REVIEW

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Role of Artificial Intelligence in Multinomial Decisions and Preventative Nutrition in Alzheimer's Disease

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Alzheimer's disease (AD) affects 50 million people worldwide, an increase of 35 million since 2015, and it is known for memory loss and cognitive decline. Considering the morbidity associated with AD, it is important to explore lifestyle elements influencing the chances of developing AD, with special emphasis on nutritional aspects. This review will first discuss how dietary factors have an impact in AD development and the possible role of Artificial Intelligence (AI) and Machine Learning (ML) in preventative care of AD patients through nutrition. The Mediterranean-DASH diets provide individuals with many nutrient benefits which assists the prevention of neurodegeneration by having neuroprotective roles. Lack of micronutrients, protein-energy, and polyunsaturated fatty acids increase the chance of cognitive decline, loss of memory, and synaptic dysfunction among others. ML software has the ability to design models of algorithms from data introduced to present practical solutions that are accessible and easy to use. It can give predictions for a precise medicine approach to evaluate individuals as a whole. There is no doubt the future of nutritional science lies on customizing diets for individuals to reduce dementia risk factors, maintain overall health and brain function.

1. Introduction

Alzheimer's disease (AD) is the leading cause of dementia worldwide and as a consequence, it leads to poor memory and orientation with gradually declining executive functioning which eventually makes a patient completely dependent on a caregiver.[1–3] This not only results in extensive patient and caregiver burnout but also burdens the system and economy in the long run. As this disease progresses, there is the need of more systematic solutions involving larger communities and population level resources, such as addressing preventive care, early education, destigmatization of disease, and increased social support for Cognitively Impaired (CI) individuals and families.

The intersection of nutrition and computer learning in treating AD involves a multidirectional approach incorporating several complex goals. From a macroscopic perspective, integration of AI technology can facilitate translational research that expands clinical tools and at a microscopic level it has the ability to aid in symptom management for the patient to optimize user-based design. Considering innumerable ways of implementing AI, this discussion will be focused on understanding the impacts of nutrition in health and disease progression and risk, how computer learning functions on a basic level, and what hurdles are present in translating these functions into clinical practice.

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2. Dietary Lifestyle, Nutrition, and Alzheimer's Disease

The genetic predisposition to develop AD contributes to less than 5% of the cases around the world. Having the Presenilin gene 1 (PS1) on chromosome 14, the Presenilin gene 2 (PS2) on chromosome 1, and Amyloid Precursor Protein (APP) gene on chromosome 21 are some of the examples of genetic factors that enhance the possibility of developing AD,[4] this form of the disease is described as Familial Alzheimer's Disease. Furthermore, APOE4 is also a risk factor for this disease, due to promoting accumulation of Amyloid-beta plaques in the brain.[5] Consequently, there is still the need to unfold the other 95 % cases, since there is clearly an interplay of lifestyle factors and comorbidities that are resulting in AD.

Recent studies have emphasized that factors ranging from sleep apnea, altered circadian rhythms, noise exposure, and sedentary lifestyle have contributed to a rise in AD cases.[6] Furthermore, the Lancet Commission has reported a few potentially modifiable risk factors for dementia throughout life, such as less

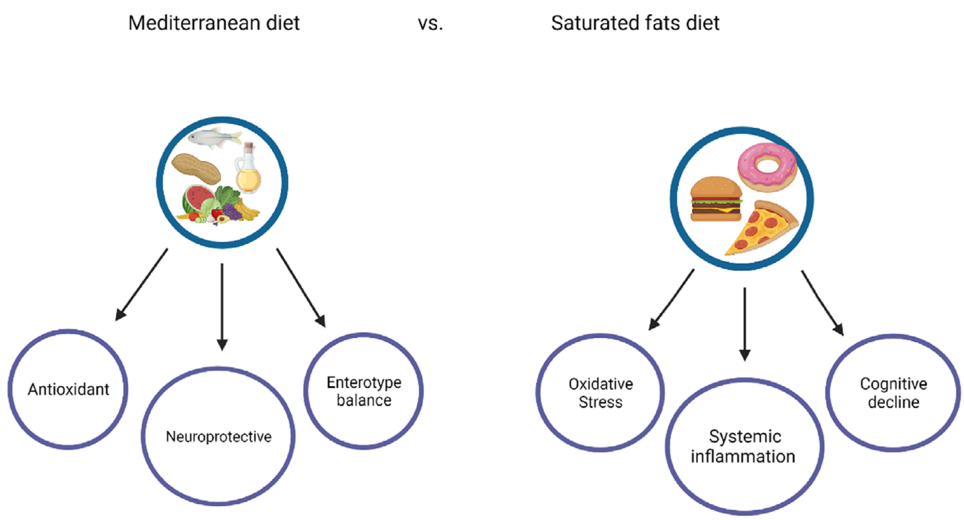

Figure 1. Mediterranean diet versus saturated fats diet. On the left side of the figure, it is possible to observe a few examples of components of the Mediterranean diet, such as olive oil, nuts, fish (source of omega-3), fruits, and vegetables. These foods are a source of nutrients that have a neuroprotective roles, are antioxidant, maintain the enterotype balance, and therefore maintain a healthy brain. On the right side of the image, it is possible to observe representative foods of a saturated fat diet, which lead to oxidative stress, systematic inflammation, and cognitive decline.

education in early life (below 45 years old), hearing loss, traumatic brain injury, bad nutrition lifestyle, and obesity in midlife (between 45 and 65 years old) and smoking, depression, social isolation, physical inactivity, air pollution, and diabetes for later life (over 65 years old).[7] All these conditions were proven to be important in risk and faster progression of dementia, thus we decided to focus on nutrition.

Nutritional epidemiology is the study of nutritional factors and their contribution to the pathogenesis of a disease.[8] There are several nutritional factors and habits that are related to a higher or lower risk of developing dementia. Higher glucose and low dietary protein, lead to lower ability for memorization and cognitive dysfunction.[9,10] On another hand, AD risk is reduced by polyunsaturated fatty acids (PUFAS), which are neuroprotective towards inflammation and oxidative stress,[11] micronutrients (such as vitamins, calcium, and magnesium) enhance learning, memory, sleep among other benefits.[11] Patients with AD have been previously reported with protein-energy malnutrition[12] and reduced presence of micronutrients and fatty acids.[13] Keeping this in mind, the Mediterranean-DASH diet (**Figure 1**) features a number of these nutrients.[14] It is important to mention that the MIND (Mediterranean-DASH Intervention for Neurodegenerative Delay) approach is currently an emerging field to prevent neurodegeneration. People who adhered to the Mediterranean-DASH diets lowered AD risk rates from 35% to 53%.[15] Furthermore, patients more receptive to the Mediterranean diet had a higher gray matter volume in two areas of the hippocampus, increased memory and a lower deposition of Aβ and pTau181.[16] This is in alignment with the findings of a study in postmortem AD patients which included dietary and pathology information, where there was a correlation of lower pathology with MIND associated diets.[17] Other dietary components such as fiber, support gut health by stimulating a healthy enterotype balance, which in turn has benefits for many health metrics.[18] More recently, research has also explored the interaction of certain compounds in the gut with neuronal health.[19] Japan has seen a drastic rise in AD from 1% in 1958 to 7% in 2008 and it is largely blamed on their transition from traditional Japanese diet to a more western diet which is richer in saturated fats.[20]

Lately, a lot of interest has emerged in studying the gut microbiota, known to influence nutrition and vice-versa. The gut microbiota has a unique reciprocal interaction with the brain referred to as the gut-brain axis.[21] The microbiome acts as a positive modulator of the brain by digesting compounds and producing secondary bioactive metabolites such as polyphenols that cross the blood–brain barrier and defend against brain aging.[22] On the other hand, gut microbiota can act as a negative modulator of brain function when disease states cause dysbiosis, leading to the secretion of bacterial amyloid and LPS.[22] It is possible to see the reciprocal effect here, since one of the major causes of dysbiosis is brain aging.[22] All these processes are influenced greatly by the diversity of intestinal bacteria harbored in the intestines and their functional composition. Studies conducted at the Wisconsin Alzheimer's Research Center discovered different bacterial species inhabiting the intestines of AD patients and healthy individuals. There were decreased numbers of Firmicutes and Actinobacteria Phyla and increased numbers of Bacteroidetes and Proteobacteria in patients of AD. There were shown differences in the distribution of bacteria from 13 genera between healthy individuals and AD patients.[23] Although it has been shown that nutritional therapy could be efficacious,[24] its implementation still has to have in consideration whom to treat, when to give preventive care, and which risk factors to consider.

Dietary changes can cause some hardships to individuals. It is a major lifestyle change that requires effort in its implementation. For elderly patients with less control over their surroundings, physical and cognitive impairment, it may be difficult not only to enact these changes but also to keep track of macronutrients and vitamins along with probiotics and other health measures. AD patients can have difficulties with the task of tracking their diet, shopping for ingredients, and cooking meals especially

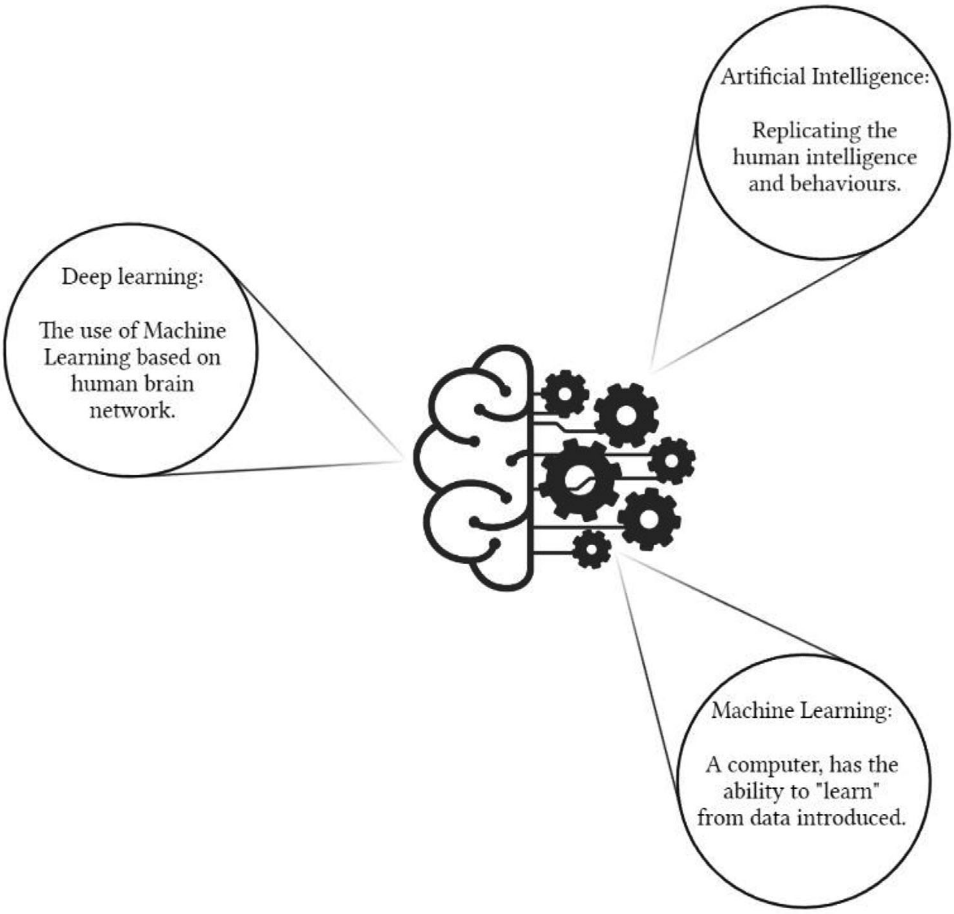

Figure 2. Artificial intelligence, machine learning, and deep learning concepts. Artificial intelligence is recreating human behavior artificially in a system, it encompasses machine learning in which this computer "learns" from a set of data and deep learning is specific for this learning to happen based on human brain network.

due to cognitive deficits. Even with phone apps that deliver locally prepared food to the door, it is critical to consider technical handicaps of the elderly. In this scenario, AI tools offer a valuable option to assist patients by simplifying user interfaces and using tailored programs to serve specific neural and motor deficits. Recurring processes can be automated or tracked, minimizing the need for action on the patient's part, and ensuring consistency on their schedule even during periods of disorientation. To recognize how these advances can support preventive care and nutritional intervention, a greater understanding of the underlying technology needs to be established. Based on this, we will next discuss Artificial Intelligence (AI) and Machine Learning (ML) process of action and tools.

3. Artificial Intelligence and Machine Learning

The past century has seen an exponential growth in the ability to store and manage data. With the advent of small gadgets like mobile phones, smart watches, and cloud spaces to store information, the age of the "Big Data" has emerged. AI enables the data mining sorts through large datasets to identify patterns and extract useful information. Artificial Intelligence (AI), as the name suggests is the capacity of a machine to carry out the cognitive processes that we typically attribute to human brain.[25] Information is given to the machine and it is then expected to operate based on the information that it has been provided by using its "own" mind, and to have the problem solving caliber of a human.[26] Machine Learning is a subset of technology that is based on AI (**Figure 2**). In ML the model is trained to segregate data and make algorithm based models to infer information from it.[27] In order to do this, a good amount of information has to be introduced. Furthermore, after the training, the machine formulates its own algorithms and then processes information based on them (**Figure 3**).[27]

There are three types of Machine Learning techniques: Unsupervised, Supervised, Reinforcement learning.[28] In Supervised ML the information is introduced into the machine, and already labeled to segregate data into categories. In unsupervised, data are segregated by the machine itself without any labeling, it "writes its own code" known as the "Black Box." Supervised learning can assist with classification and unsupervised allows the understanding of a pattern.[28] Deep Learning is a concept linked to "Deep Neural Networks"[29] and a subset of machine learning. As the machine learning model is continuously fed data, it keeps strengthening its algorithm and develops the artificial neural network that can learn and make intelligent decisions on its own.

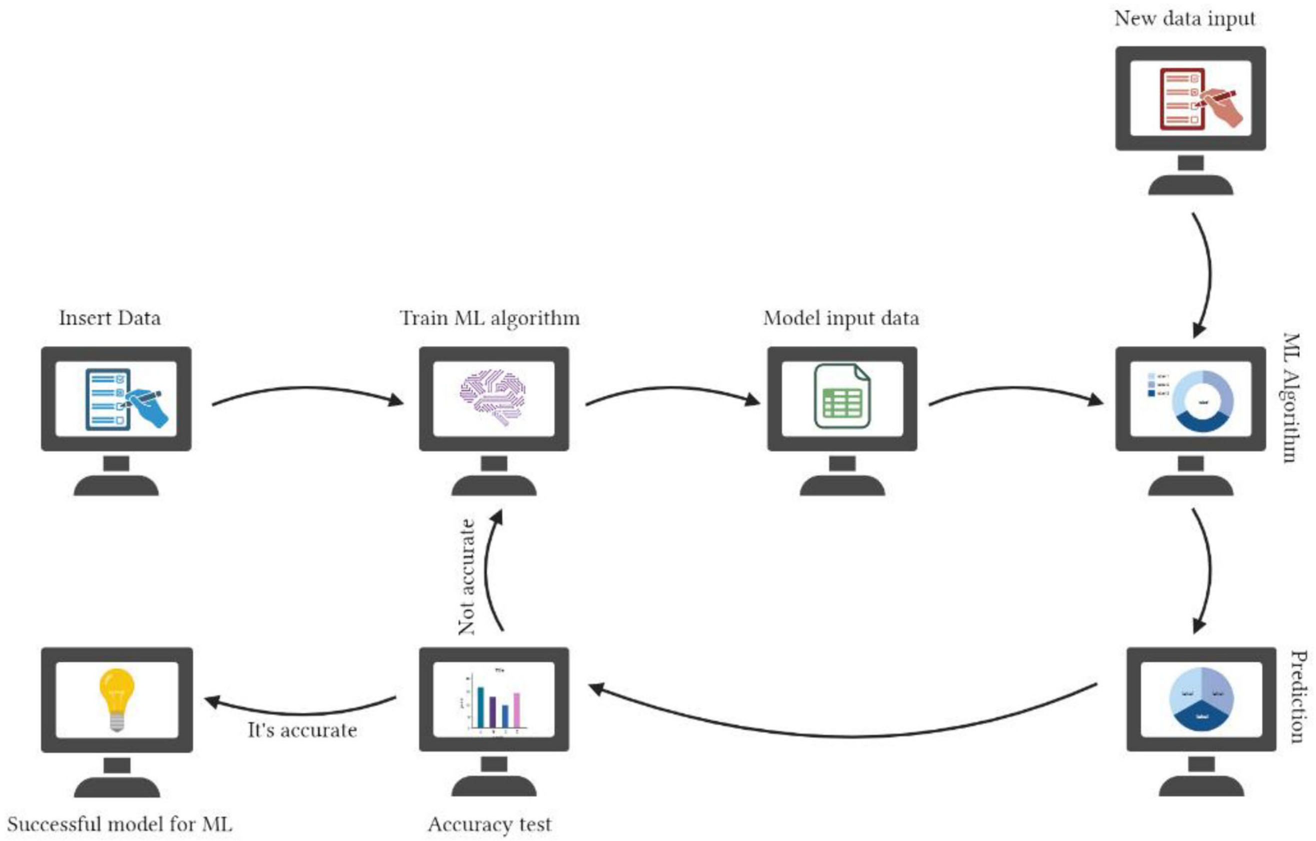

Figure 3. Machine learning in a few steps. Data are added to the system, in which the ML algorithm will start to be trained and eventually create an algorithm. Once a new data input is introduced, the model will create a prediction and test its accuracy, thus if the test is accurate a successful model is created, although if it is not accurate, the system has to go back the training the algorithm. It is important to disclose that this is a very simple mode of explanation of ML process, in a more specific example the process may have more steps and variables.

Additionally, with the applications in unsupervised learning, it is vital to enhance both the quality and volume of data due to the integration of historical predictions with new dietary and symptom data. Some possible approaches can help to improve the rate of data quality enhancement. For example, data cleaning is based on addressing nonstandard items in a dataset, such as outliers, duplicates, or other irregularities, since there is the need to decide whether to eliminate or keep the nonstandard items taking into account the study design.[30] Furthermore, feature engineering aims to produce new variables, which often present as additional columns in a tabular dataset. The process is to transform existing features into more suitable ones.[30] This process provides extensive information from dietary and symptom data, such as meal frequency, nutritional patterns, or symptom severity indices, to the machine learning model for more accurate outcomes.[30] Normalization of the dataset can prevent extreme values from showing within the dataset. The main goal is to reduce bias caused by the numerical distribution, improving the model's capacity to identify significant patterns among the datasets.[31] For the data volume, there are two suggested approaches for enhancement. One of them is data augmentation, which adds synthetic data and other changes to enhance the amount of data. For instance, the image data may be flipped, rotated, or scaled to increase the dataset. This method can be powerful when dealing with the overfitting condition and strengthens the model's capabilities. Also, data augmentation can help to resolve problems caused by class imbalance in the dataset.[32] The second approach for enhancement is transfer learning, which by leveraging an already-built model and its parameters to the other models, there is no need to train a new model. With this existing model, the size of the dataset can be increased. There are three main parts to transfer learning. First, includes the decision of what information should be shared between target domains. Second, the design of learning algorithms for effective information transformation, and third the timing, which is crucial to ensure a well machine learning performance.[33]

It is essential to understand that the more information is introduced into the machine, the better the algorithm becomes (**Figure 4**). Therefore, ML can be used to analyze huge volumes of data, develop its own statistical models known as algorithms and help derive conclusions from big amounts of data.[34]

Reinforcement learning, a subclass of ML is based on the user's response to the output.[35,36] If a user wants a response to be repeated, he rewards the machine otherwise penalizes it.[35,36] Furthermore, recommender system is based on an algorithm that recognizes the likes and preferences of a user and starts giving recommendations based on them.[35,36] The algorithms developed by ML are largely dependent on the kind

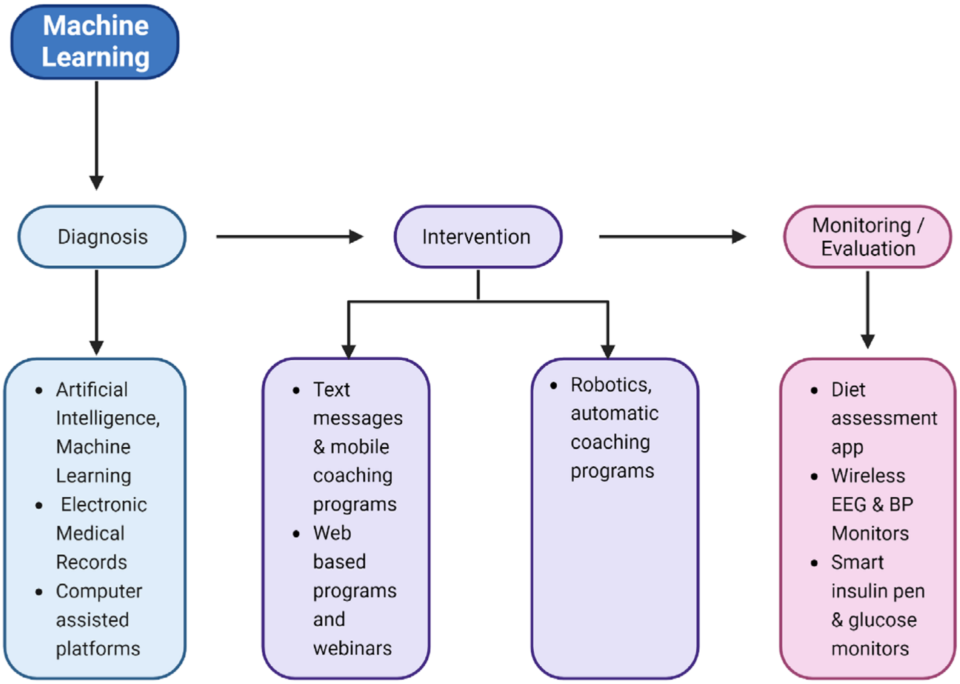

Figure 4. Machine learning role in disease diagnosis, intervention, and assessment. ML can assist in diagnosis of diseases once it has a safe and accurate model from data introduced, furthermore it can intervene in terms of AI assisting with monitoring individual patient status and disease progression through wearable technology and apps that allow patients to self-report tendencies. Finally, through multiple platforms, ML programs can suggest an alteration to the patient's diet that affects disease outcomes and overall health.

of data that is used to develop that algorithm. In the case of very large datasets, the data must be organized very carefully. The added information requires a preprocessing step involving cleaning and organized to undergo analysis. All empty columns and duplications are removed, in order for the data to be organized. It is also important to keep in mind other features of the data set like demographic variables, region specific, culture specific differences, and genetic differences,[37] therefore feature selection should be performed to prevent bias.[38] For example, another variable is that introduced healthcare data, originates mostly from urban environments rather than rural, due to lack of medical records from the population who do not have access to an urban environment and city hospitals. As a consequence, the algorithm might develop a bias. Ultimately introducing large data sets is the best way to prevent faulty models.

Taking into account that ML can process data on a large scale, it can provide solutions to problems that affect populations and require an extensive screening. AI has the ability to integrate the data from each group to identify larger trends. In India ML was applied to identify cases of anemia using machine learning algorithms.[39] Likewise it is possible to develop models to screen people with dementia, specifically populations that have high risk group patients and older age groups.

Furthermore, ML can compile personal, demographic, and metabolic data to predict the individual response to dietary interventions, like the addition or elimination of certain macronutrients. ML can analyze and provide accurate advice on nutrition taking into account individual factors such as sex, ethnic origin, genetics, metabolic traits, environment, microbiome composition, and another factors into account. While generic nutritional advice is often based on averages from large clinical studies.[40] Additionally, adding personalized data into ML, the system can create specific suggestions and solutions in terms of nutritional aspects based on an individual's metabolism and genomics, which can lead to great AD preventive tools, that will be discussed further ahead in the paper. This represents a step forward in ML functional complexity, from the identification of contributing factors to the capability of producing interventional solutions. Many recent studies have developed models for providing "personally optimized recommendations."[41] Taking into account personal information, these systems produce recommendations that differed from the ''general rule'' and were found to have better clinical outcomes in reducing body mass index (BMI).[41] As discussed previously, ML has been extensively used among various cohorts and subpopulations to identify major nutritional factors contributing to disease.[42] This highlights the significance of nutritional factors in predicting and managing health.[43] However, how is the decision of what data to introduce into the ML system made?

3.1. Introducing Data and Making Decisions

It is important to understand the data potentially incorporated into a final decision, such as the nutritional intervention recommended by ML. For complex operations ML is not simply crunching numbers in an input–output manner, but making a series of mini decisions about what data is significant over time, and weighing associations to provide an answer.[27] The processes of collecting a patient's information involving the analysis of dietary trends, personalizing predictions, and weighing outcomes includes the integration of a large amount of information at every step.

The first step to apply ML for personalized nutrition study, datasets need to be acquired. National Health and Nutritional Examination Survey (NHANES) is a program conducted by the Centers for Disease Control and Prevention (CDC) in the United States, and it provides the health and nutritional status of the US population.[44] Since the NHANES is open-source data, it can be accessed directly by visiting the website and downloading the dataset for research purposes. Global Dietary Database (GDD) project was created to identify the relationship between individual-level data and the dietary factors relevant to health, and it can provide nutritional patterns and nutrition on a global scale.[45] Typically, the GDD team must be contacted and a formal request has to be sent for access to the dataset. After acquiring large datasets, it is crucial to process data cleaning to identify and correct errors unrelated to study design, conduct, and implementation of error-prevention strategies.[46] As an example, the first step is to look through the dataset and remove the baseline variables with missing observations, then compute new variables as needed and finally, set the inclusion and exclusion criteria based on the study design.[47]

While assessing many variables, ML identifies trends, groups' data, and decides the level of importance any given factor bares on the final decision.[27] As an example, demographics is one of the aspects that can contribute to prediction along with epidemiological data. The assessment of the demographic information can highlight possible metabolic predispositions can account for the prevalence of a disease in a certain region or identify regional hazards like occupation as a pre-exposing factor.[48] The information for these regional aspects is more easily available for certain diseases, such as diabetes.[49] However, fortunately a number of variables can influence a single condition, therefore it is important to keep in mind elements such as physical activity, the circadian rhythm, and noise exposure. Moreover, besides introducing the right data, it is important to introduce quality data. This is the reason why data governance is important and it will be discussed in the next section.

3.2. Data Governance

Since ML algorithms depend heavily on data, the reliability and responsibility of the algorithms depend on the quality of data.[50,51] Every hospital and health system has a different way of record keeping, and often clinical records are incomplete. This can always introduce bias due to missing values and result in over or underrepresentation of certain populations. Data obtained from data sets in a research scenario and from clinical setting are distinct and need to fall under a guideline to counterbalance the dissimilarities and ensure models developed from them have universal applicability. It is still a topic of discussion the amount of specific data required to design a ML algorithm. Choosing the variables based on how informative they are, can predict the outcomes. One approach to select variables is the use of permutation feature importance, which involves the training of the machine learning model recursively with different variables to find the ones that provide the best model performance. Another approach is to use a methodology for feature selection using machine learning on a large dataset.[52] Although more data improve quality, there is a possibility that too much data distorts the model. In view of ensuring standards for AI/ML, it was issued in the USA an Executive Order naming "Maintaining American Leadership in Artificial Intelligence" to install principles and strategies to improve AI practice.[53] China's ministry of Science and Technology issued their framework and guidelines following the USA.[54] Next, Russia released a national strategy from AI/ML.[55]

Furthermore, it is crucial to adhere to ethical guidelines to ensure the best outcome in the study. For instance, getting an informed consent by the participants and respecting their privacy and confidentiality, will ensure the research fairness. The careful and well-thought-out modeling processes can prevent illegalities from happening.[56]

Now that we have discussed the importance of nutrition in health and disease, and understood how AI and ML work, we will next discuss how these systems can be beneficial to people and Health Care.

4. AI and Health Care

The healthcare industry has an extensive database in the form of Electronic Medical Record System. By ensuring compliance with HIPAA, using this powerhouse of information in the ML systems all over the world, it would be possible to understand what factors have led to various diseases and how to eliminate them. Analyzing health records can help identify patients before they develop symptoms, as also how and when to introduce dietary restrictions or inclusions, or what cognitive activities to engage into and which ones to cease.[57]

Nowadays, AI related applications, are being commonly used in phone apps and other handheld devices to help people keep track of their diet and exercise regimens. More complex programs can give diet recommendations based on trends in user data. As an example, M-Health is specifically aimed to gather nutritional information to serve as research data.[58] It disseminates validated information to the users and gains further data to form a cycle, or direct research to an end-user-result pipeline. This is also a good example of how AI can "learn" and optimize itself. AI models can create health professional recommendations according to the individual's situation.[59]

A ML based smart software was developed to prevent, detect and treat obesity.[60] The use of the PISIoT platform, provides ways to prevent myocardial infarction in obese elderly patients by monitoring their biomedical variables.[61] PURS and RadViz algorithms have been described to analyze biological datasets, detect, diagnose and manage cancer.[62] ML was furthermore used to predict psychiatric disorders from genetic datasets.[63] A study included 116 studies of patients with mild cognitive impairment (MCI), in which ML was applied to predict chances to ultimately develop AD.[64] ML is being implemented to improve the ability to predict and develop a better approach in detecting and managing various diseases. For this to happen, a specific amount of information about the patient must be introduced, and this is where a precision medicine approach gets involved.

4.1. From Multi-Omics to Precision Medicine

Metabolomics is an emerging field that measures metabolites resulting from biological mechanisms.[65] This assay involves the analysis and profiling of metabolic products providing a very detailed systematic information for every patient useful for disease prevention and treatment strategies. This approach has a great deal of benefit to manage chronic conditions and cancers. The integration of this knowledge from metabolomics with proteomics, transcriptomics, epigenomics and genomics originates the big umbrella multi-omics.[66]

Multi-omics provides a multi-dimensional view of human biology. As this field is evolving, techniques of analysis have improved and they have become cost effective.[67] Initial studies using ML were highly successful in predicting certain personalized diet trends such as individual postprandial glucose responses.[68] This model incorporated individual microbiota information and showed improved precision in predicting a glycemic response versus statistical models based on glucose monitoring.[68] This proves the efficacy of using AI as a tool for targeting disease that surpasses previous methods. More valuable insights can be obtained by integrating data sets from omics platforms, digital health records, and other health metrics databases. This results in an automated and adaptive approach for extracting meaningful patterns and identifying relationships between these high-dimensional input variables.[48] ML in collaboration with multi-omics can help identify a patient at high risk to develop a disease much earlier and enable a tailor made approach to their treatments based on their genomics.[59]

Metabolomics profile of 40 healthy adults was studied to predict their chances of developing insulin resistance and type 2 diabetes mellitus.[69] Based on this, ML was implemented to formulate individualized lifestyle models for them which recommended diets, physical activity and habit modifications. The resulting metabolomics profile showed a reduced chance of developing insulin resistance, type 2 diabetes mellitus and its comorbidities.

Many circumstances can increase the body's need for certain nutrients, on a day-to-day basis. This is referred to as the "external food exposome."[70] Enterotypes bacteria in the gut have a complex synergy with diet, health, and genetics and have a profound role in metabolism. The model becomes more personalized when genetic information such as Genome-Wide Association Studies (GWAS) that can impact the patient's metabolism or disease susceptibility, is incorporated.[71] Genotype offers more information based on trends that have been identified in GWAS, including the effects of certain Single Nucleotide polymorphisms (SNPs) on the metabolism.[72] Although demographic information and health status are relatively static, genetic changes and shifts in Enterotype bacteria are happening constantly and with every meal. Collectively, these factors can be called the "internal food exposome"[70] and could allow for a prediction of how the patient would respond to any given food and determination of any significant effects on disease progression. These factors allow a prediction of what happens downstream, but the digestion process is complex and varies between individuals. Consequently, understanding the metabolic profile of an individual, including the resulting secondary metabolites or bioactivity will increase our knowledge on what biological products are really involved in the disease and its progression. Searching for associations between the presence of these compounds and changes in mental state or brain physiology related to the disease would be an interesting study, expecting diet impacts on the disease course.

ML could provide detailed prediction about the association between the diet of a patient and alterations in the progression of the disease they suffer from, based on changes in the patient's symptoms. ML could then continually provide recommendations based on maximum therapeutic value to the patient. This involves a complex network, with every alteration having multifactorial downstream effects and giving feedback to earlier the availability of patient data through a ML interface, would streamline such classification and quickly provide data-based justifications for criteria. This automates a complex process while giving highly personalized health considerations, which would greatly help the health care system and professionals to better assist patients.

4.2. Health Care System and ML Models

Proper nutrition is particularly important when battling a disease, but it is difficult to assess if a patient is following a healthy lifestyle, since the symptoms of malnutrition can be confused with the disease, and ill patients might lack the ability to express their needs. There has been described a new framework for a ML program, which can identify cases of malnutrition in hospitalized patients and further provide support in individualized decisions for at-risk patients.[73] This program proved to be useful and identified several malnourished intensive care patients. ML might use similar predictive capabilities to alert an individual that they may be pre-diabetic or at increased risk of computer aided design (CAD) and urge a feasible intervention, such as starting glucose monitoring.

Another model based on artificial neural network, has been developed to measure folate and B_{12} intake, in order to inflect susceptibility to breast cancer.[74] There was a 94.2% explanation on variability about prediction of breast cancer, the authors included data not only from the micronutrients, but also from nutrition and demography.[74] Another work used ensemble method, generalized regression prediction, elastic net, and leave one out cross-validation method to evaluate prognostic factors of healthy eating index in multi ethnic colorectal cancer families.[75] Furthermore, another example of ML being applied to health care is that twins and unrelated healthy adults were studied for variability in postprandial metabolic responses (triglycerides, glucose, and insulin) as cardiovascular risk factors.[76] A ML based model was developed, that predicted responses to food intake in terms of glycemic index and triglyceride levels. Rapid automatic bite detection algorithm (RABID) was made to analyze the eating behaviors in a subject size of 59 patients.[77] RABID extracts information and processes from skeletal features from videos. The results showed agreement between algorithmic and human annotations. Another study was conducted over subjects with chronic kidney disease and used knowledge based system (KBS) using Web Ontology Language (WOL) and Semantic Web Rule Language (SWRL).[78] KBS was used to recommend appropriate serving size from different types of food and found that it demonstrated a good and reliable performance when suggesting what the system was asked for the patients involved.

Finally, AI and ML were used to propose menu construction using incremental knowledge acquisition system (MIKAS).[79]

All these studies have an important role for the health care system, it provides individuals with good and personalized predictions and solutions, and aids health care professionals to better understand and assist their patients. Therefore, we believe that it is possible to establish similar ML models to identify conditions that contribute to the pathogenesis of AD.

5. AI and Beyond

As discussed in this review, diagnosis is possible with AI, it has already been used in imaging software that detects brain lesions and could be applied to MRI scans of AD patients.[80] Nonetheless, ML based algorithms must be handled with care, and the data introduced has to be accurate and truthful. In a recent example, a ML-based skin cancer detection software was able to detect this disease in many patients, however the data introduced included only White patients, keeping in mind that the levels of melanin were the case study. This software decreased its accuracy when patients with a darker skin tone and higher amount of melanin where added to the study.[38]

An application developed for AD patients would have a simpler user interface and automated functions. AI could track a patient's schedule and order food for them, purchasing the right ingredients according to the patient's affinities and budget. This would allow the patient to maintain a schedule during periods of disorientation. It is known that a consistent schedule promotes low levels of anxiety and less episodes of disorientation in AD patients.[81] AI based apps could also help remind patients of their medications and sending automated refill requests to pharmacies. This would guarantee a regular supply of medicines for them. It would also be interesting to have AI based apps connecting them to Home Health Aides, hospital nurses, or nursing homes on regular intervals to maintain follow up. AI can also be used to ensure patients to visit the restroom every few hours, to reduce issues with incontinence and bed wetting.

In general, AI apps can help patients suffering from dementia make schedules and to-do lists. It was found that often when these patients wrote notes for themselves they were able to follow them easily.[82] AI could also facilitate medical appointments and remind the patient to give the correct information to their provider.[83] AI can be a precious tool that could take a burden off the caregiver to some extend and helps disseminate responsibility.[84]

As mentioned before, Mediterranean diet can tackle memory decline and Medio temporal atrophy caused by AD, since it has been seen that this diet can lower deposition of Aβ and pTau181.[16] AI could track and manage the adherence of Mediterranean diet and improve the life quality of AD patients. A study showed that the AI-powered solution uses a graph convolutional network (GCN) that has been trained using a noise-robust training process to identify food and drink items from a single meal photo.[85] The system recognizes food items and portion quantities from a single image, assesses a user's compliance with a healthy diet score, and offers feedback and individualized recommendations. Moreover, the mean difference between the MD adherence score calculated by the system and an expert dietitian was 3.5%, which was statistically insignificant. Another work proposed the Medipiatto Project that uses an automated smartphone app to track and evaluate users' adherence to the diet by looking at pictures of the food and beverages they consume.[86] The automated smartphone application developed by the Medipiatto Project has produced encouraging results in determining adherence to the Mediterranean diet. The minimal disease activity (MDA) scores anticipated by the proposed system are relatively like those predicted by seasoned dietitians.

6. Conclusion

Nutrition has been proven to have an impact in AD pathogenesis, reduced presence of micronutrients, fatty acids and protein lead to cognitive impairment, and are constant within AD patients.[87] The MIND dietary is an emerging field that provides nutritional interventions for common neurodegenerative diseases.[15] Consuming a balanced diet with the right nutrition intake can help improve the pathological condition. Increase in gray matter volume in certain areas of the hippocampus, improving memory, and lowering deposition of Aβ and pTau181 are some reported studies in which a proper nutrition had a positive effect on patients.[16]

ML has become a very important part of medical industry and it is being used to study diseases, improvise diagnosis, study investigations, give recommendations, and even arrange follow ups. Therefore, there is a possibility to use this tool for AD patients, to diagnose risk of dementia, assist in nutrition, improve their quality of life, and to at least decrease the rapid progression of the disease.

ML is being extensively used in the field of diabetes management, cardiovascular diseases, and cancer research.[88,89] Although, it is an uncommon practice to monitor diet while monitoring these diseases, so the available data are limited. There has been an aim to begin compiling nutrition habits data, similar to what has been done for the Parkinson's Disease Manager program in tracking Parkinson's disease.[90] However, this has raised additional questions, such as what age to start monitoring. Perhaps it would be useful to do a case study with people from different age groups, with the genetic predisposition for AD and without. Nevertheless, to start from an early age to implement a healthy lifestyle and to take care of what type of food and nutrients are being consumed is important to prevent not only AD but also many other diseases as well.

The basis of many future applications is a program's ability to integrate past predictions and new data from patient diet and symptom input, a feature of unsupervised learning.[28] However, variations in precision may arise from variations in the base data, the experimental design, and the algorithmic structure. In cases where the data were relatively simple, ML algorithms have added superfluous complexity. Similarly, the performance of a ML algorithm may be limited by a lack of data, it is only useful for large data sets. This affects the application of these models in personalized nutrition.

Understanding the model is important for troubleshooting the program and making improvements, as well as identifying potential biases. Sources of bias lie within the data that is used and the way it is maintained. Multi-omics is a powerful tool to use in ML.[91,92] It could give personalized predictions and solutions to patients and risk groups, since it has been shown to be beneficial for different illness, thus assisting the health care system and professionals.

In summary, AI is already being applied in some fields that show a high potential in disease prediction, prevention, and assistance of patients. Beyond these capabilities, its function in automating certain processes like collecting patient data can increase accessibility to care. While this can streamline research endeavors, it also can serve to address social issues and healthcare disparities. Engineering and other fields have already extensively used AI, and although newer in the nutrition field, its use is rapidly progressing.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

A.S.D.P. and V.S. contributed equally to this work. E.R., J.P., and G.M.P. conducted the design of the study; A.S.D.P., V.S., S.H.W., E.R., and S.M. wrote the paper; A.S.D.P., V.S., and G.M.P. were the responsible for the final content. All authors read and approved the final manuscript.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Keywords

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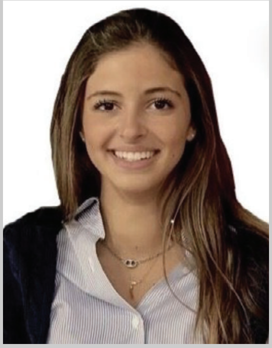

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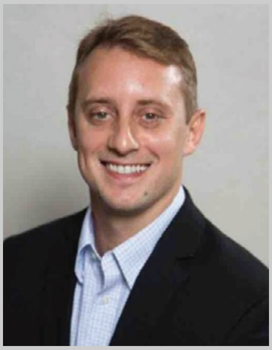

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