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A SYSTEMATIC LITERATURE REVIEW OF LIGHTWEIGHT IOT AND ML-BASED APPROACHES FOR MONITORING DIETARY COMPLIANCE AND USER ENGAGEMENT

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ABSTRACT

In mitigating disllege of Educationeases related to Nutrition, dietary compliance remains vital, however monitoring remains difficult in low-resource settings. Potential solutions that have surfaced include Internet of Things (IoT) and lightweight Machine learning (ML) technologies, but evidence remains fragmented. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines and studies from online repositories such as Google Scholar, IEEE, PubMed, Xplore, and Scopus were used in conducting this systematic literature review (SLR), and thereafter supplemented with snowballing. Research papers published between the year 2015 to 2025 were the focus of this review which examined lightweight Machine learning models such as MobileNet and TinyML, IoT-based dietary monitoring solutions, and techniques for user engagement. Among the identified records numbering 358, twenty-five (25) studies were included for qualitative synthesis. It was discovered that there was strong accuracy in food recognition by the lightweight ML models while still achieving computational efficiency. Furthermore, even though their use in African contexts were limited, positive indices for efficient diet monitoring were observed in some IoT-based systems using mobile and wearable devices. End-user compliance was enhanced via some techniques of engagement such as personalized feedback, cultural adaptation, and gamification. This review highlights opportunities for affordable, localized, and culturally relevant IoT–ML solutions in regions such as North-Central Nigeria.

Keywords: Dietary Compliance, Internet of Things (IoT), Lightweight, Low-Resource Settings, Machine Learning (ML)

INTRODUCTION

To effectively mitigate the problem of nutrition-related diseases, dietary compliance monitoring is a key measure to be implemented, yet accomplishing this remains a challenge in most resource-constrained areas and settings such as North-Central Nigeria. The integration of Internet of Things (IoT) and Machine Learning (ML) for providing personalized health solutions such as diet monitoring has gained significant attention due to the rise in the global occurrence of diet-related health issues especially in developing regions like North-Central Nigeria (Tagne et al., 2024), which is characterized by diverse dietary habits such as starchy, imbalanced, low-protein diets, and micro-nutrient deficiency. North-Central Nigeria has several resource-poor areas where access to real-time digital health solutions are limited, presenting a unique scenario for this kind of personalized health solution. Efficient computation on low-powered IoT components, could be made possible via the use of ML model pruning measures and lightweight ML models such as MobileNet and TinyML, making these devices deployable and optimally efficient in resource-constrained environments (Sosa-Holwerda et al., 2024).

Furthermore, in the healthcare sector, systems that use mobile applications and IoT wearable sensors such as miniature cameras, motion, and flex sensors have been deployed for various health services including nutrition monitoring. Considering Africa as a case study, there are insufficient researches made concerning diet monitoring despite the rise and advancements in the use of machine learning and IoT for healthcare and Nutrition monitoring. There is also not enough indications and results to show how engagement techniques such as personalized feedback and gamification, could influence dietary compliance (Sjoblom et al., 2025). To solidify the existing knowledge about lightweight IoT and Machine learning solutions for diet monitoring and user engagement, this systematic literature review would therefore identify current gaps and existing opportunities for application of these solutions in resource-poor areas and regions using North-Central Nigeria as a case study.

MATERIALS AND METHODS

To ensure reproducibility and transparency, this systematic review was structured using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines. The four steps associated with the PRISMA approach are identification, screening, eligibility, and inclusion. These PRISMA guidelines highlights the methods used such as online repositories, Keywords, the Inclusion and Exclusion criteria for selection of research papers. To begin the review, some research questions were put forward as a guide to the investigation, relevant studies were retrieved from major electronic databases and online repositories which include: ResearchGate, SpringerLink, ScienceDirect, PubMed, Google Scholar, IEEE Xplore etc. Search keywords used include: "diet monitoring", "ML", "lightweight, "IoT", "dietary compliance", "user engagement", "Nigeria", "North-Central", "wearable IoT". These keywords were combined using boolean operators to form a number of search terms used in this review. Filters between 2015–2025 (English language) and Boolean operators were applied to the search.

The criteria for Inclusion employed for picking the papers used in the review included; the time-frame for the studies which is between 2015 to 2025, the focus of the study which is ML-based IoT systems for dietary monitoring, lightweight IoT systems, deployment in low-resource settings as found in developing countries and regions like north-central Nigeria, and personalized diet monitoring which includes wearable IoT biosensor devices. Only studies that met the inclusion criteria stated above were included in the final review, this means that only studies from peer-reviewed/scholarly papers such as conference papers and journal articles which focused on food intake events and behaviours, lightweight wearable biosensors for intake monitoring, Machine learning/deep learning models for data processing, human participation in research experiments, and measurable results/outcomes such as food detection, intake vs no-intake, biting, chewing, swallowing, image classification, accuracy, precision, F1 score etc., were included in the final review. Some criteria for Exclusion used to discard some research papers already collected included; reports that had no reviews, studies that had no quantitative evaluation of system performances, studies made in other languages aside English language, studies that had no indication of Internet of Things (IoT) and Machine learning (ML). Other criteria used for exclusion were studies that had general health monitoring or diagnosis used as focus of study instead of dietary compliance, studies that were non-human/animal based, studies that used synthetic data, papers published before 2015 (except those that had foundational relevance), papers that did not reflect recent advancements in machine learning, IoT/diet monitoring, papers/articles of which their results were not clearly stated, Abstracts, and editorials. The studies that fell under these criteria were removed from this review. This review also employed some measures for the extraction of data and study selection. Firstly, duplicates were identified and removed, which was followed by the use of the stated inclusion criteria to screen all the full texts and abstracts gotten. The studies for qualitative synthesis numbered 25 out of all the 358 records identified. The data extracted include: user engagement strategies, lightweight machine learning (ML)/deep learning model types and performance, Adoption challenges to the use of the diet-monitoring systems, the lightweight IoT hardware/software used, regions/settings wherein the diet monitoring systems were deployed. At the end of the study, 25 studies were identified as meeting the Inclusion criteria. A summary of the identification and selection of the articles involved in the systematic literature review is represented in the PRISMA 2020 flow diagram shown in Figure 1.1 below.

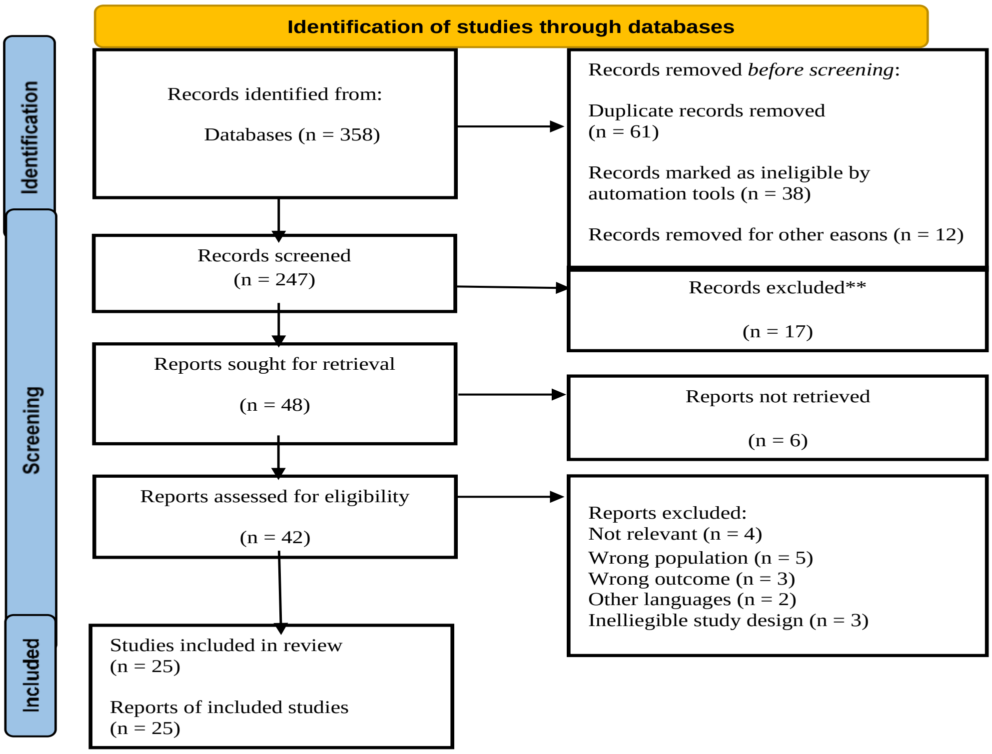

Figure 1: Prisma 2020 Flow Diagram (Page et al., 2020)

The PRISMA 2020 flow diagram was vital to this systematic review, by providing reproducibility, eliminating bias, and ensuring transparency, in the description of how various research reports and papers were identified, screened, subjected to eligibility assessment, and finally included in the review following a standardized process. To achieve quality assessment the included studies were appraised for relevance to low-resource settings, lightweight IoT components/ML models, dietary monitoring, clarity and rigor in methodology. The Prisma 2020 diagram shows the total number of reports that were retrieved from multiple repositories and online databases, the number of duplicated reports removed before the screening stage, and the number of reports excluded during the screening of titles and abstracts. The PRISMA diagram also gives the number of complete articles assessed for eligibility, the number of shortlisted studies that satisfied the Inclusion criteria as well as criteria for exclusion of removed studies.

Snowballing

Essentially, backward snowballing was used to link related references contained in the papers that were retrieved from the database that was presented earlier. The references were then filtered based on the inclusion and exclusion criteria. Snowballing was used to effectively capture additional studies which could not be identified through conventional method of "keyword search". The snowballing step include Backward snowballing: screening references of included papers, and Forward snowballing: identifying newer studies citing those works.

Snowballing Technique used in the Systematic Review

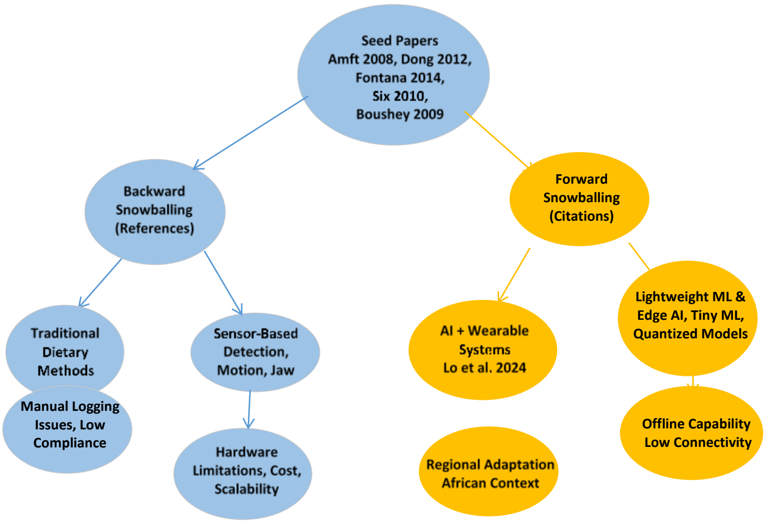

Figure 2: Snowballing Technique (Claes, 2014)

Research Questions (RQs)

The following research questions used in this systematic review were conceived due to the identified shortcomings, gaps, and limitations in existing literature concerning delivering personalized health solutions particularly diet monitoring, to people residing in resource poor regions/areas such as North-central Nigeria using lightweight machine learning (ML)- based IoT systems and applications.

RQ1: What lightweight and optimal ML and IoT frameworks have been used for monitoring dietary intake?

RQ2: Which techniques can be employed to enhance user engagement in diet monitoring systems?

RQ3: In what ways can lightweight ML algorithms be implemented on resource-constrained devices?

RQ4: What measures have been taken to tailor IoT-based systems for health monitoring in resource-poor areas?

RQ5: How can lightweight IoT technology be adapted to suit the regional peculiarities as found in North-Central Nigeria?

Proffering Answers to Research Questions

These research questions are important because they attempt to resolve existing problems in diet monitoring solutions and personalized user engagement as found mostly in resource-poor areas and settings. These questions outline the contribution of this review, it's scope and purpose in relation to machine learning (ML)-based diet monitoring and enhanced user engagement. The research questions in this systematic review provides structure to a multi-dimensional research area that cuts across fields such as Nutrition, Computer science, Health education, Food science, Engineering etc. These questions address some existing problems such as heavy-weight ML-based solutions, traditional methods of diet monitoring which are unreliable, adaptability to various IoT systems in culturally diverse regions etc., after which future directions are suggested. Comparisons made in relation to different IoT configurations, ML architectures used, and performance metrics are all evidence-based.

Question 1: What Lightweight Optimal ML and IoT Frameworks have been used for Monitoring Dietary Intake?

i. Rather than using deep learning models, simple lightweight classifiers such as Standard vector machine (SVM) and Random Forest (RF) combined with features gotten from sensor signals were used for classification of physical gestures (Juan Cui et al., 2018). Lightweight classifiers were also combined with sensor signals of the wearable temporal muscle sensor in Amft & Troster chewing detection system for detecting chewing movements in the jaw (Amft & Troster., 2008).

ii. Based on a number of studies conducted, machine learning (ML) models such as SqueezeNet, MobileNetV2, pruned CNNs, and TinyML, emerged as efficient lightweight models which are deployable on edge devices and micro-controllers (Doulah et al., 2022, Mbonu et al., 2025; Banbury et al., 2021).

iii. Model compression and Quantization were used by IoT systems like FitByte, RasberryPi, and DeepLabV3 to optimize machine learning inference by reducing latency and power consumption (Mbonu et al., 2025).

iv. Conventional machine learning (ML) models such as Multi-layer Perception (MLP), Random Forest and Logistic Regression have been used by several personalized diet monitoring systems to monitor the heart rate, temperature, body mass index (BMI), and peripheral oxygen saturation (Sp02) level of their patients by analyzing sensor data gotten from the wearable IoT components. Examples of such IoT systems; PISloT (Personalized Intelligent System for IoT-based Obesity Treatment), Step trackers, and AI nutrition assistants (Machorro-Cano et al., 2019).

v. Multi-modal machine learning (ML) frameworks integrated with wearable biosensors that draw data concerning body motion, glucose level, heart rate etc., are used for nutritional analysis specifically macro-nutrients. Examples of such systems using these frameworks: MealMeter, DietGlance, Automatic Ingestion Monitor (AIM-2) and Annapurna smartwatch device (Doulah et al., 2021; Arefeen et al., 2025; Jiang et al., 2025).

vi. Some IoT diet monitoring systems like the EatRadar, use lightweight 3D temporal CNN to detect food intake. EatRadar is incorporated with FMCW (Frequency Modulated Continuous Wave) radar sensors which detect body motions that suggest food intake (Wang et al., 2022).

vii. ML lightweight detection models such as the YOLOv8 (You Only Look Once), and NutriNet-Lite, use attention modules incorporated with object detectors for detecting food intake in real time. They also use depth-wise separable convolutions for food recognition and calorie estimation. For meals that have multiple food items, Channel Pruning is further used to eliminate filters which are not necessary, so as to achieve a high Mean Average Precision (Jocher et al., 2023; Megzec & Korousic 2017).

viii. Lightweight CNN models such as MobileNet version 2 and 3, use Neural networks which enable them run efficiently on mobile devices with less computational resources and minimal power consumption (Sandler et al., 2018).

ix. Machine learning (ML) libraries such as MLpack are useful in the development of lightweight models that run directly on IoT systems (and not on cloud platforms), consuming less computational resources. Other examples include TensorFlowLite (TSLite), Micro-Tensor, and PyTorch Edge for mobile and edge devices (Edward & Storkey, 2013; Lo Presti, 2023; Paszke et al., 2019).

Question 2: What Techniques have been Employed to Enhance user Engagement in Diet Monitoring Systems?

i. A number of commercial diet monitoring and nutrition systems were tailored to focus on features (such as weight, height, gender, calorie estimates, activity rates, etc.) which are used to create personalization and animations for end-users. Functions such as setting of goals, reminders etc., can also be performed using these features in order for behavioral persuasions that would lead to a healthier lifestyle to be made possible. But most diet monitoring systems still relied heavily on manual food logging (Khalil et al., 2023).

ii. Several Systems make use of Passive sensing and automated detection of food intake such as the AIM-2, which has some advantages and disadvantages. These systems were found to reduce privacy concerns and requires less effort from end-users but may be less efficient outside the lab, in real-life diet monitoring scenarios. Therefore, there is need for more research to be done especially for outside lab settings. Procedures such as data collection and algorithmic challenges would be effective for real-life use of the diet monitoring systems (Hossain et al., 2025; Pedram et al., 2023). Furthermore, the lasting use of diet monitoring systems with wearable biosensors is still challenging as most of these systems are unable to deliver optimal performance due to problems encountered by the end-users such as adaptability, comfort, privacy, power consumption etc (Pedram et al., 2023).

iii. Approaches such as real-time feedback, social sharing, gamification, and goal setting were used user for enhancing user engagement (Arefeen et al., 2025)

iv. Continuous user compliance were enhanced via approaches such as habit-formation algorithms, and reinforcement learning for behavioral modeling. These increased the chances for long-term user compliance (Sjoblom et al., 2025).

v. The acceptability of the systems in rural areas and settings were enhanced with the use of culture-oriented user interfaces (UI) and local language support (Hezarjaribi et al., 2018).

vi. Some diet monitoring Systems such as goFOOD 2.0 were found to have a combination of the use of passive sensors with AI-enabled Personalized feedback, dashboard visuals, behaviour persuasions and regular guidance (Ge et al., 2025; Zhang, R., et al., 2024). These systems were observed to reduce human efforts and provide real-time feedback on diet intake per time, thereby promoting adequate and effective dietary monitoring

Table 1: Summary of User Engagement Techniques of Some IoT Systems

System	Passive Detection	Personalization	Gamification	Behavioral Nudges	Real-Time Bio Feedback	Regional Food Intelligence	Social/ Community	Conversational AI
MyFitnessPal	✗ (Manual logging dominant)	☑ Calorie/macro goals	☑ Streaks & milestones	☑ Reminders	✗	✗	☑ Community forums	✗
HealthifyMe	✗ (Mostly manual)	☑ AI-based recommendations	Light progress badges	☑ Smart reminders	✗	☑ Regional food DB	Limited	☑ AI assistant (“Ria”)
NutriSense (CGM)	☑ Automatic glucose monitoring	☑ Personalized metabolic insights	✗	☑ Based on glucose spikes	☑ Continuous glucose	✗	Coach interaction (Partial)	✗
Fitbit (with food sync)	Activity passive, food manual	☑ Adaptive calorie goals	☑ Badges & challenges	☑ Smart notifications	HR & activity response (partial)	✗	☑ Leaderboards	✗
Apple Health + Food Apps	Activity passive	☑ Goal tracking	Limited	☑ Reminders	Heart/ activity (Partial)	✗	Limited sharing	✗
iEat (Research)	☑ Bio-impedance sensing	✗	✗	✗	✗	✗	✗	✗
NeckSense (Research)	☑ Chewing detection	✗	✗	Partial / secondary Intervention prompts	✗	✗	✗	✗
EgoDiet (Camera-based)	☑ Passive food capture	Partial ML recognition	✗	✗	✗	✗	✗	✗

Question 3: In What ways Were Lightweight ML Algorithms Implemented on Resource-constrained Devices?

i. Instead of using deep learning models such as Convolutional neural network (CNN) and Recurrent neural network (RNN), several researchers implemented less weighty ML models such as Random Forest, Support vector machine (SVM), Decision tree, K-nearest neighbour (KNN) etc., into their diet monitoring systems to process sensoral data gotten from wearable biosensor components of the IoT system such as Accelerometer, flex sensor, strain sensor, gyroscope etc (Tang et al., 2023; Hossain et al., 2025).

ii. Several of these diet monitoring systems such as NeckSense, AIM-2, iEat etc., implemented some frequency features; like Power distribution, Fast Fourier Transform (FFT), dominant frequency, spectral entropy etc., and time features such as Mean, Peak detection, Standard deviation, etc., in order for small models like Random forest and SVM to work and lessen memory usage (Zhang et al., 2020; Nweke et al., 2018).

iii. Some diet monitoring systems implemented ML models which were trained using image datasets such as UEC-Food (Japan), IndianFood, ChineseFoodNet etc., smaller ML models were trained with localized food datasets specific to a given region instead of large datasets that span across several areas and regions. Therefore, only a region-specific database, lower memory space, and lesser computational power were needed by the IoT systems for diet monitoring (Tanaka et al., 2015).

iv. Some techniques such as offline-capable mobile apps, region-centric food databases, and SMS-driven fallback systems which were promising were employed to achieve localization in the Nigerian contexts (NLM, 2023).

v. The adoption of some of these IoT systems such as mFR (Mobile food record), EgoDiet, eButton, and BiteCounter were unrealized in some regions because of limitations such as low digital literacy, lack of power supply, limited datasets, and opposing cultural preferences (NLM, 2023).

vi. Several diet monitoring systems such as FallSense, AIM-2, Deep X etc., used condition-triggered observance as a principle to determine when the systems would run their ML models. When food intake gestures such as head/jaw movements, chewing, biting etc., are detected, the models begin the capture and analysis of sensor data gotten from the wearable sensors (Doulah et al., 2022; Bhattacharya & Lane, 2016).

vii. Physical activity of end-users were detected in real-time using a Tri-axial accelerometer which is embedded in a wearable micro-controller that implements a lightweight version of Support Vector Machine (SVM). The lightweight SVM uses a hierarchical recognizer and enhanced signal features for classification tasks, consuming lesser power (Khan et al., 2010).

viii. Bio-impedance sensing that uses a Lightweight neural network classifier was implemented in "iEat", a diet monitoring system worn on the wrist, that analyzes sensor signals detected from bio-impedance activities via food intake gestures such as cutting, biting, ingestion etc (Liu et al., 2024).

ix. Food intake activities such as chewing and swallowing were detected using a diet monitoring system called AIM-EMG, a variant of the Automatic Ingestion Monitor (AIM) that uses Electromyography (EMG)-enabled wearable sensors incorporated with SVM for classification tasks. These EMG sensors monitor the eating pattern of the end-user and produce physiological signals from which the features are extracted. This wearable system gives haptic feedback to the user by producing physical stimuli through sensations like Force, vibration, pressure etc., rather than optical feedback on screens or sound feedback (Sazonov & Fontana, 2013).

Question 4: What Measures have been Taken to Tailor IoT-based Systems for Diet Monitoring in Resource-Poor Areas?

1. In India, a low-cost IoT-based diet monitoring system called SmartForks was used in rural areas to monitor food intake rate and patterns using sensor data gotten from mouth gestures like biting, chewing, swallowing etc., using a gyroscope and an accelerometer. The IoT components of the system were cost-effective and used less power to transmit sensor data that cover details of body features such as height, Body mass index (BMI), weight, composition etc. These data were received by cloud applications that analyze the sensor data gotten through wireless connectivity from the low-powered IoT components (Khan et al., 2014).
2. The prospects for effective usability, reliability, and trust in some IoT diet monitoring systems were enhanced via the engagement of the communities and collaborations with their health workers (NLM, 2023).
3. A wearable component called Pizzoelectric band which is embedded with a sensor is used to detect food intake and generate sensor data regarding Jaw motion activities such as biting, chewing, swallowing etc. Used in clinical trials, the system performed classification using a lightweight model and sends data through rural base stations. It had no wireless network connectivity (Sazonov et al., 2010)
4. In Ghana, an IoT system called EgoDiet was used for detection of food intake using a wearable component which is a camera that captured episodes of food ingestion by end-user under real-life scenarios. The system did not require self reporting but uploaded sensor data to network platforms for nutritional analysis, it is cost-effective for resource poor areas compared to the use of smart glasses (Lo et al., 2024).
5. An IoT system that requires minimal computing resources was used to passively monitor food intake in rural and urban areas of Uganda and Kenya. The system consist of a self-focused camera that captured food intake events and thereafter the system performs food recognition (Lo et al., 2021)
6. IoT systems used for dietary monitoring incorporate sensor networks, mobile gateways, and embedded systems (Arefeen et al., 2025).
7. A Research work that led to the development of MFED (Monitoring Family Eating Dynamics) system by Mondol et al., (2020) implemented wearable food-intake trackers with Bluetooth-based data transmission.
8. The reliance on continuous communication via cloud is curtailed with the aid of innovative computing models (such as Edge computing, Fog computing, TinyML, Model compression, and Federated learning etc.), which are effective for poor network areas and regions (Arefeen et al., 2025).

Question 5: How can Lightweight IoT Technology be Adapted to Suit the Regional Peculiarities as Found in North-Central Nigeria?

i. A lightweight food image database which is centered on the North-central region of Nigeria, should be created for capturing the images of locally consumed food items within the region, rather than using global standard food image datasets which would cause the

Machine learning model used for food image recognition and classification to perform poorly (Kong et al., 2016)

ii. Due to paucity of electricity supply and internet connectivity in the North-central region, the hardware components of the IoT systems should be configured for offline data capturing and storage in case of epileptic power supply. The IoT system should also be configured for transmission capacity using less internet connectivity. Alternative options could be the use of LoRaWAN (Low Range Wide Area Network), or Bluetooth connectivity with mobile apps which upload to cloud platforms for analysis (Ugwuanyi et al., 2021)

iii. Due to limited and unstable access to real-time cloud connectivity in north central Nigeria, lightweight ML models for classification should be trained using TinyML and quantized ML models (Heydari & Mahmoud., 2025). Another way classification can be done is performing device-based food thickness estimates which is derived using computer vision and AI algorithms (Zhang et al., 2021).

iv. Another vital means of regional adaptation by IoT systems is the incorporation of cultural measures for enhancing user engagement using local language prompts through voice and texts for different local languages domiciled within the region such as Igala, Yoruba, Ebira, Nupe, Tiv etc.. Nutritional recommendations for end-users should be made based on local cuisines (Zhou et al., 2025).

v. To ensure long term use of a regionally adapted IoT system, readily available and less costly IoT hardware components should be used such as the Espressif system 32 microcontroller (ESP32 + Camera) for capturing food images, ESP8866 microcontroller commonly used for less costly IoT endpoints, BLE (Bluetooth low energy) sensors to measure and send sensor data, sensor embedded Pizzioelectric band for bite and chew detection, and solar battery as an independent energy source for the IoT system (Xu et. al., 2014).

vi. For resource-constrained regions like North-central Nigeria, capturing of food images by IoT systems should be event triggered such as biting, chewing, swallowing, and wrist motion detections, rather than continuous image capturing to reduce consumption of storage space, battery power, and for lesser use of computational resources. Lesser but optimal frame rate should be used by an IoT system's camera for capturing images to reduce the amount of image data (Doulah et al., 2021).

vii. For a well localized User experience (UX), the user interface of an IoT system's dashboards should reflect gamification that adapts images, icons, and animations of local food items consumed within the region. Images and icons of western foods or food items from distant regions should not be included except for some which are also consumed within the given region (Berger & Jung, 2024).

viii. Some dietary compliance approaches used in some researches reviewed include sensor-spoon/fork devices, image-based food recognition, voice recognition systems, and radio frequency identification tagged (RFID) food logs (Dong et al., 2014).

ix. Cultural relevance is enhanced via nutrient estimation with the aid of ML models for food classification and region-centric food diaries and databases. It was found that among some IoT diet monitoring systems deployed in Africa, regional accuracy was limited because most models relied on non-African food datasets (Alharbi et al., 2024)..

RESULTS AND DISCUSSION

There were 25 studies extracted from the initial 358 records because they satisfied the inclusion criteria as illustrated earlier using the PRISMA 2020 diagram, therefore these studies were included in the review. Results were grouped into three thematic areas:

Lightweight ML Models

i. The following architectures: Pruned CNNs, TinyML, MobileNet, achieved 80–90% accuracy in food recognition while being resource-efficient. SVM used in AIM-2 achieved 89-94% in food intake detection, the Piezoelectric monitoring system used statistical feature extraction, and linear classifiers which achieved 80-95% accuracy in chewing and swallowing detection, (Doulah et al., 2022, Sazonov et al., 2010). The eating movement system by Amft & Troster (2008) used Decision Trees and K-Nearest Neighbor (KNN) for hand to mouth gesture detection which achieved detection accuracy of 84-90%, EgoDiet used optimized CNN and Edge Preprocessing which achieved above 80% in food intake detection and classification. DietCam and eButton used CNN for food recognition and food intake detection respectively, with both achieving 89-92% using already prepared image datasets, eButton also achieved~85% accuracy for food recognition under lab settings (Meyer et al., 2015; Jia et L., 2014). AutoDietary used feature-based classifiers and SVM for food intake detection with ~90% accuracy, and swallow detection with ~85-90% accuracy (Fontana et al., 2014), BiteCounter used Rule-base algorithms for wrist movements and food bite detection achieving an accuracy of ~86-90% (Dong et al., 2012). Only a few studies used real-world African settings to test the models. No ML food recognition and classification model has been trained specifically for North-central region of Nigeria. This study intends to develop an African food recognition model using food image datasets gotten from food items locally consumed within North Central Nigeria.

ii. In some IoT systems such as the AIM-2, Piezoelectric sensor, IMU (Inertia measurement Unit) sensors etc., Power and memory needs were reduced through ML model quantization and compression (Doulah et al. 2021; Sazonov et al., 2010). EgoDiet use quantized models for device-based classification instead of cloud connectivity, it also used optimized CNN models which work on the IoT device components directly (Lo et al., 2024). IMU diet monitoring systems used classical quantized models for compression of features that were extracted, and also used simple classifiers and threshold gating for reduction of memory usage. Instead of using deep learning models, AIM-2 used primary ML models such as Decision Trees and SVM which were implemented using 8-bits or 16-bits arithmetic making the quantization process to be simpler and direct (Sazonov et al., 2021). The Piezoelectric monitoring system used optimized ML models such as lightweight feature-based classifiers, linear classifiers, threshold decision models to save power and memory usage (Sazonov et al., 2010). Amft & Troster (2008) used lightweight ML models such as HMM (Hidden Markov Model), and Decision Trees in the gesture detection system, requiring lesser power and memory usage. BiteCounter which is recognized as one of the IoT systems with the least amount of power consumption, used optimized models which are threshold-based detection and Rule-based classification, these models enabled the IoT system to use very low memory space for storage of data (Sazonov et al., 2010).

Diet Monitoring Via IoT

i. Mobile applications, and IoT devices such as smart utensils, wearable sensors, were included. Most of the IoT devices were tested in high-income settings; It was observed that only a few were effective in African settings which mostly comprised of resource-poor areas. More lightweight IoT devices should be tested thoroughly within resource poor areas and regions which consist of people who are in dire need of health solutions such as lightweight diet monitoring systems (Sazonov et al., 2010).
ii. Some limitations encountered by several IoT diet monitoring systems examined in this systematic review include: absence of local food databases, high costs of devices. However, some IoT systems such as HealthifyMe, EgoDiet (deployed in Ghana), PEIS (Passive Egocentric Intake System, deployed in Ghana/Kenya), Indian food etc., developed region-centric databases and were incorporated for relevance and adaptability. These IoT systems also used less costly IoT hardware components for their systems (Lo et al., 2024). A Region-centric food database is yet to be curated specifically for North-central Nigeria (Lo et al., 2024). This study intends to bridge this gap by developing a localized online food database for north central Nigeria.
iii. The challenge of poor and unstable internet connectivity was handled by some of the IoT systems in several ways: the AIM-2 and Piezoelectric monitoring system, used SVM and feature-based classifiers for local computation of chewing and swallowing events, capturing of food images was only triggered by the temporalis muscle sensor which occurs when jaw movements are detected, the AIM-2 also stored image and sensor data offline inside an SD card or device memory for offline analysis, which could be later uploaded to the cloud whenever internet access is restored, thus eliminating cloud dependence (Sazonov et al., 2021). The BiteCounter monitors wrist motions and counts the number of bites, these data are stored locally and shared with computers and mobile apps whenever the internet is available, it doesn't require cloud access for data processing (Sazonov et al., 2010). In EgoDiet, the CNN model used for classification executes offline, directly on the IoT devices in the system, therefore analysis is not done in the cloud. Image data is stored locally, results are shared on the cloud whenever internet connectivity is available (Lo et al., 2024).

Techniques for User Engagement

i. The following IoT systems; AIM-2, EgoDiet, Amft & Troster recognition system, and the Piezoelectric monitoring system, through passive food intake detection and monitoring were able to enhance user engagement, food intake episodes were captured automatically and bias in recall was reduced. However there was no real-time response and animation contents which could boost user interaction, this is a much needed feature which should be incorporated in modern diet monitoring systems (Doulah et al., 2021; Sazonov et al., 2010). Users of EgoDiet could perform logging using camera images instead of manual logging (Lo et al., 2024). The mFR (Manual Food Record) system could send reminder messages for forgotten diets, it also had some means of helping users with measuring quantity of food items in every meal, studies indicated enhanced user compliance compared to ordinary text diaries (Boushey et al., 2009). The BiteCounter system could provide the users with the number of bites per meal, thus delivering feedback in real-time, users could also incorporate their mobile phones to the system for better user experience (Dong et al., 2012).
ii. Cultural adaptation (local foods, languages, interface design) by some diet monitoring systems such as EgoDiet, Indianfood etc., increased long-term use. AIM-2 only detected eating behavior and did not utilize food databases of localities, BiteCounter was designed to monitor wrist motion patterns which could be similar across several cultures and may affect the system's accuracy because of the varied styles of eating (Doulah et al., 2021; Dong et al., 2012). The Piezoelectric system monitored signals from chewing activities and not image data, inference from the signals were relevant to several cultures despite their varied food intake gestures (Sazonov et al., 2010). The mFR (Manual Food Record) system was adaptable by affording users across different cultures the ability to take photos of their local food items and upload them for analysis, this led to the growth of the system's database and food libraries, however this sacrificed some of the lightweight features of the system (Six et al., 2010; Boushey et al., 2009). The EgoDiet system was tailored to suit varied African food ingestion behaviors such as shared plates, mixed foods, hand-to-mouth etc., it used region specific food image datasets (Ghana and Ethiopia) for cultural relevance (Lo et al., 2024). The main objective of the Amft recognition system was to identify eating gestures and not image analysis, there were validations of it's detection in terms of general diet eating behaviours (Amft & Troster., 2008).

Table 2: Summary of Cultural Adaptation Techniques of Some IoT Systems

IoT System	Cultural adaptation technique	Regional food dataset
AIM-2	Behavior detection	Not used
BiteCounter	Behavior detection	Not used
Amft	Gesture detection	Not used
Piezoelectric	Physiological detection	Not used
mFR	Image capture by users	Used
EgoDiet	Region dataset	Used

iii. The engagement techniques were tested in Sub-Saharan Africa by a few studies. There is need for the incorporation of user engagement techniques by IoT systems for relevance and adaptability in North Central Nigeria.

This systematic review reveals that IoT technologies and lightweight ML are feasible for monitoring dietary compliance but are not sufficiently tailored and they remain underutilized in resource-poor areas. Some evidence revealed that constrained devices could achieve accurate recognition via the use of lightweight ML models, however the lack of regional food datasets is posing to be an acute limitation to their deployment in Nigeria (North-central). Many of these IoT devices rely a lot on power and are also not cost effective though they have shown positive prospects, to provide better alternatives suitable for deployment in resource-poor regions as found in African settings, smartphones devices with embedded ML models and solar-powered IoT devices would be cost effective, affordable and more sustainable. Although substantial progress has been made in developing Machine Learning and IoT frameworks for personalized diet monitoring, regional customization still face some limitations as well as hardware constraints. Most of the IoT solutions are designed to suit western or urban regions and populations. Resource-poor regions like North-Central Nigeria would require:

i. IoT system integrating with the taxonomies that capture local food items
ii. Use of power-saving IoT hardware components
iii. Reliable and effective strategies for engaging the populace of a community.
iv. Prioritizing the use of offline-first architecture in designing the IoT system
v. Incorporating localized food diaries/databases that capture details of Nigerian diets.
vi. Affordable and cost effective IoT solutions
vii. Engagement methods and techniques adaptable to the culture of the populace to increase user acceptance.

Directions for Future Research

The following suggestions in this systematic review are considered for future investigations and explorations to make IoT and ML-based personalized diet monitoring more suitable for resource-poor areas like north-central Nigeria:

i. Creation of food image datasets for Nigerian foods by using ML training models.
ii. Research into training of region-centric ML models for recognition, detection, and classification functions for various diet activities such as food intake, motion gestures, diet behaviours, food image classifications etc.
iii. Validation and testing of ML-based IoT diet monitoring systems in rural Nigerian healthcare programs.
iv. Research on how to incorporate lightweight programs for multilingual support and voice-driven UI/UX into IoT systems using languages commonly spoken in north-central Nigeria.
v. Research into further advancing hybrid Machine Learning architectures that would would reduce or replace cloud computing with innovative computing models such as edge computing, Fog computing, TinyML, Model compression, Federated learning etc, which require less computing power and resources and are effective for poor network areas and regions like north-central Nigeria.

CONCLUSION

The attempt to integrate personalized health solutions (particularly in diet monitoring) with Machine Learning, and IoT technology always presents ample opportunities to address dietary challenges especially in resource-poor areas like North-Central Nigeria. This systematic review highlighted significant potentials for personalized dietary monitoring and enhanced user engagement with the use of lightweight IoT technology ML models. The use of lightweight ML-based IoT systems which are region-centric, tailored for personalized diet monitoring, and are culturally adaptable for defined regions, would eventually lead to positive results and outcomes in the personal health of the people domiciled in resource-poor areas, given that infrastructural and cultural challenges are dealt with by employing innovative measures and approaches drawn from various disciplines. This systematic review indicated high accuracy levels of some IoT systems and their machine learning models for real-time tracking, eating detection, food image recognition and classification. User compliance were significantly enhanced using engagement techniques such as feedbacks and more importantly; gamification. However, a research gap is made obvious as a result of their limited cultural adaptations to various regional settings, predominant use of global datasets rather than region-centric options, and their scarce deployments to rural parts of Africa, especially North-central Nigeria as a case study.

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