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Review Article

Recognizing and Predicting the Risk of Malnutrition in the Elderly Using Artificial Intelligence: A Systematic Review

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Abstract

The global population is aging at an alarming rate, endangering conventional care models that have always relied on in-person supervision. Elderly malnutrition has been found to be a serious health problem associated with health deterioration, which has several, immediate effects on everyday activities and standard of living. Deficiency in nutrients is a frequent and serious concern in older adults and might have an impact on the emergence of geriatric diseases. The two most obvious indicators of malnutrition in the elderly include unintentional weight loss and a lower value of the body mass index (BMI). However, non-symptomatic or unnoticed insufficiencies, such as lower than expected level of different crucial micronutrients, which are quite challenging to diagnose and are typically disregarded among older residents of their communities. Artificial intelligence (AI) permeates every aspect of human existence. The current systematic review looks at how AI-based technology is currently being used and how it affects elderly malnutrition. Using the following keywords, computerized literature searches of many reliable data bases were used to compile relevant published articles: malnutrition, artificial intelligence (AI), machine learning (ML), elderly nutrition, risk factors of malnutrition among the elderly, chronic diseases, elderly. Prospective studies with original data were chosen, and their significant findings were integrated into the analysis of the state of malnutrition at the moment. In conclusion, it is challenging to deploy AI-based food and nutrient intake monitoring data because no single program is suitable for all international cuisines and eating customs. Geographic variations in the dietary habits of the population make it challenging to compile the necessary data sets for deep learning. Furthermore, even within a same region, hospital menus differ from patient to patient. It is suggested that meals served in hospitals under the same management be standardized to facilitate the procedure.

Keywords: *Ageing, Artificial Intelligence, Machine learning, Malnutrition*

Introduction

The global population is rapidly aging, which puts conventional care approaches that have depended on in-person monitoring in jeopardy (Ghosh *et al*., 2020; Ghosh *et al*., 2022). Elderly malnutrition has been found to be a serious health problem associated with physical deterioration, which has wide-ranging, immediate effects on everyday activities and general standard of living. Deficiency or over nutrition is a frequent and serious issue among older adults and might have an impact on the emergence of geriatric diseases (Ghosh *et al*., 2021; Singh *et al*., 2023). Two indicators of malnutrition in the elderly include involuntary weight loss and a reduced BMI. However, non-

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symptomatic or non-symptomatic or unnoticed insufficiencies, such as lower than expected level of different crucial micronutrients, which are quite challenging to diagnose and are typically disregarded among older residents of their communities (Ghosh *et al*., 2022). Artificial intelligence (AI) has permeated every aspect of our social lives and has grown to encompass AI-based jobs and services, including some that significantly harm people, such as healthcare. In order to satisfy the ever-increasing health requirements, particularly of the ageing population, alternative plans must be devised due to manpower restrictions in the global health and social systems. The current health resources must be improved and streamlined by these initiatives. Eating a balanced diet is crucial for overall health and the healing process. Deficiencies in both macro and micronutrients can influence the development and course of many disorders. On the other hand, a lot more study needs to be done to determine how well various screening methods identify malnutrition in a clinical setting. Not only is nutrition essential to normal growth and development, but it also prevents sickness, maintains health, and speeds up the healing process. Under nutrition affects people of all ages and is still a major public health concern. A variety of physical and psychological deficiencies are caused by dietary deficits of important macronutrients like proteins, lipids, and carbohydrates as well as micronutrients like vitamins and minerals (US Department of Agriculture, 2018). Recent research indicates that 3–5% of hospitalized patients suffer from malnutrition; however, estimates place the real number closer to 30–60% (Corkins *et al*., 2014; Agarwal *et al*., 2013; Barker *et al*., 2011). If hospital malnutrition recognition protocols are enhanced and nutritionists and healthcare professionals collaborate, it might be easier to identify malnourished individuals. The development of targeted efforts could improve post-event recovery, such as following major surgery, and minimize the burden of illness. A number of factors can lead to vitamin deficiencies and other imbalances in an elderly person. For example, functional limits, social isolation, and sensory issues associated with aging all increase the likelihood of establishing unhealthy eating habits. Moreover, the probability of forming these behaviors is higher in women (Damião *et al*., 2017; Ghosh *et al*., 2021; Ghosh *et al*., 2022; Singh *et al*., 2023). These habits could result in vitamin deficiencies or other disparities, which could then cause signs of illness like changes in body composition and mass. These physical anomalies lead to a worsening of the underlying disease, reduced physical and mental function, immune system modifications, extended hospital stays and recurrence and a poorer quality of life (QoL) (Vetta *et al*., 1999; Isabel *et al*., 2003; Artacho *et al*., 2014; Cederholm *et al*., 2017). According to Sauer *et al*., (2016), In the United States, malnutrition affects as many as 60% of hospitalized patients 65 years of age or older, but it is often overlooked and under diagnosed. Furthermore, while taking into consideration the expense of medical care, Goates, *et al*. (2016) established the potential economic impact of malnutrition on a number of ailments. The European Society of Parenteral and Enteral Nutrition (ESPEN) recommends malnutrition screening in systematic ways using a validated & standardized tool to support the diagnosis of malnutrition and serve as a basis for defining specific treatment goals and developing a comprehensive nutritional care plan (Volkert *et al*., 2019).Early identification of malnutrition is demanded by numerous scientific groups and national and international organizations. By acting quickly to alleviate the patient's nutrient shortfall, the healthcare system would be able to prevent negative health repercussions. Research conducted in Spain on the older adult population has shown the dietary conditions to which this group is subjected, both at institutional and in home settings. The PREDyCES project, which examines the occurrence of hospital malnutrition and related expenses in that country, offers an example of the data collected on nutritional status of the participants (Álvarez *et al*.,2012). According to this ground-breaking study, malnutrition was a possibility for 57% of senior hospital patients. As per the consensus agreement on the evaluation of nutrition in older adults by SEGG-SENPE, "if all those manoeuvres aimed at limiting the development of inadequacy or treating it early were carried out, then malnutrition in the elderly could be partly avoided."(de Nutrición Parenteral, 2008). Given that malnutrition is a prevalent issue that places a heavy financial strain on the public health system, it is critical to take into account cutting-edge multidisciplinary strategies for both preventing and treating malnutrition in treated multimorbid elderly patients, such as personalized nutritional guidance systems (Torres *et al*., 2022). Elderly malnutrition is being identified through the use of nutritional questionnaires. The Mini

Nutritional Assessment (MNA) is the most often utilized questionnaire for this particular demographic (Cederholm *et al*., 2017). But every time a patient is admitted to the hospital, it can take a long time for the attendants to finish this kind of survey. Additionally, research suggests that women may be more vulnerable to malnutrition, thus it is imperative that we pay extra attention to this (Damião *et al*., 2017; Ghosh *et al*., 2021; Ghosh *et al*., 2022; Singh *et al*., 2023). Thus, it is easier to identify malnourished populations and to simplify the work of health professionals by determining the variables that contribute most to malnutrition, investigating factors that may have a greater effect on older women, and developing new tools, like predictive models for assessing nutritional status. This paper offers a concise review of artificial intelligence (AI) in relation to the nutritional status of the elderly, focusing on the challenges and possible uses of AI-based systems for clinical care and research in this health state.

Methodology

Using the following keywords, computerized literature searches of many reliable data bases were used to compile relevant published articles: malnutrition, artificial intelligence (AI), machine learning (ML), elderly nutrition, risk factors of malnutrition among the elderly, chronic diseases, elderly. Prospective studies with original data were chosen, and their significant findings were integrated into the conclusion on the state of malnutrition at the moment (Figure 1).

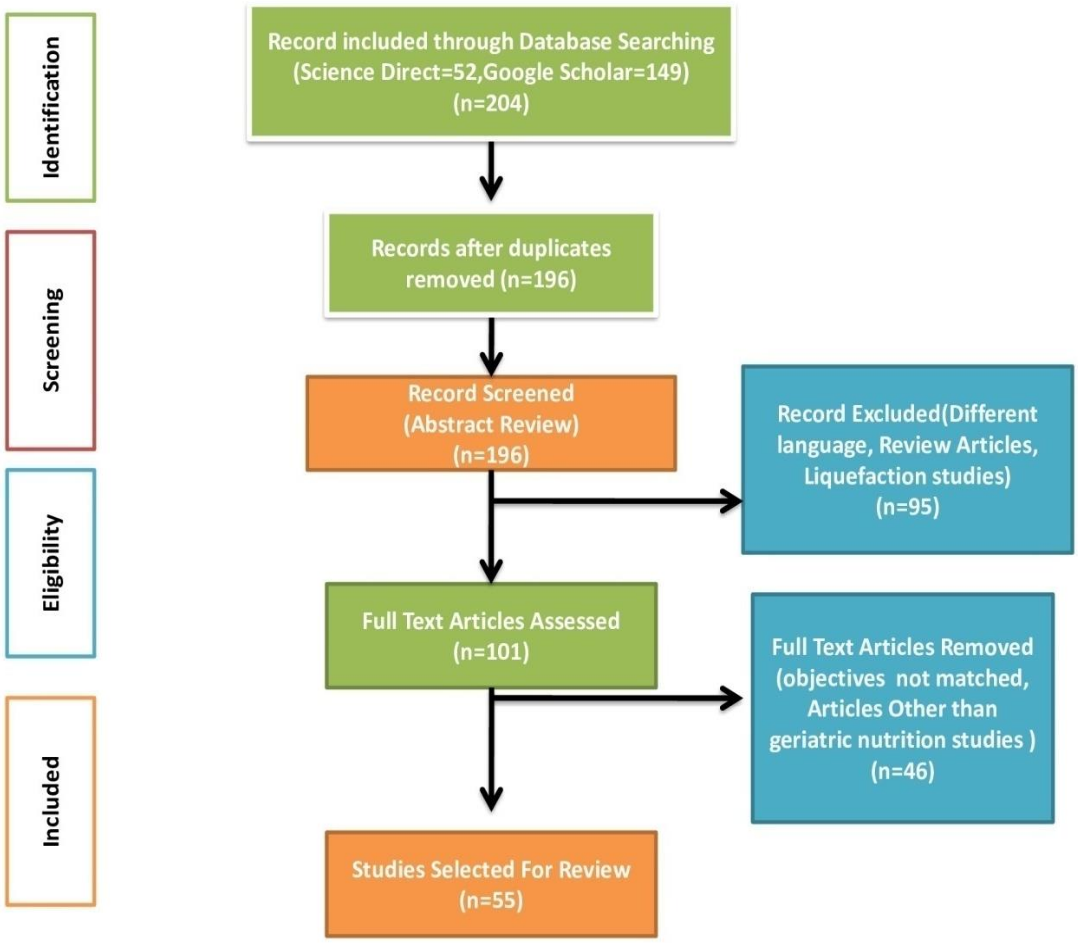

Figure 1: Prisma Diagram of the selection process of the research articles of this review.[The search string used in this study is-("Neural Network" or "Machine Learning" or "SVM" or "RNN" or "HMM" or "Hidden Markov" or "Fuzzy" or "Deep Learning" or "Data Mining" or "SVR" or "PNN" or "LSTM" or "Clustering" or "Radial Basis" or "RBF" or "Support Vector") and ("Elderly Nutrition or Geriatric nutrition") and ("Prediction"). Based on this search string, we have initially found 204 research articles from Science Direct, Google Scholar. After screening and eligibility testing, we have selected 55 research papers for this review].

Discussion

When creating a prediction model for the risk of malnutrition, it is crucial to take into account the most pertinent variables. Inadequate nutritional intake may be caused by age-related physiological changes, socioeconomic position, or cognitive issues, according to a number of studies (Drewnowski *et al*., 2001; Katsas *et al*., 2020; Fávaro-Moreira *et al*., 2016).According to physiological factors, reduced basal metabolic rate, delayed stomach emptying, altered taste and smell, and altered hormone responses can all contribute to decreased calorie intake (Fávaro-Moreira *et al*., 2016; Roy *et al*., 2016). In terms of socioeconomic and neurophysiological features, malnutrition may be associated to other factors such as social isolation, cognitive decline, marital status, and educational and depression (Drewnowski *et al*., 2001). Furthermore, O'Keeffe *et al*. (2018) provide a comprehensive analysis of the seven areas that may be modified to prevent malnutrition: oral, psychological, treatment and medication, health, lifestyle, physical function, and diet. Furthermore, studies on the differences in nutrition across genders (Damiáo *et al*., 2017; Ghosh *et al*., 2021; Ghosh *et al*., 2022; Singh *et al*., 2023) show that undernutrition in women can be caused by a number of variables, including poverty, education, ignorance, and marital status.

Screening of Malnutrition among Elderly:

Malnutrition is a prevalent condition among the elderly that puts a heavy burden on the health, social, and senior care systems. Older people are especially vulnerable because of comorbid diseases, less access to nutrient-rich diets, age-related physiological decline, and malnourishment (Dent *et al*.,2023). According to clinical standards, all older people should have routine screening for malnutrition, nutritional assessment, and, if a test results in malnutrition, individualized nutritional support. Nutritional support includes enteral or parenteral feeding as needed, fortified foods, oral nutritional supplements, and individualized nutritional counseling and recommendations. However, low-value care is pervasive in clinical practice and dietary advice are not applied sufficiently (Dent *et al*.,2023). There is still no agreed-upon definition of malnutrition, despite continuous discussion (Teigen *et al*., 2018). In 2016, a consensus process was initiated by the four dominating clinical nutrition associations worldwide (ESPEN, ASPEN, FELANPE, and PENSA) to standardise malnutrition criteria that could be used universally in all clinical settings. Together, these societies represent almost 70 national scientific organizations. In 2019, the Global Leadership Initiative on Malnutrition (GLIM) produced a list of three phenotypic parameters that are taken into account when diagnosing malnutrition. A low body mass index (BMI) of less than 20 kg/m2 if the patient is under 70 years old, or less than 22 kg/m2 if the patient is over 70 years old, decreased food consumption or integration (≤50% of energy requirements for more than a week, or a decrease for more than two weeks, or any persistent gastro-intestinal state that negatively influences food assimilation or absorption), and inflammation (injury/acute disease or chronic disease related) are some of the criteria. In a second stage, several criteria levels can be used to categorize the degree of malnutrition. The assessment of nutritional status is suggested to be based on the existence of a minimum of one etiologic and one phenotypic component. Many validation studies are now being conducted on the GLIM criteria. A recently published study (Yeung *et al*., 2020) involving community-dwelling older individuals participating in a long-term osteoporosis study in Hong Kong has revealed that the GLIM criterion is associated with an increased risk of frailty, sarcopenia, and mortality over a 14-year follow-up period. The research highlights the significance of the GLIM criterion in predicting adverse health outcomes among the elderly population. The European Society of Clinical Nutrition and Metabolism (ESPEN) guidelines on enteral nutrition in geriatrics declare that low BMI (below 20 kg/m2), which denotes exhausted physiological stores, or weight loss (>5% in six months) that indicates a catabolic state are the two indicators of clinical malnutrition in older patients (Cederholm *et al*., 2019). A patient is considered to be at risk for nutritional deficiencies if a variety of circumstances, including comorbidities, medical history, or medications that may increase dietary requirements or result in issues with metabolism or nutrient absorption, significantly impair their current state of nutrition. Aside from financial constraints that can limit their access to a range of healthful foods, other issues could be the older person's physical, mental, or cognitive health, which could make it difficult for them to take care of themselves (Cereda *et al*., 2012). In order to detect manifest malnutrition and identify the danger of developing malnutrition as previously mentioned, screening procedures appropriate for use in older individuals must concentrate on the most significant risk factors for malnutrition in high age. This way, before starting nutritional therapy, patients can be found using screening techniques. The Mini Nutritional Assessment (MNA) is the most popular and extensively studied screening tool designed specifically for use with older persons. It comes in both long and short forms. Concerns have been raised regarding the MNA's (Mini Nutritional Assessment) specificity, as its broad scope and comprehensive approach may lead to an over-identification of malnutrition cases among the elderly population. (Cereda *et al*., 2012). By including the GLIM criterion in the MNA as recommended, this issue might be solved (De van der Schueren *et al*., 2020). Furthermore, it has been recognized that screening for and treating over or undernutrition is one of the first steps required for the diagnosis and treatment of sarcopenia. (Vandewoude *et al*., 2012). Recent research has shown that malnutrition screening tools, such as the MNA short or long form, are more accurate than earlier diagnostic techniques, such as the GLIM criteria, at predicting the onset of sarcopenia (Cederholm *et al*.,2019; De Van Der Schueren *et al*., 2020). The incidence of sarcopenia in the SarcoPhAge cohort was predicted by the GLIM criteria, but not by either of the MNA variants (Lengelé *et al*., 2021). Ma *et al*. (2024) investigate the nutritional status of acute abdomen patients, providing a basis for applying GLIM criteria to diagnose malnutrition in this population. Their predictive model for malnutrition based on GLIM criteria can assist healthcare professionals in promptly identifying and intervening in patients with nutritional issues, potentially improving clinical outcomes and prognosis, though further refinement and validation are needed.

Table 1: Risk Assessment Matrix for Malnutrition Prediction

Risk	***Likelihood***	***Impact***	***Mitigation***
Lack of diverse racial representation in assessment models	Medium	Medium	Develop assessment models specifically tailored to various racial groups to improve accuracy and inclusivity. Collaborate with healthcare professionals and communities to ensure proper representation.
Insufficient stability and validation of risk assessment techniques	Medium	High	Conduct rigorous stability and validation tests on the selected risk assessment models. Verify their performance across different patient populations to ensure reliability and accuracy.
Reliance on electronic medical records for predictions	Low	Medium	Continuously monitor and update the electronic medical records used for predictions to ensure the data is up to date and comprehensive. Consider additional data sources to improve prediction accuracy.
Overreliance on AI as a supplement to conventional treatment	Low	Low	Maintain a balanced approach to healthcare management, considering AI technologies as valuable tools but not as replacements for traditional treatment. Regularly review and update treatment protocols based on the integration of AI technologies and patient outcomes.

The Idea of AI and its Advantages:

Theoretically, information theory, control theory, computer science, neuropsychology, linguistics and philosophy all support the multidisciplinary idea of artificial intelligence (Russell *et al*.,2016). AI, in general, uses artificial methods to give computers intelligence. It was in 1956 when the phrase "artificial intelligence" was first used. The concept was taken further, and in the research that followed, technologies and ideas that would allow computers to simulate human intelligence were created. By imitating and improving human brain processes, AI is said to be able to relieve human from physically and psychologically demanding jobs. Machine intelligence, another name for artificial intelligence, is a broad field. Three categories of AI techniques can be used, based on the goals of the application pertaining to diabetes: information discovery and exploration, information utilization, and information inference (Contreras *et al*., 2018). "Knowledge discovery in databases" refers to the process of searching databases and developing algorithms to locate relevant data (KDD). Finding pertinent and intelligible information is the primary objective of KDD, which calls for both a thorough understanding of the pertinent field of research and a broad understanding of it (Li *et al*., 2020).

K-nearest neighbors (KNN) algorithms, K-means and hierarchical clustering are the most representative research-related technologies. In terms of the learning from type of knowledge, the goal is to make machine learning capable of operating independently, without the need for human input or support, so that it can improve decision-making and forecast the future state of complex systems (Li *et al*., 2020). All of the inductively based processes in this approach have advantages when used suitably to various circumstances. Deep learning (DL), Artificial neural networks (ANNs), naïve bayes (NB), support vector machines (SVMs), decision trees (DTs), random forest (RF) algorithms, regression algorithms (RAs) and evolutionary algorithms (EAs), are the methods that are most commonly employed (Li *et al*., 2020; Ghosh *et al*., 2024).

Expert systems are frequently used to make inferences from data in the final category. Inference engines, knowledge bases of information and rules, and knowledge acquisition interfaces are often the three primary parts of these systems (Table 1). These systems assess unclear ideas and uncertainty and aid in decision-making in novel circumstances by utilizing data from prior examples along with the expertise of specialists. In this subject, fuzzy logic (FL), case-based reasoning (CBR), and rule-based reasoning (RBR) are the most often utilized methodologies. Artificial neural networks

(ANNs), support vector machines (SVMs), random forest (RF) algorithms, evolutionary algorithms (EAs), deep learning (DL), naive bayes (NB), decision trees (DTs), and regression algorithms (RAs) are some of the techniques that are most commonly utilized (Li *et al*., 2020). Expert systems are frequently used to make inferences from data in the final category. These systems usually consist of three key parts: inference engines, knowledge bases containing information and rules, and knowledge acquisition interfaces. These systems assess unclear ideas and uncertainty and aid in decision-making in novel circumstances by utilizing data from prior examples along with the expertise of specialists. Fuzzy logic (FL), case-based reasoning (CBR), and rule-based reasoning (RBR) are the methods that are most commonly applied in this discipline (Li *et al*., 2020).

Application of AI in managing Malnutrition among elderly: discussion on recent development

The majority of current AI-based nutritional assessment tools primarily concentrate on two key capabilities: autonomously identifying food items from digital images, and estimating the volume or portion size of those foods. By leveraging Smartphone cameras or other imaging sensors to visually capture food items, these AI solutions aim to determine daily nutrient and calorie consumption levels by cross-referencing recognized foods against databases containing nutritional data for various food types, as summarized in Table 2.

Table 2: Previous Research has shown noteworthy Results

Methods used	**Description**	**Application in malnutrition related health conditions**	**References**
SSD-MobileNet V2 Convolutional Neural Network (CNN) architecture	The framework makes use of the SSD-MobileNet V2 Convolutional Neural Network (CNN) architecture to categorise smartphone food images into distinct macronutrients, and it then implements an interactive interview mode to let the user choose the appropriate food item from the discovered group.	The estimation of food intake was done using manually entered conventional household quantities.	Elfert *et al*.,2021
Random Forest (RF) classifier	The system consists of a Multi-Task Contextual Network for segmenting food, a few-shot learning-based classifier for identifying food, and finally an algorithm for building 3-D surfaces.	Capable of identifying food intake in hospitalized patients by processing 3-D RGB images of the food tray that were taken by depth camera sensors both before and after meals were consumed.	Lu *et al*.,2020

Artificial Neural Network (ANN) model.	A clinical decision support system was created using 17 key variables, including information from demographic, clinical, anthropometric, and lab test data, to identify and classify malnutrition in cancer patients.	Multiple ML models have been tried for malnutrition prediction after the system incorporates a multi-stage K-means clustering to automatically recognise various malnutrition severity levels within observable data.	Yin *et al*.,2021
RF and gradient boosting models	The system utilising a combination of demographic, clinical, and laboratory data, as well as hospitalisation determinants. It suggested an AI framework to classify malnutrition risk in hospitalised older women	This initially created ML models to differentiate between no risk and risk conditions, and then they created more models to find low risk versus high risk in people who had previously been categorized as at risk.	Larburu *et al*.,2021
XAI	This system suggested a novel AI-based method for metabolic syndrome (MetS) screening in adolescents from anthropometric data and blood tests.	This technique combines medical knowledge with an RF-based Mean Decrease in Impurity (MDI) approach. When the learned function was used, the classification accuracy outperformed five clinical definitions that were used as a guide for the diagnosis of Mets.	Benmohammed *et al*.,2022

Given that these solutions usually call for some awareness and engagement from end users in order to maintain a satisfactory level of usefulness, their primary purpose is to support healthy people living independently. Elfert *et al*. (2021), for instance, suggested a method to assist senior citizens who reside at home in maintaining an electronic nutrition journal. Food photographs from cellphones are classified into distinct food macro categories using the framework, which uses the SSD-MobileNet V2 Convolutional Neural Network (CNN) architecture. After that, it includes an interactive interview mode that lets the user choose their preferred food item from the detected category. Lastly, food intake is estimated using manually recorded normal household quantities.

Despite being necessary, a completely automated, trustworthy, economical, and time-efficient monitoring system that is easy to include into the daily routine of clinical and nursing care personnel has not been developed specifically for clinical contexts, such as hospitals or long-term care facilities (with a focus on older adults) (Doulah *et al*., 2019). In order to determine food consumption in hospitalized patients, Lu *et al*. (2020) published a sequential method that involved analyzing 3-D RGB images of the food tray taken by depth camera sensors both before and after meals were consumed. The proposed system consists of three main components: an algorithm designed to generate 3D surfaces, a few-shot learning-based classifier for food item recognition, and a Multi-Task Contextual Network for segmenting food items. Similarly, Ruenin *et al*. (2020) introduced a two-step convolutional neural network (CNN) approach for meal classification and food weight estimation, aiming to assess calorie intake in hospitalized elderly individuals. More recently, Pfisterer *et al*. (2022) recommended utilizing a specialized deep neural encoder-decoder network with depth refinement to estimate the remaining volume of mixed food items on long-term care (LTC) plates by analyzing RGB-D camera images. While these approaches are valuable, they generally do not explore the relationship between dietary intake and changes in nutritional status over time, particularly in cases of malnutrition. Additionally, they fail to incorporate other heterogeneous sensing data that could serve as risk factors, such as anthropometric measurements, physiological indicators, behavioral patterns, and so forth. This limitation restricts their ability to provide a comprehensive understanding of the complex interplay between various factors and an individual's nutritional state. Presently, the great majority of AI frameworks for dietary problem prediction primarily rely on clinical and demographic static data obtained from national health surveys, along with biochemical markers obtained from a limited number of examinations. Consequently, not much study has been done on how m-health data (mobile health data) might be integrated to allow for a more precise and ongoing evaluation. There is a lack of solutions specifically tailored for the elderly population. Kang *et al*. (2019) developed a knowledge-based feature selection approach combined with a Random Forest classifier to predict sarcopenia, or age-related muscle loss, in older adults and hospitalized patients. Sarcopenia was used as a proxy indicator of nutritional health. However, the input data primarily consisted of blood test results, while information on nutrient intake was derived from a cross-sectional national dietary survey.In another study, Panagoulias *et al*. (2021) proposed an artificial neural network model capable of classifying an individual's body mass index category based on their metabolomic data. This approach aimed to provide insights into nutritional status by leveraging metabolomic biomarkers. While these studies offer valuable contributions, there remains a need for comprehensive solutions designed specifically for the elderly population, integrating diverse data sources to holistically assess and monitor their nutritional well-being over time. Specifically, the model used concentrations of various metabolites found in blood plasma samples to classify individuals into categories such as underweight, normal weight, or overweight. The study involved a diverse sample of 6,413 subjects from different ethnic backgrounds and age groups. By analyzing metabolite profiles, the ANN model aimed to provide insights into the relationship between an individual's metabolic state and their BMI status. Yin *et al*. (2021) developed a clinical decision support system to detect and categorize malnutrition in cancer patients based on 17 important characteristics, including data from anthropometric, clinical, demographic, and lab test data. After the system integrates a multi-stage K-means clustering to automatically detect different levels of malnutrition severity within observable data, several machine learning models have been explored for malnutrition prediction. Finally, Larburu *et al*., (2022) proposed an AI framework to classify malnutrition risk in hospitalized older women by combining clinical, laboratory, and demographic data with hospitalization determinants. Initially, they developed ML models to distinguish between situations with no risk and those with risk, and later they developed further models to identify low risk versus high risk in individuals who had previously been classified as at risk. For both challenges, the most effective models were the gradient boosting and RF models.

Few studies employ XAI to understand predictions of malnutrition and nutrition-related illnesses in terms of explainability. Many applications use simpler and naturally interpretable machine learning models (e.g., linear models) or knowledge-based techniques to trade off between interpretability and performance. On the other hand, Azevedo *et al*., (2022) created multivariate logistic regression models tailored to a particular gender in order to evaluate the significance of various clinical, laboratory, and body composition factors in predicting sarcopenic obesity in older adults. An ontology-based expert system was created by Cioara *et al*. (2018) to detect malnutrition in elderly persons at an early stage. Nonetheless, there aren't many justifications for extremely successful but "black-box" models. Benmohammed *et al*. (2022) developed a novel artificial intelligence (AI) technique aimed at screening for metabolic syndrome (MetS) in adolescents. Their approach leverages explainable AI (XAI) methods to estimate the decision function learned by the AI model. Specifically, they employed the soft margin technique, which identified four key features – waist circumference, mean blood pressure, triglyceride levels, and age – as the most influential factors for predicting MetS risk.By utilizing these four features, the researchers derived a polynomial formula that approximated the decision function of the best-performing artificial neural network (ANN) architecture. This method combined medical domain knowledge with a random forest-based feature importance measure called Mean Decrease in Impurity (MDI). Remarkably, using the learned polynomial function as a reference model achieved higher classification accuracy for MetS diagnosis compared to five commonly used clinical definitions. This demonstrates the potential of combining AI techniques with domain expertise to develop more accurate screening tools for metabolic disorders. Pang *et al*., (2019) proposed a XAI technique to investigate the major risk factors for childhood obesity.They trained an eXtreme Gradient Boosting (XGBoost) model using Electronic Health Record (EHR) data from over 860 pediatric patients in order to achieve this. They then obtained global model explanations using the SHapley Additive Explanations (SHAP) technique (Lundberg *et al*., 2017). The obtained results show that well-known risk factors for obesity, such as weight, height, weight-for-height, geography, race, and ethnicity, are found among the most significant characteristics. On the other hand, SHAP also discovered that the body temperature and respiration rate are important components of human metabolism that may be developing indicators requiring future investigation. A variety of machine learning (ML) models have been developed by Shi *et al*., 2022 to predict the incidence of post-operative malnutrition in children with congenital heart disease within a year following surgery. The occurrence of underweight status was the primary outcome of interest, whereas stunted and wasting state were the secondary outcomes. XGBoost consistently yielded the best results when various machine learning (ML) models were trained to predict the aforementioned outcomes separately using data collected from the intra-operative and follow-up EHR. Feature permutation methods and SHAP have been used to identify the most influential features for each condition linked to malnutrition. The health of patients in long-term care facilities may be improved by innovative technology that tracks and records food consumption. Malnutrition affects 54% of senior citizens living in nursing homes. The gadget uses artificial intelligence (AI) to analyze photos of users' plates and determine how much they've ingested (Keller *et al*., 2019; Pfisterer *et al*., 2023).It is possible for even the most watchful caregivers to miss signs of malnutrition in elderly patients, which is thought to be brought on by people who stop eating. Based on the amount ingested, the AI system determines each dish's nutritional worth by analyzing color, depth, and other visual clues. The platform is linked to the recipes that the specific care facility that is being evaluated uses. To make sure seniors have a balanced meal, the gadget employs artificial intelligence to track how much of each dish was ingested. The AI system was accurate to within 5% and gave reliable information on the consumption patterns of the people. To make the system better, researchers collaborated with dieticians and caregivers. Idealistically, the system need to be connected to employee PCs that are already equipped with electronic record-keeping features. The researchers claim that the technology can no longer identify between the various food groups that a person has eaten. Most nursing homes have staff members manually record how much food residents have eaten by looking at the dishes after they have done eating. This raises the possibility of mistakes. This is especially crucial for older adults, who may have unique dietary needs as they get older. Since many of the elderly are unable to talk for themselves or remember what they ate, it is imperative that the residents' diet be properly monitored for their health. Recent data indicates that there is an urgent need for systems to assist long-term care staff in their work. "Automated tools may provide a time-efficient, cost-effective, and objective alternative," (Keller *et al*., 2019). As of right now, there was no automated way to tell if an elderly patient was eating solely carbohydrates or only protein. However, in due course, technology will be able to track infection control and identify fluctuations in staff food consumption.

Challenges and Consideration:

Current AI-based food and nutrient intake monitoring systems face limitations in accounting for cultural and geographic variations in dietary habits. These systems may struggle to recognize and accurately classify traditional or region-specific foods, leading to inaccurate nutrient estimations. Additionally, they may lack contextual understanding of cultural dietary practices, food preparation methods, and ingredient substitutions, which can significantly impact nutrient profiles. Overcoming these challenges requires training AI models on diverse, culturally representative datasets and incorporating contextual knowledge about regional cuisines and dietary norms.

One of the significant challenges lies in the integration and standardization of diverse data sources. Genomic, metabolomic, microbiome, and lifestyle data often originate from different platforms and formats, making it difficult to combine and analyze them effectively. Establishing standardized data collection and storage protocols, as well as developing robust data integration pipelines, is crucial for enabling comprehensive analyses and deriving meaningful insights.AI models are now classified as 'Software as a Medical Device' (SaMD). Currently, there is a notable absence of universally agreed-upon standards or criteria to govern the tunable parameters of AI algorithms, which is crucial for their safe and effective use in clinical nutrition. This issue becomes paramount when addressing ethical and cultural concerns such as hydration and the fundamental human right to adequate nutrition, which are frequently debated in the medical realm. Establishing appropriate governance and regulations is imperative for the utilization of AI in healthcare, encompassing both data utilization and machine implementation (van de Sande *et al*., 2022). Internationally recognized regulatory bodies like the Conformité Européenne (CE) in Europe and the Food and Drug Administration (FDA) in the USA play pivotal roles in this domain. Given that AI in healthcare heavily relies on patient data, ensuring the privacy and security of digital data is of utmost importance (Zhou *et al*., 2018). Regulations like the General Data Protection Regulation (GDPR) set the bar for safeguarding patient data. Consequently, all AI systems must be meticulously designed with robust security measures and privacy protocols to prevent any compromise of patient data integrity (Bond *et al*., 2023). In the context of geriatric nutrition, AI can play a crucial role in addressing the unique nutritional needs and challenges faced by the elderly population. Factors such as age-related changes in metabolism, appetite, and nutrient absorption, as well as the presence of chronic conditions and polypharmacy, can significantly impact nutritional requirements and dietary recommendations. AI algorithms can be trained on extensive data from geriatric populations, including medical records, dietary intake information, and outcomes, to develop personalized nutrition plans tailored to individual needs and health conditions. Additionally, AI-powered monitoring systems can be employed to track adherence to dietary recommendations and provide real-time feedback and adjustments, ensuring optimal nutritional support for the elderly.

Concerns about Ethics and Privacy

Implementing AI-based food and nutrient intake monitoring systems faces challenges such as obtaining high-quality, diverse data on food composition and dietary habits, accounting for variability in food preparation and cultural practices, ensuring user adherence and engagement, addressing privacy and data security concerns, integrating with existing healthcare systems, and meeting regulatory and ethical requirements related to data privacy, bias, and transparency. Overcoming these challenges requires interdisciplinary collaboration, robust data strategies, user-centric design, and rigorous testing before implementation. The collection and analysis of personal health data, including genetic information and dietary habits, raise significant privacy and ethical concerns. Ensuring data security, maintaining strict data protection protocols, and obtaining informed consent from individuals are critical to upholding ethical standards and building trust in personalized nutrition solutions (Brooks-Warburton *et al*., 2022). The integration of AI systems in healthcare introduces the risk of perpetuating existing biases and discrimination. When AI models are trained on biased or incomplete data, they tend to reinforce the biases present within the dataset. For example, if an AI model is predominantly trained on data from a specific gender, ethnic group, or socioeconomic class, it may struggle to accurately diagnose or treat individuals from other demographics (Brooks-Warburton *et al*., 2022). Moreover, since AI models are created and programmed by humans, the conscious or unconscious biases of developers can seep into the algorithms during the development phase. To mitigate these issues, developers must ensure that their systems are trained on diverse datasets, undergo rigorous testing and evaluation for biases, involve diverse stakeholders throughout the development process, and sustain this engagement even after the implementation of AI systems in healthcare (Brooks-Warburton *et al*., 2022).Furthermore, it is essential that the data used to build such AI models have appropriate provenance, undergo thorough cleaning, and adhere to legal and governance standards to prevent harm while minimizing variability. Regular audits should also be conducted to identify and address any potential biases that may arise over time. Ensuring the integrity and fairness of AI systems in healthcare is crucial to promote equitable access and prevent perpetuating existing disparities in health outcomes.

Future Research & Advancement:

Further study and developments are required to address the multifaceted difficulties related with malnutrition among the senior population. Creating AI models that are especially suited to the distinct dietary requirements and physiological changes experienced by older persons, accounting for elements like as poly-pharmacy, chronic illnesses, and age-related metabolic changes. Combining many data sources, such as anthropometric measures, dietary intake, medical records, and functional evaluations, to provide a thorough picture of a person's risk factors and nutritional status. Improving artificial intelligence (AI) nutritional tracking systems to precisely record and interpret the food preparation techniques, cultural customs, and dietary preferences that are common across various senior populations. Examining how AI-powered assistive technologies, such voice interfaces and environmental sensing, can make it simpler for senior citizens with cognitive or physical limitations to track and manage their diets. evaluating the efficacy and long-term effects of AI-driven nutritional treatments on older individuals' health outcomes and quality of life through extensive, longitudinal research.

Integrating mobile health (m-health) data into AI frameworks holds promising potential for continuous evaluation of nutritional status among older adults. The ability to monitor dietary intake, physical activity, and other relevant data in real-time through wearable devices and mobile apps can enable personalized and timely nutritional recommendations based on an individual's current health status and lifestyle factors. Early detection of nutritional deficiencies or risk factors for malnutrition becomes possible, allowing for prompt interventions. However, challenges arise in ensuring data privacy and security, addressing potential biases and data quality issues, integrating diverse data streams into a cohesive AI framework, overcoming barriers to technology adoption among older adults, and establishing regulatory frameworks for the validation and clinical use of such AI-driven m-health solutions. Collaborative research, robust data management strategies, and user-centered design approaches will be crucial to leverage the benefits while mitigating the challenges of integrating m-health data into AI frameworks for continuous nutritional evaluation in the aging population.

Conclusion

It is challenging to apply AI-based food and nutrient intake monitoring data since no single application is suitable for all cuisines and eating customs around the globe. Geographic variations in the dietary habits of the population make it challenging to compile the necessary data sets for deep learning. Furthermore, even within a same region, hospital menus differ from patient to patient. It is suggested that meals served in hospitals under the same management be standardized to facilitate the procedure. Even while life expectancy is increasing, a serious shortage of caregiver professionals is a problem in many countries across the world. Replacing the aging medical workforce remains a challenging task. By completing the present care provision, alleviating the stress on family caregivers, and improving the quality of care, AI in surveillance technology may play an innovative and major role in addressing the human resource shortages in the provision of care for the elderly. To ensure that automated systems can genuinely improve care and health outcomes for senior persons, it is imperative to capitalize on the opportunities these emerging technologies bring. It makes the case that in order for contemporary health monitoring technologies to empower older adults and improve their quality of life—while also respecting their wishes to age in place—we must have a clear grasp of how stakeholders can compromise between their concerns regarding privacy, safety, and relational care. Only if overlapping clinical and ethical problems are taken into consideration during the design process will artificial intelligence health monitoring technologies enable independent living, enhance effective relationship care, support the health outcomes of older adults, and reduce waste.

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Conflict of Interests

Author declares no conflict of interests.

Reference:

Álvarez Hernández, J., Planas Vilá, M., León Sanz, M., Garcia de Lorenzo y Mateos, A., Celaya Pérez, S., García Lorda, P., ... & Sarto Guerri, B. (2012). Prevalence and costs of multinutrution in hospitalized patients; the PREDyCES study. *Nutr Hosp, 27*, 1049–1059. https://doi.org/10.3305/nh.2012.27.4.5986

Artacho, R., Lujano, C., Sanchez-Vico, A. B., Sánchez, C. V., Calvo, J. G., Bouzas, P. R., & Ruiz-López, M. D. (2014). Nutritional status in chronically-ill elderly patients. Is it related to quality of life?. *The Journal of nutrition, health and aging*, *18*(2), 192-197. https://doi.org/10.1007/s12603-013-0385-0

Barker, L. A., Gout, B. S., & Crowe, T. C. (2011). Hospital malnutrition: prevalence, identification and impact on patients and the healthcare system. *International journal of environmental research and public health*, *8*(2), 514-527. https://doi.org/10.3390/ijerph8020514

Benmohammed, K., Valensi, P., Omri, N., Al Masry, Z., & Zerhouni, N. (2022). Metabolic syndrome screening in adolescents: New scores AI_METS based on artificial intelligence techniques. *Nutrition, Metabolism and Cardiovascular Diseases*, *32*(12), 2890-2899. https://doi.org/10.1016/j.numecd.2022.08.007

Bond, A., Mccay, K., & Lal, S. (2023). Artificial intelligence & clinical nutrition: What the future might have in store. *Clinical nutrition ESPEN*, 57, 542-549. https://doi.org/10.1016/j.clnesp.2023.07.082

Brooks-Warburton, J., Ashton, J., Dhar, A., Tham, T., Allen, P. B., Hoque, S., ... & Sebastian, S. (2022). Artificial intelligence and inflammatory bowel disease: practicalities and future prospects. *Frontline Gastroenterology*, *13*(4), 325-331. https://doi.org/10.1136/flgastro-2021-102003

Cederholm, T., Barazzoni, R. O. C. C. O., Austin, P., Ballmer, P., Biolo, G. I. A. N. N. I., Bischoff, S. C., ... & Singer, P. (2017). ESPEN guidelines on definitions and terminology of clinical nutrition. *Clinical nutrition*, *36*(1), 49-64. https://doi.org/10.1016/j.clnu.2016.09.004

Cederholm, T., Jensen, G. L., Correia, M., Gonzalez, M. C., Fukushima, R., Higashiguchi, T., Baptista, G., Barazzoni, R., Blaauw, R., Coats, A., *et al*. (2019). GLIM criteria for the diagnosis of malnutrition–A consensus report from the global clinical nutrition community. *Clin Nutr, 38*, 1–9. https://doi.org/10.1016/j.clnu.2018.08.002

Cereda, E. (2012). Mini nutritional assessment. *Curr Opin Clin Nutr Metab Care, 15*, 29–41. https://doi.org/10.1097/MCO.0b013e32834d7647

Cioara, T., Anghel, I., Salomie, I., Barakat, L., Miles, S., Reidlinger, D., ... & Pop, F. (2018). Expert system for nutrition care process of older adults. *Future Generation Computer Systems*, *80*, 368-383. https://doi.org/10.1016/j.future.2017.05.037

Corkins, M. R., Guenter, P., DiMaria-Ghalili, R. A., Jensen, G. L., Malone, A., Miller, S., ... & American Society for Parenteral and Enteral Nutrition. (2014). Malnutrition diagnoses in hospitalized patients: United States, 2010. *Journal of Parenteral and Enteral Nutrition*, *38*(2), 186-195. https://doi.org/10.1177/0148607113512154

Correia, M. I. T., & Waitzberg, D. L. (2003). The impact of malnutrition on morbidity, mortality, length of hospital stay and costs evaluated through a multivariate model analysis. *Clinical nutrition*, *22*(3), 235-239. https://doi.org/10.1016/S0261-5614(02)00215-7

Damião, R., Santos, Á. D. S., Matijasevich, A., & Menezes, P. R. (2017). Factors associated with risk of malnutrition in the elderly in south-eastern Brazil. *Revista Brasileira de Epidemiologia*, *20*, 598-610. https://doi.org/10.1590/1980-5497201700040004

de Nutrición Parenteral, S. S. E. (2008). Valoración Nutricional en el anciano: recomendaciones prácticas de los expertos en geriatría y nutrición.

De Van Der Schueren, M., Keller, H., Cederholm, T., Barazzoni, R., Compher, C., Correia, M. I. T. D., ... & GLIM Consortium. (2020). Global Leadership Initiative on Malnutrition (GLIM): Guidance on validation of the operational criteria for the diagnosis of protein-energy malnutrition in adults. *Clinical nutrition*, *39*(9), 2872-2880. https://doi.org/10.1016/j.clnu.2019.12.022

Dent, E., Wright, O. R., Woo, J., & Hoogendijk, E. O. (2023). Malnutrition in older adults. *The Lancet*, *401*(10380), 951-966. https://doi.org/10.1016/s0140-6736(22)02612-5

Drewnowski, A., & Shultz, J. M. (2001). Impact of aging on eating behaviors, food choices, nutrition, and health status. *The journal of nutrition, health & aging*, *5*(2), 75-79. Impact of aging on eating behaviors, food choices, nutrition, and health status - PubMed (nih.gov)

Elfert, P., Tiryaki, E., Eichelberg, M., Rösch, N., & Hein, A. (2021, September). A deep learning assisted digital nutrition diary to support nutrition counseling for people affected by the geriatric frailty syndrome. In *2021 IEEE Symposium on Computers and Communications (ISCC)* (pp. 1-7). IEEE. http://dx.doi.org/10.1109/ISCC53001.2021.9631394

Fávaro-Moreira, N. C., Krausch-Hofmann, S., Matthys, C., Vereecken, C., Vanhauwaert, E., Declercq, A., ... & Duyck, J. (2016). Risk factors for malnutrition in older adults: a systematic review of the literature based on longitudinal data. *Advances in nutrition*, *7*(3), 507-522.https://doi.org/10.3945/an.115.011254

Ghosh, J.& Ghosh,D., (2021). Nutritional Assessment and Associated Factors in the Elderly: An Overview. *Journal of Nutraceuticals and Food Science, 6*(4), 21.

Ghosh, J., Chaudhuri, A. N., Saha, I., & Chaudhuri, D. (2021). Antimicrobial Effect of 1, 25 Dihydroxy Vitamin D on Vibrio cholerae and its Association with Serum 25-Hydroxy Vitamin D Level in Rural Elderly Women: An

Experimental Study. *Journal of Clinical & Diagnostic Research*, 15(10), 34-37. https://doi.org/10.7860/JCDR/2021/49439.15571

Ghosh, J., Chaudhuri, D., Saha, I., & Chaudhuri, A. N. (2020). Prevalence of metabolic syndrome, vitamin D level, and their association among elderly women in a rural community of West Bengal, India. *Medical Journal of Dr. DY Patil University*, *13*(4), 315-320. https://doi.org/10.4103/mjdrdypu.mjdrdypu_229_19

Ghosh, J., Chaudhuri, D., Saha, I., & Chaudhuri, A. N. (2022). Association of conicity index with different cardiovascular disease risk factors among rural elderly women of West Bengal, India. *Indian Journal of Community Medicine*, *47*(1), 18-22. https://doi.org/10.4103/ijcm.ijcm_595_21

Ghosh, J., Chaudhuri, D., Saha, I., & Chaudhuri, A. N. (2022). Prevalence of anaemia and its association with metabolic syndrome and its components among rural elderly women of Amdanga block, North 24th PGS West Bengal. *Indian Journal of Gerontology*, *36*(2), 148-158.

Ghosh, J., Choudhury, S. R., Singh, K., & Koner, S. (2024). Application of Machine Learning Algorithm and Artificial Intelligence in Improving Metabolic Syndrome related complications: A review. *International Journal of Advancement in Life Sciences Research*, *7*(2), 41-67. https://doi.org/10.31632/ijalsr.2024.v07i02.004

Katsas, K., Mamalaki, E., Kontogianni, M. D., Anastasiou, C. A., Kosmidis, M. H., Varlamis, I., ... & Yannakoulia, M. (2020). Malnutrition in older adults: Correlations with social, diet-related, and neuropsychological factors. *Nutrition*, *71*. https://doi.org/10.1016/j.nut.2019.110640

Larburu, N., Artola, G., Kerexeta, J., Caballero, M., Ollo, B., & Lando, C. M. (2022). Key factors and AI-based risk prediction of malnutrition in hospitalized older women. *Geriatrics*, *7*(5), 105. https://doi.org/10.3390/geriatrics7050105

Lengelé, L., Bruyère, O., Beaudart, C., Reginster, J. Y., & Locquet, M. (2021). Impact of Malnutrition Status on Muscle Parameter Changes over a 5-Year Follow-Up of Community-Dwelling Older Adults from the SarcoPhAge Cohort. *Nutrients*, *13*(2), 407. https://doi.org/10.3390/nu13020407

Lu, Y., Stathopoulou, T., Vasiloglou, M. F., Christodoulidis, S., Stanga, Z., & Mougiakakou, S. (2020). An artificial intelligence-based system to assess nutrient intake for hospitalised patients. *IEEE transactions on multimedia*, *23*, 1136-1147. https://doi.org/10.1109/embc.2019.8856889

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems*, *30*. A Unified Approach to Interpreting Model Predictions (nips.cc)

Ma, W., Cai, B., Wang, Y., Wang, L., Sun, M. W., Lu, C. D., & Jiang, H. (2024). Artificial intelligence driven malnutrition diagnostic model for patients with acute abdomen based on GLIM criteria: a cross-sectional research protocol. *BMJ open*, *14*(3). https://doi.org/10.1136/bmjopen-2023-077734

O'Keeffe, M., Kelly, M., O'Herlihy, E., O'Toole, P. W., Kearney, P. M., Timmons, S., ... & O'Connor, E. M. (2019). Potentially modifiable determinants of malnutrition in older adults: A systematic review. *Clinical Nutrition*, *38*(6), 2477-2498. https://doi.org/10.1016/j.clnu.2018.12.007

Pang, X., Forrest, C. B., Lê-Scherban, F., & Masino, A. J. (2019, December). Understanding early childhood obesity via interpretation of machine learning model predictions. In *2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA)* (pp. 1438-1443). IEEE. https://doi.org/10.1016/j.ijmedinf.2021.104454

Pfisterer, K. J., Amelard, R., Keller, H. H., & Wong, A. (2023). Characterizing Canadian long-term care home consumed foods and their inflammatory potential: a secondary analysis. *BMC Public Health*, *23*(1), 261. https://doi.org/10.1186/s12889-022-14934-8

Roy, M., Gaudreau, P., & Payette, H. (2016). A scoping review of anorexia of aging correlates and their relevance to population health interventions. *Appetite*, *105*, 688-699. https://doi.org/10.1016/j.appet.2016.06.037

Sauer, A. C., Alish, C. J., Strausbaugh, K., West, K., & Quatrara, B. (2016). Nurses needed: Identifying malnutrition in hospitalized older adults. *NursingPlus Open*, *2*, 21-25. https://doi.org/10.1016/j.npls.2016.05.001

Shi, H., Yang, D., Tang, K., Hu, C., Li, L., Zhang, L., ... & Cui, Y. (2022). Explainable machine learning model for predicting the occurrence of postoperative malnutrition in children with congenital heart disease. *Clinical Nutrition*, *41*(1), 202-210. https://doi.org/10.1016/j.clnu.2021.11.006

Singh, K., Choudhury, S. R., Ghosh, J., Koner, S., & Pal, R. (2023). Ageing and its relationship with psychoneuroimmunology. *Journal of Comprehensive Health*, *11*(2). 34-47. Ageing and its relationship with psychoneuroimmunology - Journal of Comprehensive Health

Teigen, L. M., Kuchnia, A. J., Nagel, E. M., Price, K. L., Hurt, R. T., & Earthman, C. P. (2018). Diagnosing clinical malnutrition: Perspectives from the past and implications for the future. *Clinical nutrition ESPEN*, *26*, 13-20. https://doi.org/10.1016/j.clnesp.2018.05.006

Torres, J., Artola, G., Larburu, N., Agirre, A., Narbaiza, E., Berges González, I., & Lizaso, A. (2022). Personalized nutritional guidance system to prevent malnutrition in pluripathological older patients. *In Proceedings of the 8th*

International Conference on Information and Communication Technologies for Ageing Well and e-Health—ICT4AWE 2022, 338–343. http://hdl.handle.net/10810/63353

U.S. Department of Agriculture, Economic Research Service. (2018). Fertilizer use and markets (Economic Information Bulletin No. 197). https://www.ers.usda.gov/webdocs/publications/90201/eib-197.pdf

Van de Sande, D., Van Genderen, M. E., Smit, J. M., Huiskens, J., Visser, J. J., Veen, R. E., ... & van Bommel, J. (2022). Developing, implementing and governing artificial intelligence in medicine: a step-by-step approach to prevent an artificial intelligence winter. *BMJ health & care informatics*, *29*(1). https://doi.org/10.1136/bmjhci-2021-100495

Volkert, D., Beck, A. M., Cederholm, T., Cruz-Jentoft, A., Goisser, S., Hooper, L., ... & Bischoff, S. C. (2019). ESPEN guideline on clinical nutrition and hydration in geriatrics. *Clinical nutrition*, *38*(1), 10-47. https://doi.org/10.1016/j.clnu.2018.05.024

Yin, L., Song, C., Cui, J., Lin, X., Li, N., Fan, Y., ... & Xu, H. (2021). A fusion decision system to identify and grade malnutrition in cancer patients: machine learning reveals feasible workflow from representative real-world data. *Clinical Nutrition*, *40*(8), 4958-4970.. https://doi.org/10.1016/j.clnu.2021.06.028

Zhou, Y., Cahya, S., Combs, S. A., Nicolaou, C. A., Wang, J., Desai, P. V., & Shen, J. (2018). Exploring tunable hyperparameters for deep neural networks with industrial ADME data sets. *Journal of chemical information and modeling*, *59*(3), 1005-1016. https://doi.org/10.1021/acs.jcim.8b00671