly convolutional neural networks (CNN), are also prominent in food recognition algorithms (Bruno et al., 2017). Merchant and Pande (Merchant and Pande, 2019) have developed a smartphone application based on a CNN for food recognition to provide nutritional assessment and suggest food recipes to diabetic patients. The algorithm recognized food with an accuracy of 70%. Fang *et al.* (Fang et al., 2019) have developed a CNN to estimate total energy intake based on a single image of a meal, yielding predictions with an average error of 209 kilocalories. Since such algorithms are training-based, capturing more images with distinct food types and sizes will help generate more accurate predictions. Another study has shown that a trained ANN can reconstruct a 3D point cloud of a single food image taken

in depth on a smartphone and predict its volume with an accuracy of up to 93% (Lo et al., 2018). Other studies have developed CNN algorithms to recognize foods and drinks among voluminous datasets of images. For example, CNN algorithms were able to recognize 11 food groups among thousands of images with an accuracy of up to 82% (Gözde Özsert and Özyildirim, 2017). Quite similarly, Jia *et al.* (Jia et al., 2019) have developed a CNN algorithm that differentiates food items from non-food items with an accuracy of 86.4% using images passively taken by a wearable camera among free-living individuals and Liu *et al.* (Liu et al., 2016) developed CNN algorithms trained using food images taken by smartphones that recognized different foods with an accuracy of up to 77%.

The performance of ML algorithms to recognize and identify food on images is improving rapidly due to the voluminous and increasing number of food image datasets available (Tahir and Chu, 2021). Indeed, the training-based nature of ML algorithms implies that the use of more images of distinct food types and sizes will inevitably improve their performance. Popular food datasets used to develop such algorithms include the Food-101 dataset (11 categories, 101 000 images (Bossard et al., 2014)), the Food-5k (2 categories, 5000 images (Singla et al., 2016)), the Food-11 (11 categories, 16 643 images (Singla et al., 2016)), the UEC-FOOD-100 (100 categories, 14 361 images (Matsuda et al., 2012)) and the UEC-FOOD-256 (256 categories, 25 088 images (Kawano and Yanai, 2015)). Other studies are developing databases by extracting images from publicly available data, like Mezgec *et al.* (Mezgec and Korousic Seljak, 2017), who generated a dataset of 225 953 images of food and drinks from the Internet, or Rich *et al.* (Rich et al., 2016) who generated a dataset with 808 864 food-related images from Instagram.

These examples are just a glimpse at the numerous AI applications that exist for collecting nutritional data and assessing food intake (Kirk et al., 2021, Lo et al., 2020, Tahir and Chu, 2021). Multiple ML, NLP and DL algorithms are being developed to assess food intake more accurately, relying more on objectively recorded food intake and behaviours, thus potentially attenuating biases known to be associated with self-reported dietary intake data as well as decreasing participation burden (Zhao et al., 2020, Morgenstern et al., 2021). However, conventional dietary assessment tools and AI-based tools are to date complementary methods because most new AI-based tools cannot yet fully replace conventional tools (Zhao et al., 2020, Morgenstern et al., 2021).

Nutritional metabolomics and biomarkers

Principal component analysis, multivariate data analysis and partial least squares discriminant analysis are among the most common models used to analyze metabolomics data. However, AI and related algorithms and methods, like ANN, RF and SVM are particularly well-tailored to decipher the nonlinear nature of complex associations found in large nutritional metabolomics datasets. More specifically, AI techniques combined with metabolomics are used to identify biomarkers of foods or nutrients. For example, Shinn *et al.* (Shinn et al., 2021) have developed a RF algorithm to identify fecal bacteria biomarkers of 6 specific foods. The overall classification accuracy of the 6 foods was 70% using 22 fecal bacteria biomarkers. KNN, SVM and RF algorithms have been developed to predict total antioxidant properties of food matrices based on datasets of flavonoid food content, which may ultimately reveal new roles of these bioactive molecules on health and disease (Guardado Yordi et al., 2019). In the sports nutrition realm, ML has been employed to investigate the impact of nutrient intake on biomarkers of hydration in

cyclists (Munoz et al., 2020). Since multicollinearity between variables can increase errors in traditional statistical modelling, thus augmenting the chance of observing null associations, researchers used k-means clustering to first identify clusters representing one or more nutrients that may serve as mediators of body water status in cyclists.

AI-based methods applied to large metabolomics datasets may help identify biomarkers of health outcomes. For instance, SVM, a supervised ML algorithm, and Random Walks, an unsupervised ML algorithm, were developed to predict anti-cancer molecules within different foods (Veselkov et al., 2019). The researchers were able to show that specific plant-based foods contained molecules with anti-cancer properties that were similar to those seen with existing cancer drugs on molecular networks. The relationship between food addiction and the brain-gut-microbiome axis has been explored using metabolomics and brain imaging among female participants with obesity (Dong et al., 2020). Researchers were able to accurately classify participants according to criteria related to food addiction using a RF algorithm that processed fecal metabolites and brain imaging data. Algorithms like RF, SVM and ANN have also been used to process mass spectrometry-based metabolomics, through selection and processing of peaks, normalizing, imputing and interpreting data, for biomarker detection, classification or regression (Liebal et al., 2020).

Finally, AI-related approaches are widely used to facilitate analysis and interpretation of multiple omics datasets (Khorraminezhad et al., 2020, Liebal et al., 2020, Mendez et al., 2020). For example, Perakakis *et al.* (Perakakis et al., 2019) applied SVM, KNN and RF algorithms to metabolomics, lipidomics and glycomics data to predict non-alcoholic steatohepatitis (NASH)

and non-alcoholic fatty liver (NAFL). The SVM algorithm classified healthy, NASH or NAFL participants with an accuracy of 90%. Hence, there is no doubt that advanced AI-based methods are revolutionizing our capacity to take advantage of the multidimensional nature of datasets available in the nutritional “omics” fields.

Social media content analysis

In social media lies exceptional amounts of data for health research, including a breadth of nutrition-related information to which large segments of the population are exposed and influenced by. AI-based applications, like NLP and ML, can gather, structure and analyze information from a variety of social media platforms to monitor and better understand nutritional behaviours and perceptions among populations of interest. For example, models have been developed to analyze the textual and image content of social media, like Twitter and Reddit, to assess content and perceptions regarding weight loss, emotional eating, diet, diabetes, obesity or exercise (Karami et al., 2018, Hwang et al., 2020, Liu and Yin, 2020, Shaw and Karami, 2017). For example, NLP topic modeling and clustering algorithms have been used to process and analyze posts on *r/loseit*, an online community built around weight management and weight loss (Liu and Yin, 2020). More classical linear regression models were then used to investigate associations between the content of the posts and the user’s weight loss. Another study trained ML classification algorithms, including DT, SVM, and KNN, to detect emotional eating posts in the *r/loseit* community (Hwang et al., 2020). NLP was then used to categorize the emotional eating posts in four main topics: addressing feelings, sharing physical changes, sharing or asking for dietary information and sharing dietary strategies (Hwang et al., 2020). Karami *et al.* (Karami et al., 2018) analyzed 4.5 million Twitter posts mentioning obesity (51.7%), diet (23.7%), exercise (16.6%) or diabetes (8%)

and identified related topics and correlations. For instance, sub-topics for obesity, apart from diet, exercise and diabetes, included Alzheimer, cancer and children. Sub-topics for diet, apart from obesity, exercise and diabetes, included vegetarian, pregnancy, celebrities, weight loss, religious and mental health. Strong correlations existed between topics related to exercise and obesity, while notable correlations were found between topics related to diet and obesity as well as diabetes and obesity.

AI-based methods are also being developed to better understand the spatial pattern of nutrition-related information found in social media. For example, NLP and geocoding of social media posts have provided information on the real-time distribution of nutritional behaviours, habits and health outcomes, which may help in turn identify populations at risk (Ghosh and Guha, 2013, Nguyen et al., 2016, Shah et al., 2019, De Choudhury et al., 2016, Cesare et al., 2019, Widener and Li, 2014). Such information may be proven to be of great value from a public health perspective. For instance, NLP and ML algorithms have been developed to collect and analyze data from Twitter to assess Canadian's health and nutritional habits (Shah et al., 2019). Using NLP to analyze social media content has the advantage of being less time consuming than traditional dietary assessment methods and allow quick access to information and data collected in real time (Shah et al., 2019). The developed model classified food and non-food posts with an accuracy of 93% and provided information such as approximate caloric ratio (caloric intake vs energy expenditure) of Twitter posts per province as well as foods and activities most tweeted about per province in Canada. Another study estimated the quality of available foods in different geographical locations using data from 3 million food-related posts shared on Instagram to better understand healthy food availability (De Choudhury et al., 2016). Notably, Instagram posts made by people located in food

deserts were higher in fat, cholesterol and sugar intake and lower in protein and fiber. Nguyen *et al.* (Nguyen et al., 2016) used geotagged Twitter posts to create a neighbourhood database with indicators of well-being and health behaviours, to better understand the effects of neighbourhood on health. For example, the study found that social and economic disadvantage, high urbanicity and a higher density of fast-food restaurants was associated with lower happiness and fewer healthy behaviours. A study also used an NLP framework to geolocate social media posts to map out availability of healthy and unhealthy foods (Widener and Li, 2014). They demonstrated among others that there was a higher number of unhealthy food-related Twitter posts in disadvantaged areas with low access to healthy food stores.

In sum, social media has the potential to contribute to time-dependent and geospatial surveillance of physical activity, dietary habits and a multitude of other topics. Such information, along with more conventional data on dietary habits, may eventually become an integral part of the evidence considered to craft public health policy and initiatives.

Research gaps

Studies have shown that AI-based approaches do not always outperform conventionally used classification and prediction models. For example, many studies have reported no advantage of using AI in disease and health outcome prediction compared to using traditional statistical models (Christodoulou et al., 2019, Gravesteijn et al., 2020, Lynam et al., 2020, Nusinovici et al., 2020, Kuhle et al., 2018). For outcome variables that can be measured with less signal to noise ratio, like survival rate or readmission rate in hospitals, ML algorithms have been shown to perform better than traditional statistical models (Feng et al., 2019, Mortazavi et al., 2016). However, for outcome variables that have more signal to noise ratio, such as predicting risk of major chronic diseases,

depression or prognosticating traumatic brain injury, ML algorithms have not always outperformed conventionally used models (Nusinovici et al., 2020, Gravesteyn et al., 2020, Oh et al., 2019). ML algorithms may also have little to no impact on improving performance when applied to smaller sample sizes and/or used with a small number of variables, because the advantage of added model complexity is not necessary in these cases. Finally, there are other examples where ML algorithms did not outperform traditional statistical models. For example, in a study that compared classification performance of eight different linear and ML approaches on ten clinical metabolomics datasets, linear classification models performed similarly to ML algorithms, like SVM and ANN, in most datasets, because the outcome was linearly separable (Mendez et al., 2019b). Therefore, classification performance depends not only highly on the structure and the amount of data, but also on the need for more complex algorithms (Mendez et al., 2019b). The contradictions regarding the best models for disease and health outcome prediction suggests that AI-based modeling should always be compared to traditional statistical models to identify for which types of variables and for which outcomes traditional statistical models or AI algorithms are better suited (Goldstein et al., 2016, Liebal et al., 2020). This is particularly the case in nutrition where there is only a paucity of studies having compared AI-based and traditional approaches. Another limitation is the fact that datasets, which are necessary to improve performance of AI algorithms, are not always available. As indicated above, voluminous datasets are available for image and social media analysis, as well as in metabolomics analysis. However, the same cannot be said for precision nutrition and other nutrition-related disease and health prediction, which may rely on smaller sample sizes with fewer variables. Generating voluminous datasets for precision nutrition and nutrition-related predictions is inevitable to improve performance of algorithms. Also, the challenge of interpretability of the output from AI algorithms

remains a significant limitation in many instances, including when trying to identify sets of metabolites that predict a given outcome in nutritional metabolomics studies (Mendez et al., 2019a, Mendez et al., 2020, Sen et al., 2021), as interpretability relates to the understanding of the model's design, i.e., how the model works, and explainability relates to the understanding of what the model is saying, i.e., being able to understand and explain its prediction output (Marcinkevics and Vogt, 2020). Like interpretability, explainability is also a limitation of AI, especially in the realm of health where legal, medical and ethical issues must be considered (Amann et al., 2020). Inherent interpretability and explainability must be a priority beyond performance and error rates, especially for algorithms labeled as "black-box models". Therefore, one must adopt a critical stance towards AI when developing and validating algorithms for specific data structures and outcome variables. Such posture applies fully to the nutrition research field.

While AI-based dietary assessment tools may address certain challenges and limitations associated with the use of conventional dietary assessment instruments such as 24-hour recalls, food diaries and FFQ, they are not exempt of important limitations. While AI-based dietary assessment tools may be less subjective to biases associated to self-reported data, this is not always the case as reactive biases remain when participants knowingly wear a sensor or take pictures of their meals (Zhao et al., 2020). For example, Ji *et al.* (Ji et al., 2020) demonstrated that participants using an AI-based dietary assessment smartphone application alone under-reported food intakes compared to when a dietician could adjust the participants intake on the application. Food image analysis is also limited in its capacity to determine the nutrient content of certain foods, such as the fat percentage of dairy products. Identifying hidden or mixed foods and precisely estimating nutrients and calories from food images have also been mentioned as important challenges when using AI-

based tools (Bruno et al., 2017). Hence, AI-based dietary assessment tools cannot currently address all the challenges and limitations inherent to traditional tools. Using AI for dietary assessment is promising, but more research is needed to improve and validate algorithms (Zhao et al., 2020). Therefore, it may be more appropriate and even recommended for the time being at least to combine AI-based and traditional tools to improve dietary assessment and the quality of dietary intake data (Zhao et al., 2020).

Finally, many limitations and ethical concerns exist regarding the use of AI for social media analysis. Social media information comes in large amounts and concerns a wide variety of topics. However, this information can be incomplete, incorrect or biased and algorithms have inherent limitations in this regard (Lanfranchi et al., 2017, Matheny et al., 2020). For example, people may post about what they eat in a different location from where they live, creating a geographical bias (Shah et al., 2019). Also, algorithms may not always be developed to identify food words or posts that were used in a metaphorical way (Shah et al., 2019, Widener and Li, 2014). The type and number of posts can also be affected by other factors, like seasons, special events or new social media trends (Shah et al., 2019, Widener and Li, 2014). More importantly, social media data is inevitably biased because of missing information concerning people who do not use the social media of interest, with notable underrepresentation of minority and low socioeconomic groups (Lanfranchi et al., 2017, Widener and Li, 2014, Hwang et al., 2020, Matheny et al., 2020, Safdar et al., 2020). This is an important concern from a public health nutrition perspective, where we wish to identify populations at risk. There have also been ethical and regulation concerns related to the use of AI to extract and use social media data. Many users may be unaware that their information is used for research because of a misunderstanding of what “publicly available data”

means (Kern et al., 2016). Therefore, meticulousness is necessary to avoid training algorithms with strongly biased and inequitable data and results should always be interpreted with nuance. It may be of more interest to use social media as a tool for *taking the pulse*, for more time-dependent monitoring and for comparison purposes with other public health datasets rather than using it as the only data source (Widener and Li, 2014).

Conclusion

Has AI revolutionized nutrition research? Not quite yet. Application of AI-based methods may contribute to improving predictive models of diet and disease outcomes, to better collecting, processing and understanding complex nutrition-related data, and to better monitoring of a population's nutritional status. However, several limitations and concerns regarding the use of AI in nutrition research emphasize the importance of further research to develop and identify the algorithms best suited to nutrition data. The remaining gaps between the promises and the true enhancements of research through AI reinforces the importance of deploying AI-based approaches with caution and realism, with emphasis on legal and regulatory issues as well as on prioritization of equity, inclusion, and a human rights lens for this work while addressing implicit and explicit biases (Matheny et al., 2020).

Competing interests

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