

ARTIFICIAL INTELLIGENCE FOR PERSONALIZED NUTRITION: MOBILE DIETARY ASSESSMENT, CHILDHOOD NUTRITIONAL CLASSIFICATION, AND INDIVIDUALIZED FOOD RECOMMENDATIONS

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Abstract

The convergence of artificial intelligence (AI) and nutritional science is reshaping how dietary intake is measured, how malnutrition is detected, and how personalized dietary guidance is delivered. This review synthesizes recent advances across three interconnected domains: (1) AI-based mobile dietary assessment, (2) AI for childhood nutritional classification, and (3) AI-driven individualized food recommendations. We identified and analyzed over 290 papers retrieved from SciSpace, PubMed, Google Scholar, and ArXiv, focusing on peer-reviewed studies published primarily between 2018 and 2026. Mobile dietary assessment systems employing convolutional neural networks (CNNs) and 3D volumetric reconstruction have achieved accuracy comparable to trained dietitians in controlled settings, though field validations in low- and middle-income countries (LMICs) reveal persistent challenges in portion estimation and cross-cultural generalizability. In childhood nutrition, multimodal fusion of anthropometric imaging and socioeconomic tabular data using ensemble methods (XGBoost, Random Forest) and deep learning has yielded area-under-the-curve (AUC) values up to 0.95 for malnutrition screening, with promising deployment potential on edge devices. Personalized food recommendation systems have evolved from collaborative filtering to large language model (LLM)-powered frameworks, with federated learning architectures enabling privacy-preserving, culturally adaptive meal planning. Cross-cutting challenges include data heterogeneity, model explainability, equity across populations, and the absence of large-scale randomized clinical trials linking AI outputs to health outcomes. We conclude with a roadmap for future research priorities including multimodal dataset development, clinical validation, and responsible AI deployment in nutrition care.

1. INTRODUCTION

Nutrition is a fundamental determinant of human health across the life course, yet accurate dietary assessment, timely detection of malnutrition, and individualized dietary guidance remain significant challenges in both clinical and public health settings [1]. Traditional methods of dietary assessment such as 24-hour dietary recalls (24HRs), food frequency questionnaires (FFQs), and weighed food records are resource-intensive, prone to recall bias, and difficult to scale, particularly in low-resource environments [2]. Similarly, nutritional classification in children has historically depended on manual anthropometric measurements and population-level growth reference standards, processes that are time-consuming and require trained personnel [3]. Personalized dietary counseling, meanwhile, is constrained by the limited availability of registered dietitians and the inability of static guidelines to accommodate individual metabolic, cultural, and behavioral variation [4].

The rapid advancement of artificial intelligence (AI) encompassing machine learning (ML), deep learning (DL), computer vision, natural language processing (NLP), and generative models offers transformative solutions to these challenges [5]. Mobile smartphones equipped with high-resolution cameras and on-device processors now enable automated food recognition and nutrient estimation in real time [6]. AI-powered image classifiers and multimodal fusion models can screen children for malnutrition from photographs and basic demographic data with accuracy approaching that of clinical specialists [7]. Recommendation systems, augmented by large language models (LLMs) and retrieval-augmented generation (RAG), can generate personalized meal plans that respect individual clinical constraints, preferences, and cultural contexts at scale [8].

Despite this rapid progress, the field is fragmented across disciplines computer science, clinical nutrition, public health, and biomedical engineering and critical gaps remain in clinical validation, equity, and real-world deployment. This review provides a comprehensive synthesis of the current state of AI applications across three

interconnected domains of personalized nutrition: (1) mobile dietary assessment, (2) childhood nutritional classification, and (3) individualized food recommendations. We identify common technical approaches, evaluate evidence quality, highlight persistent challenges, and propose a forward-looking research agenda.

The review is organized as follows: Section 2 describes the literature search methodology; Sections 3–5 address each domain in depth; Section 6 discusses cross-cutting themes; and Sections 7–8 present future directions and conclusions.

2. Methods: Literature Scope and Search Strategy

2.1 Search Strategy

A systematic literature search was conducted across five academic databases: SciSpace (semantic and full-text search), PubMed (MEDLINE), Google Scholar, and ArXiv. Three independent searches were performed using the following primary queries:

1. "AI-based mobile dietary assessment" – targeting studies on smartphone-based food recognition, image-assisted dietary logging, and AI-powered nutrient estimation.
2. "AI for childhood nutritional classification" – targeting studies on machine learning and deep learning for pediatric malnutrition screening, stunting prediction, and overnutrition classification.
3. "AI-driven personalized food recommendations" – targeting studies on recommendation systems, LLM-based meal planning, and personalized dietary guidance.

2.2 Inclusion and Exclusion Criteria

Inclusion criteria:

- Peer-reviewed journal articles, conference papers, and preprints published between 2015 and 2026
- Studies employing AI/ML/DL methods for dietary assessment, nutritional classification, or food recommendation
- Studies reporting quantitative performance metrics (accuracy, AUC, precision, recall, F1, MAE, or concordance)

Exclusion criteria:

- Studies focused exclusively on wearable sensors without AI dietary components
- Reviews without original empirical contributions
- Studies not available in English

2.3 Results Summary

Search Domain	Total Retrieved	After Deduplication & Reranking
AI-based mobile dietary assessment	260	110
AI for childhood nutritional classification	250	96
AI-driven personalized food recommendations	240	90
Total	750	296

Papers were ranked by semantic relevance using AI-powered scoring. The most relevant papers from each domain were selected for detailed synthesis in this review.

3. AI for Mobile Dietary Assessment

Automated dietary assessment using mobile devices has emerged as one of the most active areas at the intersection of computer vision and nutritional science. The fundamental pipeline involves three stages: (1) food detection and recognition from images or video, (2) portion size estimation, and (3) nutrient database lookup and computation. Recent systems have integrated all three stages into end-to-end mobile applications, with AI driving each component [6].

3.1 Food Image Recognition Architectures

Convolutional neural networks (CNNs) form the backbone of most food recognition systems. Early approaches used standard architectures (AlexNet, VGG) fine-tuned on food datasets, but modern systems employ deeper and more efficient backbones including ResNet, EfficientNet, and MobileNet variants optimized for on-device inference [9].

Object detection frameworks, particularly Faster R-CNN and its variants, have been applied to multi-dish meal recognition a critical capability for real-world dietary logging where plates contain multiple food items simultaneously. The *Smart Diet Diary* application, trained on 16,000 images across 14 food categories using a pretrained Faster R-CNN, achieved an overall accuracy of approximately 80.1% with calorie computations within 10% of reference values [4]. This study demonstrated the feasibility of real-time food recognition on consumer smartphones, though the limited category coverage (14 classes) constrains applicability to diverse dietary patterns. The *goFOOD™* system extended this approach to fine-grained recognition across 319 food categories using deep neural networks for detection, segmentation, and classification, combined with 3D reconstruction for volume estimation [10]. In validation studies, *goFOOD™* performed comparably to experienced dietitians on a fast-food database and outperformed them on a non-standardized meal database, highlighting the potential for AI to match human expert performance in structured settings [10]. More recently, transformer-based architectures and vision-language models have begun to

influence food recognition. These models leverage large-scale pretraining to achieve stronger generalization across food categories and cuisines, though their computational demands pose challenges for on-device deployment [11].

3.2 Portion Estimation and 3D Reconstruction

Accurate portion estimation is arguably the most technically challenging component of automated dietary assessment, as nutrient content depends critically on serving size. Two-dimensional image-based portion estimation introduces substantial errors because depth information is absent [12].

The goFOOD™ system addressed this by incorporating 3D reconstruction from two images or a short video clip, enabling volumetric estimation of food items [10]. This approach significantly reduces portion estimation errors compared to 2D methods but requires users to capture multiple images, introducing usability trade-offs. Alternative approaches include depth sensors (e.g., LiDAR on modern smartphones), reference object calibration (placing a known-size object near food), and multi-view stereo reconstruction [13].

The *Automatic Image Recognition (AIR)* system evaluated in a randomized controlled trial (RCT) among young adults in real dining conditions found that 86% of dishes were correctly identified and 68% were accurately reported, with faster reporting and higher accuracy compared to voice input ($p < .001$) [14]. This study underscores that while recognition accuracy is improving, portion estimation remains a limiting factor in field

settings.

3.3 Clinical Validation Studies

Several rigorous validation studies have assessed the accuracy of AI-based mobile dietary assessment against reference methods.

Keenoa (Image-Assisted Mobile Diary): A randomized crossover study in 136 adults compared the Keenoa AI-assisted food diary against the ASA24 automated self-administered 24-hour dietary recall [15]. The mean energy difference was -32 kcal (limits of agreement: -789 to 725 kcal), with macronutrient correlations ranging from $r = 0.48$ to 0.73 . Importantly, Keenoa received higher usability scores, suggesting that AI-assisted tools may improve adherence to dietary monitoring protocols even when absolute accuracy is comparable to existing methods [15].

FRANI (Field Validation in Adolescents, Ghana): A validation study of an AI-enhanced image-assisted mobile application in 36 adolescent females in Ghana over three days, compared against weighed food records, found energy equivalence within a 10% margin and concordance correlation coefficients (CCCs) of 0.30 – 0.68 depending on the nutrient [16]. Omission rates of 31% and intrusion rates of 16% relative to weighed records were observed, highlighting the challenges of deployment in LMIC settings with diverse, locally specific food items [16].

Summary of Validation Studies:

System	Population	Reference Method	Energy Agreement	Key Nutrient CCCs
goFOOD™ [10]	Controlled setting	Dietitian assessment	Comparable/superior	Not reported
Keenoa [15]	Adults (n=136)	ASA24	-32 kcal mean diff.	$r = 0.48-0.73$
FRANI [16]	Adolescents, Ghana (n=36)	Weighed records	Within 10%	CCC 0.30-0.68
AIR RCT [14]	Young adults (n=42)	Voice input	68% accurate	N/A
Smart Diet Diary [4]	Controlled	Reference values	Within 10% calorie	N/A

These validation studies reveal a consistent pattern: AI-based mobile dietary assessment achieves reasonable accuracy in controlled settings but faces greater challenges in free-living, diverse, and LMIC contexts.

3.4 Usability, Behavioral Integration, and Real-World Deployment

Beyond accuracy, the practical value of mobile dietary assessment tools depends on user adherence, ease of use, and integration with behavioral change strategies. The *MedDietAgent* application exemplifies this integration by combining computer vision, NLP, ML, and reinforcement learning (RL) to provide dynamic, personalized recommendations nudging users toward Mediterranean diet adherence [17]. The system achieved a mean absolute percentage error (MAPE) of 3.73% for image-based dietary assessment and an average RL subsystem reward of 96%, demonstrating the feasibility of closed-loop dietary coaching [17].

Usability studies consistently show that image-based capture is preferred over text entry and voice input for dietary logging, particularly among younger users, though the burden of capturing multiple images for portion estimation can reduce compliance over time [14][15]. Hybrid

approaches that combine image capture with voice or text correction, and that include human-in-the-loop editing, have been proposed to balance accuracy with usability [14].

Privacy considerations are increasingly important as mobile dietary apps collect sensitive health and behavioral data. On-device inference, differential privacy, and federated learning are emerging technical strategies to address these concerns [17].

4. AI for Childhood Nutritional Classification

Childhood malnutrition—encompassing stunting, wasting, underweight, and overnutrition—remains a global public health crisis, affecting hundreds of millions of children worldwide [18]. Traditional nutritional assessment relies on trained health workers measuring height, weight, and mid-upper arm circumference (MUAC), followed by comparison to WHO growth standards. AI offers the potential to automate, scale, and improve the accuracy of these assessments, particularly in resource-limited settings [7].

4.1 Anthropometric Imaging and Deep Learning

A landmark study by Adewumi et al. demonstrated the potential of multimodal deep learning for childhood malnutrition screening in a Nigerian dataset comprising 2,000 children with 6,000

anthropometric images and tabular socioeconomic and dietary data [7]. The study evaluated three modalities:

- **Image-only model** (ResNet50, MobileNetV3): Accuracy 84.7%
- **Tabular ensemble model** (Random Forest, XGBoost, LightGBM): Accuracy 87.2%, F1 = 0.85
- **Multimodal fusion model**: Accuracy 92.5%, Precision 0.89, Recall 0.91, ROC-AUC 0.95

The multimodal fusion model substantially outperformed single-modality approaches, with an AUC of 0.95 representing near-clinical-grade screening performance [7]. Crucially, the study validated deployment feasibility on edge devices, suggesting potential for community-level screening in LMICs without reliable internet connectivity.

NutriAI, developed by Khan et al., applied deep learning classifiers to 2D multi-pose images for malnutrition detection in low-resource environments, demonstrating baseline feasibility for image-based screening tools that require only a standard smartphone camera [19].

4.2 Ensemble and Tabular Machine Learning Methods

For datasets based on anthropometric measurements and demographic variables (without imaging), ensemble tree methods have consistently outperformed single classifiers. Key findings from the literature include:

- **Random Forest** achieved ROC-AUC up to 0.979 in stunting prediction studies using Indonesian national survey data [20].
- **XGBoost** frequently emerged as the top-performing single model across multiple studies, benefiting from its ability to handle missing data, mixed feature types, and class imbalance common in nutritional survey datasets [21].
- **Gradient Boosting and LightGBM** provided competitive performance with faster training times, relevant for iterative model updates as new survey data becomes available [7].
- **Logistic Regression and SVM** achieved approximately 90% accuracy for overweight classification and ~97% for obesity classification

in a Moroccan national survey dataset, demonstrating that simpler models can perform well when features are well-engineered [22].

Yamasari et al. conducted a comparative analysis of ML algorithms for toddler nutritional status classification using anthropometric data, confirming that ensemble methods generally outperform single decision trees and logistic regression, and that feature selection preprocessing substantially improves performance on small clinical datasets [23].

4.3 Stunting Prediction and SDG Monitoring

Stunting (low height-for-age) is a key indicator of chronic malnutrition and a target of the UN Sustainable Development Goals (SDGs). ML-based stunting prediction models have been developed to support early intervention and population surveillance.

Hasmin et al. applied classification-based ML approaches to predict stunting risk for prevention intervention planning in children, finding that decision trees and random forests achieved accuracies of approximately 88.3–88.6% on Indonesian datasets, with potential for integration into national health information systems [21]. Fujiati et al. further developed a stunting prediction model explicitly designed to support SDG achievement in Indonesia, demonstrating that ML-based tools can be aligned with national policy objectives [24].

A study using Indian Demographic and Health Survey (DHS) data applied multiple ML techniques to investigate childhood nutritional status at the population level, finding that ensemble methods provided the best balance of sensitivity and specificity for identifying at-risk children in large national datasets [25].

These studies collectively suggest that ML-based stunting prediction models, trained on routinely collected survey and clinical data, can serve as scalable decision-support tools for public health programs targeting early childhood nutrition.

4.4 Overnutrition and Obesity Classification

While much of the AI nutrition literature focuses on undernutrition, the growing global burden of childhood overweight and obesity has motivated

parallel work on AI-based overnutrition classification. Berrouyne et al. applied logistic regression, SVM, gradient boosting, and random forest to Moroccan national survey data, achieving approximately 90% accuracy for overweight and ~97% for obesity classification [22]. The study highlighted the utility of AI tools for targeting prevention programs in settings experiencing the double burden of malnutrition.

A hybrid AI methodology for advancing nutritional status classification, combining multiple algorithmic approaches, was evaluated by Alotaibi et al., who reported improved performance over single-algorithm approaches for classifying both undernutrition and overnutrition in pediatric populations [26].

Summary of Key Models and Performance in Childhood Nutritional Classification:

Study	Dataset	Models	Best Metric	Application
Adewumi et al. [7]	Nigeria (n=2,000)	ResNet50 + XGBoost (fused)	AUC = 0.95	Malnutrition screening
NutriAI [19]	Multi-pose images	CNN classifiers	Feasibility demonstrated	Community screening
Hasmin et al. [21]	Indonesia survey	DT, RF	Accuracy ~88.3-88.6%	Stunting prediction
Fujiati et al. [24]	Indonesia national	ML ensemble	SDG-aligned accuracy	Policy support
Berrouyne et al. [22]	Morocco survey	LR, SVM, GB, RF	~90-97% accuracy	Overnutrition prevention
Yamasari et al. [23]	Toddler anthropometrics	Multiple ML	Ensemble best	Clinical classification
DHS India [25]	Indian DHS	Multiple ML	Ensemble best	Population surveillance

5. AI-Driven Personalized Food Recommendations

Personalized food recommendation systems represent the most complex and rapidly evolving domain within AI-driven nutrition. These systems must integrate individual dietary preferences, nutritional requirements, clinical constraints (e.g., diabetes, allergies), cultural food patterns, ingredient availability, and sustainability considerations into coherent, actionable meal plans [27].

5.1 Recommender System Architectures

Classical recommendation system architectures collaborative filtering (CF), content-based filtering (CBF), and hybrid approaches form the foundation of most food recommendation systems. CF leverages patterns of user-item interactions (e.g., ratings, consumption history) to identify similar users and recommend items they have enjoyed, while CBF matches item attributes (nutritional profile, ingredients, cuisine type) to user preferences [28].

The *Smart Meal Planner (SMP)* represents a state-of-the-art hybrid system trained on 85,000 annotated recipes across 18 cuisines within a federated

learning framework [29]. Incorporating pantry context (available ingredients) alongside personalized preferences, SMP achieved:

- Precision@5 = 0.86
- Recall@5 = 0.82
- nDCG@5 = 0.84
- Nutritional MAE = 14.2
- Pantry utilization rate = 90.2%

These metrics place SMP among the highest-performing food recommendation systems in the literature, with the federated learning architecture additionally ensuring privacy preservation across distributed user populations [29].

Nezis et al. proposed a fully personalized food recommendation tool integrating user health profiles, dietary restrictions, and real-time contextual factors, demonstrating the feasibility of multi-constraint optimization in recommendation pipelines [30].

5.2 Generative Models and Large Language Models

The emergence of large language models (LLMs) and generative AI has opened new possibilities for personalized nutrition planning. Unlike traditional recommender systems that select from a predefined item catalog, LLMs can generate novel, contextually appropriate meal plans in natural language, explain nutritional rationale, and adapt to complex multi-constraint scenarios [31].

NutriGen LLM Framework: Ramesh et al. evaluated two LLMs Llama 3.1 8B and GPT-3.5 Turbo—for generating personalized meal plans aligned to individual caloric targets using prompt engineering and a curated nutrition database [32]. Llama 3.1 8B achieved a percentage error of only 1.55% relative to caloric targets, outperforming GPT-3.5 Turbo (3.68% error), demonstrating that smaller, locally deployable open-source models can achieve competitive nutritional accuracy [32].

Deep Generative Model + ChatGPT: Papastratis et al. combined a Variational Autoencoder (VAE) for structured meal plan generation with ChatGPT for recipe variety and natural language elaboration, evaluated on 3,000 virtual and 1,000 real user profiles [33]. The system demonstrated

high accuracy in generating nutritionally aligned weekly plans across large-scale experiments, with ChatGPT providing the natural language interface that users found accessible and engaging [33].

AI-Driven Dietary Planning Framework: An IEEE-published framework for AI-driven personalized dietary recommendation and meal planning integrated multiple ML components nutritional analysis, preference modeling, and constraint satisfaction into a unified pipeline, demonstrating broad applicability across dietary scenarios [34].

Retrieval-Augmented Generation (RAG) approaches, which ground LLM outputs in curated nutritional databases and clinical guidelines, have been proposed as a mechanism to improve the nutritional accuracy and safety of LLM-generated meal plans, addressing concerns about hallucination and guideline misalignment [35].

5.3 Clinical Applications and Disease-Specific Recommendations

Diabetes Management: Sequence models have shown particular promise for diabetic dietary management. An LSTM-based recommender achieved F1 = 0.96 and precision of 97% in classifying and recommending meals that meet diabetic carbohydrate thresholds, with prospects for integration with continuous glucose monitoring (CGM) data for closed-loop dietary management [36]. Gavai developed an AI-based system generating personalized smoothie recipes for managing obesity and Type 2 diabetes, demonstrating the application of generative AI to specific clinical dietary needs [37].

Allergy Management: Text extraction and ML classification pipelines have been applied to menu recommendation for users with food allergies, enabling automated identification of safe menu items from unstructured restaurant menus [38]. Such systems address a critical safety need for the estimated 220–520 million people globally affected by food allergies.

Mediterranean Diet Adherence: The MedDietAgent system, discussed in Section 3.4,

demonstrated that RL-based recommendation components can nudge users toward evidence-based dietary patterns (Mediterranean diet) with high reward rates, bridging dietary assessment and behavioral intervention [17].

Personalized Smoothie and Recipe Generation: Beyond structured meal planning, AI systems have been applied to generate specific recipe recommendations tailored to individual metabolic profiles, demonstrating the granularity of personalization achievable with modern generative approaches [37].

5.4 Privacy-Preserving and Federated Approaches

A growing concern in AI-driven nutrition is the privacy implications of collecting sensitive dietary, health, and behavioral data. Federated learning (FL) addresses this by training models across distributed devices without centralizing raw user data, making it particularly suitable for health applications [29].

The Smart Meal Planner's federated architecture demonstrated that privacy-preserving personalization need not sacrifice recommendation quality—achieving Precision@5 = 0.86 comparable to centralized systems while enabling pantry-aware, culturally adaptive recommendations [29]. This approach also supports food waste reduction by prioritizing available ingredients, aligning nutritional personalization with sustainability objectives.

On-device inference using lightweight model architectures (e.g., MobileNet, TinyBERT) further supports privacy by eliminating the need to transmit sensitive dietary data to cloud servers, a consideration increasingly mandated by data protection regulations [7][17].

6. Cross-Cutting Themes and Discussion

6.1 Data Quality, Diversity, and Generalizability

A pervasive challenge across all three domains is the quality, diversity, and representativeness of training data. Food recognition models trained primarily on Western food datasets exhibit reduced accuracy for Asian, African, or Latin

American cuisines [10][16]. Childhood nutritional classification models trained on single-country datasets may not generalize to other populations with different genetic, environmental, and socioeconomic contexts [7][23]. Food recommendation systems trained on recipe databases from specific culinary traditions may fail to accommodate users from different cultural backgrounds [29][32].

Addressing these limitations requires the development of large-scale, culturally diverse, and carefully annotated datasets—a resource-intensive undertaking that necessitates international collaboration and community engagement. Initiatives such as the Food-101 dataset, the ECOC food dataset, and WHO-aligned nutritional databases represent important steps, but significant gaps remain, particularly for LMIC food systems [10][16].

6.2 Model Explainability and Clinical Trust

The adoption of AI tools in clinical nutrition practice depends critically on clinician and patient trust, which in turn requires model explainability. Black-box deep learning models, while often highly accurate, provide limited insight into the features driving their predictions—a significant barrier to clinical adoption [23][26].

Explainable AI (XAI) methods, including SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and attention visualization for image models, are increasingly applied to nutritional AI systems to provide feature importance insights and support clinical interpretation [7][21]. Ensemble tree methods (XGBoost, Random Forest) offer inherently greater interpretability than deep neural networks, which may explain their continued dominance in clinical nutritional classification tasks where regulatory and clinical acceptance is paramount.

6.3 Equity, Fairness, and Low-Resource Deployment

AI nutritional tools have the potential to exacerbate health inequities if developed primarily for high-income, technologically advanced populations. The FRANI validation in

Ghana [16] and the Nigerian malnutrition screening study [7] represent important efforts to develop and validate AI tools specifically for LMIC settings, but such studies remain underrepresented in the literature.

Edge deployment running AI models directly on smartphones or low-power devices without cloud connectivity is essential for LMIC applicability where internet infrastructure is unreliable. Studies by Adewumi et al. [7] and NutriAI [19] have demonstrated the feasibility of edge-deployed nutritional AI, but systematic benchmarking of model accuracy, inference speed, and energy consumption on low-cost devices remains limited.

6.4 Integration with Wearables and Continuous Monitoring

The integration of mobile dietary assessment with wearable physiological monitoring—including continuous glucose monitors (CGM), accelerometers, heart rate monitors, and smartwatches—offers the prospect of truly closed-loop personalized nutrition systems [36]. Such integration would enable real-time dietary adjustments based on postprandial glucose responses, physical activity levels, and metabolic state, moving beyond static meal planning to dynamic, responsive nutrition management.

Early work in this space has demonstrated the feasibility of CGM-informed dietary recommendations for diabetic patients [36], and several commercial platforms are beginning to integrate dietary logging with wearable data streams. However, the clinical validation of closed-loop AI nutrition systems through rigorous RCTs remains a critical unmet need.

6.5 Regulatory and Ethical Considerations

As AI nutritional tools increasingly influence clinical decision-making, regulatory oversight becomes essential. In many jurisdictions, AI systems that provide dietary advice or nutritional diagnoses may be classified as medical devices, subject to regulatory approval processes (e.g., FDA 510(k), EU MDR) [35]. The ethical dimensions of AI-driven nutrition include informed consent for data collection, algorithmic bias and fairness, liability for incorrect recommendations, and the

potential for AI tools to substitute for rather than augment qualified nutrition professionals [31].

7. Future Directions

Based on the synthesis of the current literature, we identify the following priority areas for future research:

7.1 Multimodal Dataset Development

Development of large-scale, culturally diverse datasets combining dietary images, anthropometric measurements, clinical biomarkers, socioeconomic variables, and longitudinal dietary records across multiple geographic regions. Such datasets would support more robust and generalizable AI models across all three domains reviewed here.

7.2 Rigorous Clinical Validation

Randomized controlled trials and prospective cohort studies linking AI dietary assessment outputs, nutritional classification decisions, and food recommendation adherence to clinically meaningful outcomes (e.g., glycemic control, growth trajectories, body composition, diet quality scores). The current literature is dominated by technical performance metrics with insufficient evidence of clinical impact.

7.3 Portion Estimation Innovation

Development of markerless, depth-aware portion estimation methods using LiDAR sensors, neural radiance fields (NeRF), or multi-view stereo reconstruction that are accurate, usable, and deployable on consumer smartphones without specialized hardware.

7.4 LLM Safety and Alignment for Nutrition

Development of nutrition-specific alignment methods, RAG pipelines grounded in authoritative dietary guidelines (e.g., Dietary Reference Intakes, EFSA guidelines), and evaluation frameworks for assessing the nutritional accuracy, safety, and cultural appropriateness of LLM-generated dietary advice.

7.5 Federated and Privacy-Preserving Architectures

Scaling of federated learning approaches for food recommendation and dietary monitoring, with formal privacy guarantees (differential privacy), to enable large-scale personalization without centralizing sensitive health data.

7.6 Closed-Loop Integration with Wearables

Development and clinical validation of closed-loop AI nutrition systems integrating mobile dietary assessment, wearable physiological monitoring (CGM, accelerometry), and personalized recommendation engines for metabolic disease management.

7.7 Equity-Centered AI Development

Systematic inclusion of LMIC populations in AI training datasets, validation studies, and deployment contexts, with explicit evaluation of model fairness across demographic subgroups (age, sex, ethnicity, socioeconomic status).

7.8 Explainability and Regulatory Pathways

Development of standardized explainability frameworks for nutritional AI tools, and engagement with regulatory bodies to establish clear pathways for clinical deployment of AI dietary assessment and recommendation systems.

8. Conclusion

This review has synthesized the rapidly evolving landscape of AI applications in personalized nutrition across three domains: mobile dietary assessment, childhood nutritional classification, and individualized food recommendations. The evidence demonstrates substantial technical progress: CNN-based food recognition systems now approach dietitian-level accuracy in controlled settings; multimodal fusion models achieve AUC values up to 0.95 for childhood malnutrition screening; and LLM-powered meal planning systems can generate nutritionally accurate, personalized meal plans with caloric errors below 2%.

However, the translation of these technical achievements into clinical practice and public health impact remains incomplete. Portion

estimation errors, cross-cultural generalizability gaps, the absence of large-scale clinical trials, and challenges in model explainability and equitable deployment represent the primary barriers to broader adoption. The field would benefit from greater emphasis on rigorous validation in diverse populations, particularly in LMICs where the burden of malnutrition is greatest.

Looking forward, the convergence of mobile AI, wearable sensors, federated learning, and large language models creates an unprecedented opportunity to deliver truly personalized, continuously adaptive nutritional guidance at global scale. Realizing this potential will require sustained interdisciplinary collaboration between AI researchers, clinical nutritionists, public health practitioners, ethicists, and regulatory bodies—and a commitment to ensuring that the benefits of AI-driven nutrition reach those who need them most.

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