AI-POWERED NUTRITION ANALYZER FOR FITNESS ENTHUSIASTS

LITERATURE SURVEY

AI in Biomedical Nutrients Research:

In the area of biomedical nutrients research, there were identified studies in which advanced AI methods and systems were applied in relation to the study of the composition of food products, optimization of nutrient production, the effects of nutrients on the functioning of the human body in health and disease and research on the gut microbiota. Among the works on the influence of nutrients on the functioning of the human body in health and disease and studies on the gut microbiota, ML domain algorithms were used almost exclusively. The fuzzy logic methodology was used occasionally.

AI in Food Composition Study:

The use of AI techniques in studying the composition of food products and testing their originality dates back to the 1990s. Dettmar et al. used the ANN technique to identify the region of origin of fruit from a set of 16 variables characterizing samples of orange juice. The effectiveness of the applied calculation technique was 92.5%. Yang et al. used the isobaric tag for a relative and absolute quantification proteomic approach to analyze differentially expressed whey proteins in the human and bovine colostrum and mature milk to understand the different whey proteomes. It may provide useful information for the development of nutrient food for infants and dairy products. Moreira et al. used topological maps of the Kohonen neural network in the assessment of the procedure for sample preparation of cashew nuts. Shen et al. used laser-induced breakdown spectroscopy (LIBS), least squares support vector machines (LS-SVM) and LASSO models for the detection of six nutritive elements in Panax notoginseng (traditional Chinese medicine) samples from eight producing areas. Rasouli et al. applied the whole space genetic algorithm-radial basis function network (wsGA-RBFN) method to determine the content of microminerals of Fe2+, Zn2+, Co2+ and Cu2+ in various pharmaceutical products and vegetable samples (tomato, lettuce, white and red cabbages). This group Nutrients 2021, 13, 322 5 of 16 of studies also includes the research of Soltani et al. who used three different quantitative structure bitter taste relationship (QSBR) models (artificial neural network, multiple linear regression and support vector machine) to predict the bitterness of 229 peptides.

AI in Research on Production of Nutrients:

With regard to research on the optimization of the production of certain nutrients, several studies have been identified in which AI modeling was intentionally applied. Huang et al. implemented methods of production of a retinol derivative named retinyl laurate by an artificial neural network (ANN). Zheng et al. studied the optimization of producing 2,6-dimethoxy-ρ-benzoquinone (DMBQ) and methoxy-ρ-benzoquinone (MBQ) as the potential anticancer compounds in fermented wheat germ. They used algorithms of an artificial neural network (ANN) combined with the genetic algorithm (GA). The ANN model with a Levenberg–Marquardt training algorithm was applied for modeling the complicated non-linear interactions among 16 nutrients in this production process. Kumar et al. used GA-Fuzzy—an evolutionary algorithm comprised of the genetic algorithm (GA) and the fuzzy logic methodology (FLM) for the optimization of the production of phycobiliproteins (PBPs) from cyanobacteria.

AI in Research on the Influence of Nutrients on Physiological and Pathophysiological Functions:

The most numerous group of works presenting applications of AI models in biomedical nutrients research is research on vitamins. Pavani et al. used the neuro-fuzzy model to investigate the influence of alterations in vitamin K (K1, K2 and K3) on modulating the warfarin dose requirement . An AI model was used to predict the warfarin dose, and higher vitamin K1 was observed in the CYP4F2 V433M polymorphism in this study.Yu et al. compared the expression profiles of miRNAs, lncRNAs, mRNAs and circRNAs, between 1,25-(OH)2D3- treated endothelial progenitor cells (EPCs) and control cells. They used bioinformatics analyses to identify differentially expressed RNAs and constructed the competing endogenous RNA (ceRNA) networks with Cytoscape software. Zhang et al. investigated the effect of 1,25-dihydroxy-vitamin D3 (1,25-(OH)2D3) on primary chondrocytes cultured from patients with an osteoarthritis protein–protein interaction (PPI) by a PPI network . They suggested that their study might provide a theoretical basis for the use of vitamin D in treating osteoarthritis. Kolhe et al. tried to verify the hypothesis that vitamin C mediates proliferation and differentiation of bone marrow stromal cells through miRNA regulation. They performed bioinformatics analyses to identify novel target genes and signaling pathways. Gene Ontology word clouds were generated using the online Wordle software. Huang et al. investigated an influence of the active ingredients of licorice for muscle fatigue by RNA-Seq and bioinformatics analysis. They used a machine learning model and a docking tool to predict active ingredients.

AI in Research on Gut Microbiota:

In recent years, results of research on nutrients and the gut microbiota using AI techniques have been published. Devika and Raman used genome-scale metabolic models to differentiate between 36 important Bifidobacterial strains. Shima et al. performed analyses concerning the gut microbiota, based on a combination of machine learning and network visualization. Mohammed and Guda used AI in the research on enzymes produced by strains of gut bacteria. They developed ECemble, an approach to identify enzymes and study the human gut metabolic pathways. ECemble uses an ensemble of machine learning methods to predict and identify the enzyme classes. They identified 48 pathways that have at least one bacteria-encoded enzyme and are involved in metabolizing nutrients.

AI in Clinical Nutrients Research:

In the past studies in the field of clinical nutrients research, AI techniques have been used in projects aimed at creating tools supporting dietary activities and in supplementation, as well as in the diagnosis and prediction of the risk of chronic diseases. According to the graphical characteristics of the analyzed works (Figure 2), the DL methodology dominated in the group of studies on clinical nutrients intake. A marginal use of the fuzzy logic methodology was noted—it appeared only in one study.

AI in Nutritional Epidemiology:

In the area of nutritional epidemiology research, there were identified studies in which advanced AI methods and systems were applied in relation to the dietary assessment, physical monitoring systems and environmental trace elements monitoring systems. In this research area, the algorithms of ML and DL were used predominantly. The methodology of ANN was used in environmental trace elements monitoring systems. The application of the IoT methodology was noted in the physical monitoring systems topic.

AI in Dietary Assessment:

Mobile applications based on systems using AI are of significant importance in the field of nutritional prophylaxis.In 2008, Sun et al. proposed an electronic photographic approach and associated image processing algorithms to estimate food portion size.Lu et al., in a recent publication, offered goFOODTM as a dietary assessment system based on AI. It can estimate the calorie and macronutrient content of a meal, on the sole basis of food images captured by a smartphone.Yang et al. proposed a new methodological approach in the field of nutritional epidemiology, Ontology for Nutritional Epidemiology.It is a resource to automate data integration, browsing and searching. ONE can be used to assess reporting completeness in nutritional epidemiology. Lo et al. created an objective dietary assessment system based on a distinct neural network.They used a depth image, the whole 3D point cloud map and iterative closest point (ICP) algorithms to improve the dietary behavior management. Fang et al. estimated food energy based on images and the generative adversarial network (GAN) architecture.Ji et al. assessed the relative validity of an image-based dietary assessment app Keenoa and a 3-day food diary in a sample of healthy Canadian adults.The authors in this randomized controlled trial showed that Keenoa had better validity at the group level than the individual level and it can be used when focusing on the dietary intake of the general population. Hsu et al. used the fuzzy decision model to develop a web-based support system that searches food composition databases and calculates dietary intake. This research project was carried out due to the lack of integrated databases for Chinese menus and the need for a decision-making tool for dietitians in Taiwan.

AI in Physical Monitoring Systems:

AI techniques have found their application not only in monitoring the quality and quantity of nutrients, but also in terms of the level of their expenditure. In the face of the obesity epidemic, these AI applications are very important, described the use of a monitoring system as an effective diagnosis tool of physical activities by a wearable smart-log patch with Internet of Things sensors. Tragomalu et al. analyzed e-health applications for the management of cardiometabolic risk factors in Nutrients 2021, 13, 322 10 of 16 children and adolescents. Ramyaa et al. tried to phenotype women based on dietary macronutrients and physical activity using machine learning, support vector machine (SVM), neural network and k-nearest neighbors (kNN) algorithms.

AI in Environmental Trace Elements Monitoring Systems:

Novic and Groselj used an ANN to create a methodology for food specifications associated with the origin of food. The methodology was tested on honey samples collected by the TRACE UE project. The data were collected from various regions of Europe and analyzed for the content of trace elements. Research on the content of trace elements and rare-earth elements in honey was also carried out by Drivelos et al.They used probabilistic neural network (PNN) analysis and constructed a partial least squares (PLS) model for classifying of honey samples according to their geographical origin and organic characterization. Tunakova et al. used an ANN to create a neural network model describing the retentions of trace elements in the human body. They calculated the microelement levels in the body, knowing the trace element levels in drinking water and urine.

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