A Comprehensive Survey on Artificial Intelligence based methods and Technologies Used to Detect Nutrition Level (Malnourishment)

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2023 IEEE International Carnahan Conference on Security Technology (ICCST) | 979-8-3503-1587-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICCST59048.2023.10726846

Abstract

The ability of a machine to execute cognitive activities that are traditionally accomplished by human minds is known as artificial intelligence. There are now an increasing number of tools, platforms, and applications for nutrition surveys thanks to the advent of the Internet, which has made it possible to conduct online nutrition surveys using sizable food and nutrition databases connected to automated eating records. Nutritional AI To better understand eating habits and public sentiments, artificial intelligence (AI) systems can harvest, organize, and analyze vast amounts of data from social media platforms. In conclusion, AI-based methods will probably enhance and progress nutrition research and support the investigation of novel applications. The systems improve in accuracy because AI algorithms have the chance to understand training data. This enables people to gain knowledge about the variability of therapy, care procedures, diagnostics, and patient outcomes that were previously unattainable.AI-enabled digital tools and devices can forecast, screen, and monitor treatment processes, assisting physicians, patients, and more broadly the entire healthcare system

Medical professionals can identify numerous ailments and promptly and efficiently treat them by understanding the nutrition status of the human body. They employ a pathology lab and a manual, time- and money-consuming approach to perform nutrition tests. The use of AI in healthcare has made it possible to test for nutrient levels quickly and inexpensively. We concentrate on how to identify malnutrition because nutrition AI is one of the key themes in modern medicine. The goal is to provide a comprehensive list of all the studies and techniques that have been done to monitor nutritional status and identify malnutrition. The aim of this work is to describe existing nutrition detection methods, list the many datasets used for incorporating AI to detect human nutrition and malnourishment, and list and discuss several mobile apps for nutrition.

Definitions: *Nutrition*, the foods you eat, and how they impact your health [Ref. 1]. *Artificial Intelligence,* the ability of a machine to execute cognitive activities that are traditionally accomplished by human minds is known as artificial intelligence [Ref. 2].

***Keywords**:* Nutrition, Artificial Intelligence, Healthcare, Malnourishment, Digital health, Smartwatches, Wearables Gadgets, Precision Nutrient Analysis, Chat-boat

Abbreviations AI: Artificial Intelligence, BMI: Body Mass Index, ACM: Association of Computing Machinery, IEEE: Institute of Electrical and Electronics Engineers, PK: Process Knowledge, KiL: Knowledge-infused Learning NLG: Natural Language Generation, NCS: Nutrition Coaching Systems, MAS: Multi-Agent Chat-boat System, FRS: Food Recommender Systems, ML: Machine Learning

Section I: Introduction

Nutrition is the biochemical and physiological processthrough which an organism utilizes food to sustain its life. It supplies nutrients that can be processed by living things to produce energy and chemical structures. [Ref.3]. Utilizing artificial intelligence (AI), researchers have been able to diagnose illnesses, forecast clinical outcomes, and create innovative medicines [Ref. 4]. Measurable clinical gains have been attained through the use of AI in ophthalmology [Ref. 5], radiological [Ref. 6], and cardiac [Ref. 7] diagnostics. Research on novel medications utilizing AI [Ref. 8]. Additionally, the growth of AI opens up new possibilities for nutrient and medical sensing technology research [Ref. 9]. There are now an increasing number of tools, platforms, and applications for nutrition surveys thanks to the advent of the Internet, which has made it possible to conduct online nutrition surveys using sizable food and nutrition databases connected to automated eating records [Ref. 10]. The three most prevalent categories of AI approaches are deep learning (DL), machine learning (ML), and natural language processing (NLP) [Ref. 11]. *AI in Nutrition:* Nutritional AI To better understand eating habits and public sentiments, artificial intelligence (AI) systems can harvest, organize, and analyze vast amounts of data from social media platforms. In conclusion, AI-based methods will probably enhance and progress nutrition research and support the investigation of novel applications [Ref 12,13]. *Role of AI in Healthcare:* The systems improve in accuracy because AI algorithms have the chance to understand training data. This enables people to gain knowledge about the variability of therapy, care procedures, diagnostics, and patient outcomes that were previously unattainable [Ref.14].

Top 10 AI Apps for Nutrition [Ref. 15]

Sr. No.	App Name	Description
1)	*Neutrino*	*AI Nutrition App*
2)	*FitnessAI*	*Ultimate Workout at Home Solution*
3)	*Fit Genie*	*Smart Calorie Counter*
4)	*Freeletics*	*Europe's Fitness AI App*
5)	*Suggestic*	*AR-Based App*
6)	*Vi Trainer*	*Virtual Coach*
7)	*Calorie Mama*	*Cultural Food Identifier*
8)	*Whoop*	*Improve Sleep Patterns*
9)	*Eat Right*	*Tailored Food Recommendation System*
10)	*Lark*	*Training and AI Fitness Coach*

Fig 1: Table 1: AI Apps for Nutrition

AI-enabled digital tools and devices can forecast, screen, and monitor treatment processes, assisting physicians, patients, and more broadly the entire healthcare system [Ref. 16, Table 1]. Process Knowledge (PK): It has proven challenging to use AI in delicate, high-value, or safety-critical applications like self-management for tailored diet or health. [Ref. 17]. This article's goal is to review the current approaches and tools for artificial intelligence-based nutrient level detection. In Section II (Existing *Nutrition Detection Methods)*: We describe the different methods and technologies to detect Nutrition levels. In Section III (Mobile Apps): We mentioned different mobile applications that implement the features of AI. In Section IV (Nutrition Datasets and Research Papers): We listed the Literature survey, and we very specifically selected the research papers from IEEE, ACM, Springer, and Elsevier. In Section V (Conclusion and Future

Work): We Concluded the survey work and described the future work that is to be required. In Section VI: (References) We listed the References from different resources we collected and studied the Research papers.

Section II: Existing Nutrition Detection Methods

AI Methods and Technologies for ***Nutrition*** *Detection:* The Application of Digital Technologies and Artificial Intelligence are used in healthcare by utilizing the basis of Nutrition Assessment [Ref. 18]. In recent years researchers have done a lot of surveys on AI Nutrition Recommender Systems [Ref. 19]. The level of trust in the decision-making process has increased as a result of the requirement for quantification of uncertainty in artificial intelligence for clinical data processing [Ref. 20] It has proven difficult to utilize AI in high-value, delicate, or safety-critical applications like self-management for personalized health or tailored nutrition. These call for the AI system to adhere to rules or well-defined procedures established by authorities, groups, or standards. These are what we refer to as process knowledge. (PK) [Ref. 21]. Artificial Intelligence is also playing an important role in the Wearable System for Cardiac Disease Detection [Ref. 22]. The Use of Artificial intelligence-based Vision and voice Assistant are popular among the social community [Ref.23]. IEEE Standard for Performance and Safety Evaluation of Artificial Intelligence-Based Medical Devices are rapidly implemented and captured in the healthcare Market. [Ref.24] Clinical nutrition applications are presently being developed as a result of the decades-long ubiquitous integration of digital technology in the medical sector [Ref. 25]. Granular nutrition-related data may now be gathered in real-time using wearables and smartphone applications. Examples of tools include diet optimization, risk prediction, and decision support tools [Ref. 25]. Evidence demonstrates that these mobile and web- based applications improve clinical outcomes, such as weight management and nutrition education, and follow-up, data gathering, monitoring, and care processes. [Ref. 26 - 29]

A Precision Nutrient Analysis Model: The researchers have created a framework for precision nutrient management based on digital data collection [Ref. 30]. The Precision Nutritional Analysis was enhanced by the integration of a total of two AI models, including semantic and nutritional analysis models.

Few Traditional Methods: There are three typical ways of gathering nutritional information: the Food Record, the 24-hour dietary recall (24HR), and the Food Frequency Questionnaires (FFQs). The 24HR technique evaluates a respondent's dietary intake for the previous 24 hours. A dedicated interviewer typically conducts the 24HR approach over the phone or in person [Ref. 31]. The FFQ measures a person's overall nutritional intake during a predetermined time period, typically a longer time period, and inquires as to how frequently they eat [Ref. 32].

Few AI Models based on Precision Nutrition

Sr. No.	Name of Models	Ref
1)	Artificial Intelligence Semantic Analysis Model	*[Ref.33]*
2)	Okapi BM25(Best Matching)	*[Ref. 33-35]*
3)	TF-IDF (Term Frequency Inverse Document Frequency)	*[Ref.36]*
4)	Artificial Intelligence Nutritional Analysis Model	*[Ref.37]*
5)	Nutritional Ingredient Analysis)	*[Ref.38]*

Fig 2: Table 2- AI Models

The AI Precision Nutrient Analysis Model was used to assess the ingredients of the dishes and automatically analyze the dishes to calculate nutrient intake [Ref. Table 2]. A digital data semantic analysis model was employed to examine portion sizes.

Food Image Recognition: Image recognition often makes use of deep learning. The analysis of radiographic images for the diagnosis of pneumonia, endoscopic images for the detection of colonic polyps, and cutaneous images for the detection of melanoma have all been done in the medical area using deep learning [Ref. 39–41].

Knowledge-infused Learning (KiL): KiL is a group of neuro-symbolic AI systems that incorporates knowledge from lexical, linguistic, domain-specific, common sense, process, and constraint-based knowledge into deep neural networks [Ref. 42]. Under semi-deep and deep knowledge infusion, two of the three forms of knowledge infusion covered by KiL (i.e., shallow, semi-deep, and deep3), process knowledge infusion generates a new and complementary set of methodologies, datasets, and evaluation procedures. We will conceptually outline strategies for incorporating process knowledge into statistical AI systems with an emphasis on natural language generation (NLG) [Ref. 43]. The researchers have created a customized agent-based chatbot for nutritional counselling. [Ref. 44]. Groups having particular needs, such as the elderly [Ref. 45], diabetics [Ref. 46], or critical consumers [Ref. 47], can be the focus of NCS. Chatbots Powered by Agents Recent research supports the viability of designing and deploying conversational agents in many domains utilizing multi-agent systems (MAS) [Ref. 48, 49].

Machine Learning into Nutrition: Machine learning (ML) is used to detect trends in nutrition and make predictions. The most relevant trend when it comes to the back-end of agent-based chatbots (the bot/agent brain) is the employment of machine learning (ML) techniques in the decision-making process (leading to a shift towards Python-based back-ends with some reliance on proprietary platforms) [Ref. 50, 51]). However, the number of agent-based chatbots has also increased dramatically as a result of the introduction of specialized APIs by well-known chatbot platforms like Facebook, WhatsApp, and Telegram [Ref. 52]. Similar to other recommender systems (RS), food recommender systems (FRS) can use a variety of recommended approaches. These methods include collaborative filtering, which makes use of the similarities between users [Ref. 53], content-based filtering, which suggests related products based on similar profiles' prior knowledge of the user's preferences and restrictions [Ref. 54], and hybrid recommendation. (Combines the methods outlined above to get over the shortcomings of the individual strategies [Ref. 55]). Multiple communication interfaces are supported by EREBOTS, but the version used here uses Telegram IM to increase reach [Ref. 56]. The EREBOTS paradigm for individualized nutritional counseling is expanded by this [Ref. 57]. For dietary goal recommendations, researchers are attempting to blend expert knowledge and machine learning [Ref. 58]. An AI-Based System to Assess Nutrient Intake for Hospitalized Patients has been implemented by researchers [Ref. 59]. Two examples of dietary assessment systems based on AI are Im2Calories [Ref. 60] for calorie estimation and GoCARB [Ref. 61] for carbohydrate (CHO) estimation. The systems divide the food into constituent components, identify the food, and estimate the amount of the meal in three stages of analysis. Therefore, nutritional content can be calculated using the food nutrition database. These days, it is possible to track activity and nutrition in everyday situations using a textile capacitive neckband [Ref. 62].

Section III: AI-Based Mobile Apps for Nutrition Detection

Mobile Apps available for Nutrition detection based on AI
Applications for mobile health give a chance for remote monitoring of outcomes, data collection, and improved patient interaction outside of the hospital. Numerous people use diet and weight loss-related applications, and it is estimated that there are over 10,000 of them available right now. [Ref. 63]. *Weight Loss Mobile apps:* Cronometer, My FitnessPal, Noom *Diabetes Mobile Apps:* Day Two, Glucose Buddy, Dario Health *Gastrointestinal Condition Mobile apps:* Cara Care, Gali Health, My Symptoms, *UbiFit Garden*: It is a mobile application made to encourage users to continue engaging in regular physical activity. The smartphone wallpaper shows the clients' weekly development [Ref. 64]. *Snap-n-Eat*: By merely analyzing the photographs directly captured by the user using the mobile phone, it is feasible to estimate food intake, calorie content, and nutrient intake [Ref. 65]. *Keenoa*: It functions similarly, but furthermore sends the nutritional analysis to a dietician immediately [Ref. 65]. *mHealth:*

Mobile health technologies can aid in self-management by using behavior modification techniques to assist and scaffold daily decisions [Refs. 66, 67]. With the use of mobile and wearable technology, it is also feasible to gather data on one's own health, including details about diet and exercise, which can shed light on the relationship between a person's behavior and their level of health [Refs. 68, 69]. The field of personal informatics examines the use of personal data for self-reflection and higher self-awareness, which may result in better health [Ref. 70]. *GlucoGoalie:* It provides individualized advice on nutritional goals for those with T2D. It addresses the relationship between dietary consumption and changes in BG after meals by using machine learning (ML) to detect patterns in self-tracking data, including meals and BG levels collected with the GlucoGoalie smartphone app. It helps users define and achieve dietary improvement goals, and it creates personalized nutrition goals by analyzing data from each user with at least 8 meals [Ref. 71].

Section IV: AI to Detect Malnourishment

Body mass index (BMI) This is calculated by the weight in kilograms divided by the height in meters squared. A healthy BMI for adults usually lies between 18.5 and 24.9. Those with a BMI between 17 and 18.5 could be mildly malnourished, those with BMIs between 16 and 18 could be moderately malnourished and those with a BMI less than 16 could be severely malnourished. In general, all with a BMI less than 18.5 in the course of a few months need to be evaluated. Pregnant women, elderly living in care homes, and children are at greater risk [Ref. 72]. Mid-upper arm circumference (MUAC) has been extensively used to classify pediatric malnutrition. The MUAC z score [Ref. Table 3] Tape was designed for construction using a semidurable, flexible, non-stretchable strip of plastic or plasticized paper with prespecified tolerances, MUAC value in millimetres [Ref. 73].

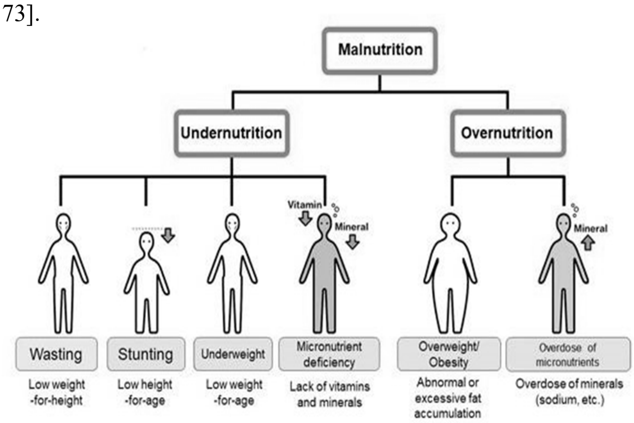

Fig 3: Types of Malnutrition

According to the International Food Policy Research Institute report, "one in three people is malnourished in one form or the other." Malnutrition is manifested in various forms such as wasting (low weight for height), stunted growth (low weight for age), micronutrient deficiencies, obesity, and high sugar or cholesterol content in blood [Ref. 74]. *Mobile Apps and software tools to detect malnourishment Ref.75]: 'WHO Anthro' is a software application developed by WHO to help and assist in monitoring development and growth in children below five years of age, as per the new WHO Child Growth Standards published in 2006. Govt schemes: Free India of Malnutrition – Kuposhan Bharat chhor do*

Z-Score Values	Classification
< -3	Severe malnutrition
>= -3 and < -2	Moderate malnutrition
>= -2 and < -1	Mild malnutrition
>= -1 and (Z < +1)	Normal weight
(+1 <= Z)	Over weight

Fig: 4 : Table 3 - World Health Organization growth reference for children aged 0-5 years

Identification of malnutrition and prediction of BMI from facial images using real-time image processing and machine learning is also possible. Body fat Indicator the BMI (body mass index) is calculated as **BMI = W(kg)/[H(m)]** ^{2}, where W and Hare the weight and height, respectively. Face detection is done with the Multi-task Cascaded Convolutional Neural Networks (MTCNN) on pictures with single/multiple faces. BMI, age, and gender are estimated from a person's face using residual neural networks [Ref. 76].

Section V: Malnourishment – India Concern

Over 33 lakh children in India are malnourished and more than half of them fall in the severely malnourished category [Ref. 77]. The country ranked 94th among 107 and 107th among 121 countries in the Global Hunger Index 2020 and 2022, way behind many other developing countries [Ref.79]. Stunting among children under five years in India dropped from a prevalence rate of 41.6% in 2012 to 31.7% in 2022 — with the numbers dropping from 52 lakh to 36 lakh. This was accompanied by India's share of the global burden of stunting declining from 30% to 25% in the past decade [Ref. 79]. Responding to a question in Rajya Sabha, Women and Child Development Minister Smriti Irani said under Poshan Tracker, the ICT application for monitoring service delivery under Mission Poshan 2.0, out of approximately 5.6 crore children measured in the month of February 2023, the percentage of severely malnourished children is 2.6 per cent. The number comes to be 14,56,000 [Ref.80].

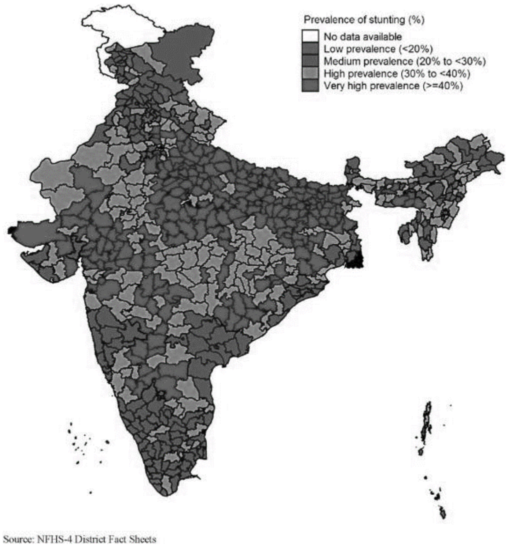

Fig 5: Prevalence of Stunting

Regional pattern of child undernutrition, calorie consumption, non-food expenditure and wealth in India is Serious Concern [Ref. 81]. Children with severe acute malnutrition (SAM) have an elevated risk of mortality and morbidity. Manifold increase in SAM prevalence in several Indian districts is a public health emergency that re quires urgent policy response. Worsening of SAM in districts which were already identified as undernutrition hotspots in India requires prioritized policy action [Ref. 82].

Section VI: Literature Survey

(Existing Nutrition Datasets and Research Papers)

The **IFCDB** Irish food composition database, the **NEVO** Dutch food composition database, the **NUTTAB** Australian food composition database, the **NCCDB** Nutrition Coordinating Center food and nutrient database, and the **CNF** Canadian nutrient file Fast food image dataset **PFID Pittsburgh** [Ref. 61]. The **Food101** database is displayed and includes 101,000 photos that are divided into 101 different food classifications [Ref. 62]. Recently, it was suggested and deployed for the "IFOOD2019" food classification challenge to create a large-scale food image database [Ref. 63], consisting of 158,000 photos from 251 fine-grained food categories [Ref. 64].**Recipe1M+** With more than 1 million cooking instructions and 13 million food photos overall, it is the largest image-recipe library

[Ref. 65]. The "Nutrient Intake Assessment Database" (**NIAD**) [Ref. 58] has RGB-D image pairings of 322 actual meals, 1281 individual food items, and a total of 521 food categories. The **MTCNet** Multi-Task Contextual Network has recently been introduced for image segmentation, and it simultaneously outputs segmentation maps for the plate type and food type 2 from an input color image [Ref. 66, 67]. **GAN** Generative Adversarial Networks based approach has been investigated for data augmentation [Ref. 68].

Section VII: Conclusion and Future Work

We come to the conclusion that there are a lot of cutting-edge devices and wearables being developed and implemented and that the survey on AI-based approaches and technologies for nutrition detection is expanding daily. We will undoubtedly see some of the most effective AI methods for detecting and observing nutrition in the future. There are 'n' apps and software tools that can identify malnourishment, but in order to use them, you need the internet and a smartphone. Such facilities are still inaccessible to residents of isolated rural locations. We suggest the creation of a tool that assesses malnutrition and nutrition levels automatically, without the need for trained personnel, and in both online and offline modes. We suggest fixing the device in remote rural areas so that a local person can run it and then use that local center to get the nutrition status report, malnutrition report, and nutrition food given to the patient while working with government programs concurrently and with the assistance of NGO workers.

Funding: This Research work is not funded by any organization. ***Acknowledgment:*** We thank Mr. Sanmukh for helping us with the English Vocab and Grammar and Mr. Nazmul for Plagiarism checking, Mr. Ajay for helping us understand the LaTeX tool.

Declarations Conflict of interest*:** All authors have no conflict of interest. ***Institutional Review Board Statement*:** Not Applicable ***Data Availability Statement: No New Data were created in this study ***Informed Consent Statement**:* Not Applicable

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