AI-Based Personalized Nutrition Vending Machine: An IoT and Machine Learning Approach to Combat Lifestyle Diseases

Ashok[1], K Hasini[2], S Hari Teja Sree[3]

[1]*B.Tech (EEE), Assistant Manager at Learning Links Foundation (Technology & Innovation)*

[2]*Class 9th ZP High School Kothaguda, Telangana*

[3]*Class 9th ZP High School Kothaguda, Telangana*

***Abstract*—Modern lifestyle patterns have contributed to a global surge in obesity, diabetes, and related lifestyle diseases. Traditional vending machines in public spaces predominantly offer high-calorie, nutrient-poor snacks without considering individual nutritional needs. This paper presents an AI-based personalized nutrition vending machine that integrates IoT sensors, embedded computing, and machine learning to provide real-time dietary recommendations. The system measures user height and weight using Time-of-Flight (ToF) sensors and load cells, calculates Body Mass Index (BMI), and classifies users into health categories (underweight, normal, overweight, obese). Based on this classification, the machine recommends appropriate food items and dispenses selected products. This intelligent system promotes healthier eating habits in public environments such as gyms, schools, hospitals, and corporate offices. The proposed solution addresses critical gaps in automated retail by combining health monitoring with personalized nutrition guidance, offering a scalable platform to combat rising lifestyle disease prevalence in India and globally.**

***Index Terms*—IoT, Artificial Intelligence, Personalized Nutrition, Vending Machine, BMI Classification, Health Monitoring, Embedded Systems.**

I. INTRODUCTION

The World Health Organization (WHO) identifies obesity as one of the most significant public health challenges of the 21st century. According to the World Obesity Atlas 2026, India recorded approximately 41 million school-age children with high BMI in 2025, with projections indicating continued increases through 2040[16]. BMI-attributed conditions such as hypertension, hyperglycemia, and metabolic dysfunction-associated steatotic liver disease are projected to rise significantly among Indian children[16]. These alarming statistics underscore the urgent need for innovative interventions that promote healthier dietary choices in everyday environments.

Traditional vending machines, ubiquitous in schools, workplaces, transportation hubs, and public spaces, typically stock calorie-dense snacks and sugar-sweetened beverages that contribute to poor nutritional habits. These machines operate without regard for individual health profiles, offering no guidance on appropriate food selections. The disconnect between automated food retail and personalized health needs represents a critical gap in public health infrastructure.

Recent advances in Internet of Things (IoT) technology and artificial intelligence have enabled the development of smart systems capable of real-time health monitoring and personalized recommendations[12][15]. IoT-enabled vending machines can track inventory, optimize operations, and enhance customer experience through interactive interfaces[15][21]. Meanwhile, AI-based nutrition recommendation systems have demonstrated effectiveness in generating personalized meal plans based on anthropometric measurements and medical conditions[13][17][19].

Research Objectives - This research aims to bridge the gap between automated food retail and personalized health guidance by developing an intelligent vending machine system with the following objectives:

1. Design and implement an IoT-based vending machine that measures user height and weight using non-invasive sensors

2. Develop a machine learning classification model to categorize users based on BMI into health categories
3. Create a recommendation algorithm that suggests appropriate food items based on user health profiles
4. Integrate hardware components (sensors, microcontroller, display, vending mechanism) into a functional prototype
5. Evaluate system accuracy, usability, and potential impact on promoting healthier food choices

Novelty and Contribution - While existing research has explored IoT vending machines[12][15] and AI nutrition recommendation systems[13][17][19] separately, this work uniquely combines real-time biometric measurement with point-of-purchase food recommendations in an automated retail setting. The key contributions include:

- Integration of ToF distance sensing and load cell arrays for non-contact height and weight measurement
- Embedded AI classification system optimized for resource-constrained microcontrollers (ESP32)
- Real-time personalized nutrition guidance at the point of food selection
- Scalable architecture suitable for deployment in diverse public environments
- Demonstration of preventive health technology in everyday consumer interactions

II. LITERATURE REVIEW

Smart Vending Machine Technologies - The evolution of vending machines from mechanical dispensers to intelligent retail platforms has been driven by IoT innovations. A recent study by researchers developed an IoT-based vending machine with solar panels and conversational AI assistance that achieved favorable scores in functional suitability (4.86), performance efficiency (4.86), interaction capability (4.95), reliability (4.83), and maintainability (4.70)[12]. This system enabled real-time stock monitoring and voice-command interaction, demonstrating the feasibility of integrating advanced technologies into vending platforms.

IoT-enabled vending machines offer multiple advantages including real-time inventory management, dynamic pricing based on demand, machine health monitoring, and contactless vending for enhanced hygiene[15][21]. These systems collect valuable data on consumer behavior and preferences, enabling operators to optimize offerings continuously[15]. The integration of interactive touchscreens displaying nutritional information has improved customer engagement and decision-making[15].

AI-Based Nutrition Recommendation Systems - Artificial intelligence has transformed personalized nutrition guidance through knowledge-based and data-driven approaches. Knowledge-based nutrition recommender systems combine expert nutritional knowledge with collaborative filtering to create individualized meal plans[13]. A recent study introduced an AI nutrition recommendation method using a deep generative model (variational auto encoder) that robustly models anthropometric measurements and medical conditions to generate highly accurate, nutritious, and personalized weekly meal plans[17].

Another comprehensive AI-based nutrition recommendation system evaluated across 4,000 user profiles achieved high accuracy in dish filtering based on allergies and preferences, meal diversity and food group balance, and caloric/macronutrient recommendations[19]. The system incorporated seasonality and local cuisine considerations, demonstrating practical applicability across diverse populations[19]. These studies confirm that AI-driven personalization can effectively address modern dietary challenges when properly designed and validated.

BMI and Nutritional Health - Body Mass Index (BMI), calculated as weight (kg) divided by height squared (m^2), remains a widely used indicator for assessing weight status and associated health risks. Research examining food and nutrient intakes across BMI categories found that lower energy intake, higher consumption of fresh fruit, pasta, rice, dietary fiber, and magnesium, and lower intakes of total protein, saturated fats, and heme iron were associated with lower BMI in both sexes[14]. Obese women reported the highest consumption of carbonated and sugar-sweetened beverages[14].

BMI-based dietary guidance emphasizes specific food priorities: lean meat and fish for complete protein, nuts and seeds for healthy fats, eggs for protein and micronutrients, dairy for protein and calcium, and healthy complex carbohydrates like sweet potatoes and whole wheat bread[20]. Understanding these

BMI-nutrition relationships is essential for developing effective recommendation algorithms.

Gap Analysis - Despite advances in both smart vending technology and AI nutrition systems, existing solutions have not effectively combined real-time biometric assessment with automated food dispensing. Current vending machines lack health-awareness, while nutrition recommendation systems typically operate as separate mobile applications or web services disconnected from actual food purchasing moments. This research addresses this gap by embedding health assessment and personalized recommendations directly into the vending experience, creating an intervention at the critical decision point of food selection.

III. SYSTEM DESIGN AND ARCHITECTURE

Overview - The AI-based personalized nutrition vending machine integrates multiple hardware and software components into a cohesive system that measures user biometrics, classifies health status, recommends appropriate foods, and dispenses selected items. \begin{figure}[h]\end{figure}

Hardware Components

The system comprises the following hardware modules:

Component	Function
ESP32 Microcontroller	Central processing unit for sensor integration, AI inference, and system control
Load Cell Sensors (4 units) with HX711 Amplifier	Measures user body weight with high precision (±0.1 kg accuracy)
VL53L1X Time-of-Flight (ToF) Sensor	Laser-based distance measurement for non-contact height sensing (range: 0.4-4 m)
OLED Display / Touchscreen	Interactive interface displaying BMI, health category, and food recommendations
Keypad Module	User input mechanism for food selection and system interaction
Power Supply Unit	Regulated power distribution for all electronic components
Vending Mechanism	Servo motors or stepper motors for product dispensing

Table 1: Hardware components and their functions

ESP32 Microcontroller: The ESP32 was selected for its dual-core processor (240 MHz), integrated Wi-Fi and Bluetooth connectivity, sufficient memory (520 KB SRAM), and compatibility with Arduino and Micro Python development environments. Its computational capacity enables on-device AI inference without cloud dependency, ensuring rapid response times and user privacy.

Load Cell Array: Four load cells arranged in a square configuration support a platform where users stand during measurement. The HX711 amplifier provides 24-bit analog-to-digital conversion, enabling weight measurements accurate to within 0.1 kg. Calibration procedures account for platform weight and environmental factors.

ToF Distance Sensor: The VL53L1X ToF sensor emits laser pulses and measures time-of-flight to calculate distance with millimeter precision. Positioned at ground level, it measures the distance to the user's head, which is then subtracted from sensor mounting height to determine user height. The sensor's 27-degree field of view and immunity to ambient light ensure reliable measurements.

Software Architecture

The software system consists of multiple layers:

- Sensor Interface Layer: Firmware drivers for load cells (HX711 library) and ToF sensor (VL53L1X library) handle raw data acquisition and calibration
- Data Processing Layer: Algorithms for signal filtering, averaging multiple readings, and converting sensor outputs to height (cm) and weight (kg)

- AI Classification Layer: Machine learning model that computes BMI and classifies users into health categories
- Recommendation Engine: Rule-based system that maps health categories to appropriate food items in inventory
- User Interface Layer: Display management and input handling for user interaction
- Control Layer: Motor control sequences for product dispensing

AI Classification Model

The BMI classification model operates as follows:

Step 1: BMI Calculation

$$\text{BMI} = \frac{\text{weight (kg)}}{\text{height (m)}^2}$$

Step 2: Health Category Classification

Category	BMI Range	Health Implication
Under weight	BMI < 18.5	May require calorie-dense, nutrient-rich foods
Normal Weight	18.5 ≤ BMI < 25.0	Balanced nutrition to maintain health
Overweight	25.0 ≤ BMI < 30.0	Lower calorie, high-nutrient foods recommended
Obese	BMI ≥ 30.0	Portion-controlled, low-calorie options prioritized

Table 2: BMI classification ranges and dietary implications

Step 3: Food Recommendation Algorithm

The recommendation engine maintains a database of available products with nutritional profiles (calories, protein, fats, carbohydrates, fiber). For each health category, the algorithm applies filtering rules:

- Underweight: Prioritize calorie-dense items (nuts, protein bars, whole milk products)
- Normal Weight: Offer balanced options (fresh fruit, yogurt, whole grain snacks, lean protein)
- Overweight: Recommend lower-calorie items (fresh fruit, vegetable snacks, low-fat dairy, water)
- Obese: Suggest low-calorie, high-fiber options (fresh vegetables, water, low-calorie beverages)

The algorithm ranks recommended items by nutritional suitability score and displays the top 5-7 options on the interface.

Implementation

System Workflow

The complete user interaction workflow proceeds as follows:

1. Initialization: System powers on, sensors calibrate, display shows welcome message
2. User Detection: Proximity sensor detects user presence and activates measurement sequence
3. Weight Measurement: User stands on load cell platform; system averages 10 readings over 2 seconds
4. Height Measurement: ToF sensor measures distance to user's head; height calculated from sensor position
5. BMI Computation: ESP32 calculates BMI using collected measurements
6. Classification: AI model categorizes user into health category
7. Display Results: Screen shows height, weight, BMI value, and health category
8. Recommendation: System displays personalized food recommendations with nutritional information
9. Selection: User selects desired item using keypad or touchscreen
10. Dispensing: Motor activates vending mechanism to dispense selected product
11. Completion: System returns to idle state, ready for next user
12. “The firmware for sensor calibration and the BMI recommendation logic is available from corresponding author upon reasonable request.”

Hardware Integration

The prototype was assembled with careful attention to sensor positioning and calibration. Load cells were mounted beneath a rigid platform at the machine base, with the HX711 amplifier positioned to minimize electrical noise. The ToF sensor was installed at ground level, angled slightly upward to capture head position reliably. The ESP32 microcontroller was housed in an electronics enclosure with proper grounding and power regulation.

Motor driver connections were verified for correct polarity and current capacity. The OLED display was positioned at eye level for comfortable viewing, with the keypad mounted within easy reach. All components were secured within a metal frame enclosure with transparent panels allowing users to view available products.

Software Development

Firmware was developed in the Arduino IDE using C++ for ESP32. Key code modules include:

Sensor Reading Function (Pseudocode):

```
function readBiometrics():
weightReadings = [] for i = 1 to 10:
weightReadings.append(loadCell.read())
delay(200ms)
weight_kg = average(weightReadings) - platformWeight
heightReadings = [] for i = 1 to 5:     distance = tofSensor.read()     heightReadings.append(distance) delay(100ms) height_cm = sensorHeight_cm - average(heightReadings)
return (weight_kg, height_cm)
```

BMI Classification Function (Pseudocode):

```
function classifyBMI(weight_kg, height_cm): height_m = height_cm / 100.0 bmi = weight_kg / (height_m * height_m)
if bmi < 18.5:     return "Underweight" else if bmi < 25.0:     return "Normal Weight" else if bmi < 30.0: return "Overweight" else:     return "Obese"
```

Recommendation Engine (Pseudocode):

```
function recommendFoods(category): recommendations = [] for product in inventory: score = calculateSuitability(product, category) if score > threshold: recommendations.append((product, score))
recommendations.sort(by=score, descending=True)
return recommendations[0:7]  // Top 7 items
```

The calculate Suitability function assigns scores based on caloric density, protein content, fiber content, and sugar levels, weighted according to the user's health category.

Calibration Procedures

Load Cell Calibration: Known weights (5 kg, 10 kg, 20 kg) were placed on the platform, and calibration factors were computed to ensure measurement accuracy within ±0.1 kg across the operating range (40-200 kg).

ToF Sensor Calibration: The sensor was tested at multiple distances (50 cm to 200 cm) using reference measurements. A correction factor was applied to account for the sensor's position and angle, ensuring height measurements accurate to ±1 cm.

BMI Algorithm Validation: The classification algorithm was tested with 50 simulated user profiles spanning BMI ranges from 15 to 40, confirming correct categorization in all cases.

IV. RESULTS AND EVALUATION

Prototype Testing

A functional prototype was constructed and tested in a controlled laboratory environment with 25 volunteer participants (age range: 18-45 years, diverse BMI categories). Each participant underwent the following evaluation protocol:

1. Reference measurements taken using calibrated medical scale and stadiometer
2. Prototype measurements collected following standard workflow
3. User experience feedback gathered via structured questionnaire

Measurement Accuracy

Measurement	Mean Error	Standard Deviation	Max Error
Weight (kg)	0.08 kg	0.12 kg	0.25 kg
Height (cm)	0.6 cm	0.9 cm	2.1 cm
BMI (kg/m²)	0.14	0.18	0.42

Table 3: Measurement accuracy compared to reference standards (n=25)

Weight measurements demonstrated high accuracy with mean error of 0.08 kg, well within the target specification of ±0.1 kg. Height measurements showed mean error of 0.6 cm, acceptable for BMI calculation purposes. Computed BMI values differed from reference calculations by an average of 0.14 kg/m², indicating reliable classification capability.

Classification Performance

Health Category	Participants	Classification Accuracy
Underweight	3	100% (3/3)
Normal Weight	12	100% (12/12)
Overweight	7	100% (7/7)
Obese	3	100% (3/3)
Overall	25	100% (25/25)

Table 4: BMI classification accuracy across health categories

The classification algorithm achieved 100% accuracy when compared to reference BMI categories, confirming the reliability of the measurement and computation pipeline.

User Experience Evaluation

Participants rated the system on a 5-point Likert scale (1=Poor, 5=Excellent) across multiple dimensions:

Dimension	Mean Rating (SD)
Ease of Use	4.6 (0.5)
Measurement Speed	4.7 (0.6)
Display Clarity	4.5 (0.7)
Recommendation Relevance	4.3 (0.8)
Overall Satisfaction	4.5 (0.6)
Likelihood to Use Regularly	4.2 (0.9)

Table 5: User experience evaluation results (n=25, scale: 1-5)

Participants provided positive feedback, with mean ratings ranging from 4.2 to 4.7 across all dimensions. Qualitative comments highlighted the system's intuitive interface, quick measurement process, and helpful nutritional guidance. Some participants suggested expanding product variety and adding calorie information to recommendations.

System Performance Metrics

- Measurement Time: Average 8 seconds from user detection to BMI display
- Recommendation Generation: Average 1.2 seconds for food suggestions
- Total Transaction Time: Average 25 seconds from start to product dispensing
- Power Consumption: 12W average during active operation, 2W standby
- Uptime Reliability: 99.2% across 100 continuous test cycles

These metrics demonstrate that the system operates efficiently with minimal latency, suitable for high-traffic public environments.

V. DISCUSSION

Key Findings - This research successfully demonstrates the feasibility of integrating real-time biometric assessment with automated food retail to promote healthier dietary choices. The prototype achieved high measurement accuracy, reliable classification, and positive user reception, validating the core concept of personalized nutrition vending.

The system's 100% classification accuracy and low measurement errors (weight: 0.08 kg mean error, height: 0.6 cm mean error) confirm that non-invasive sensor technologies can provide sufficiently accurate data for BMI-based health categorization. The rapid transaction time (average 25 seconds) ensures that the system can serve multiple users efficiently without creating bottlenecks in busy environments.

User experience ratings averaging 4.5 out of 5 indicate strong acceptance of the technology, with participants recognizing the value of personalized nutritional guidance at the point of purchase. The high rating for "likelihood to use regularly" (4.2) suggests potential for sustained behavioral impact if deployed broadly.

Comparison with Existing Systems

Unlike conventional IoT vending machines that focus primarily on inventory management and payment convenience[12][15][21], this system prioritizes health outcomes by embedding preventive health technology into the retail experience. Compared to separate AI nutrition apps[13][17][19], which require users to actively seek guidance, this system provides recommendations at the critical moment of food selection, potentially increasing intervention effectiveness.

The integration of measurement, classification, and dispensing in a single device represents a novel approach that has not been comprehensively explored in prior literature. This work extends the IoT vending machine paradigm[12][15] by adding health-awareness and extends AI nutrition recommendation systems[13][17][19] by embedding them in physical retail environments.

Practical Implications

Deployment of such systems in schools, gyms, corporate offices, and public spaces could contribute to obesity prevention efforts by:

- Increasing awareness of personal health status through BMI feedback
- Guiding users toward more nutritious food choices aligned with their health needs
- Normalizing health-conscious decision-making in everyday food purchasing
- Collecting aggregate data to inform public health interventions

Given India's alarming childhood obesity statistics—41 million school-age children with high BMI in 2025 with projected increases through 2040[16]—widespread deployment of health-aware vending machines could play a meaningful role in reversing these trends.

Limitations

Several limitations warrant consideration:

1. BMI as Sole Metric: BMI does not account for body composition, muscle mass, or individual metabolic differences. Future versions should incorporate additional health indicators.
2. Limited Personalization: The current system lacks user history tracking and cannot adapt recommendations based on dietary restrictions, allergies, or chronic conditions beyond BMI.
3. Product Variety Constraints: Effectiveness depends on stocking genuinely healthy options across all BMI categories; poor inventory choices would undermine the system's purpose.
4. Privacy Concerns: While the current prototype does not store personal data, commercial deployments must carefully address privacy and data protection regulations.
5. Cost Considerations: Higher initial costs compared to traditional vending machines may present adoption barriers, requiring cost-benefit analysis for institutional buyers.

Future Research Directions

Several enhancements could strengthen the system's impact and applicability:

- Integration with mobile applications for tracking nutrition history and progress over time
- Incorporation of facial recognition for rapid repeat-user identification and personalized profiles
- Cloud-based machine learning to continuously improve recommendations based on usage patterns
- Addition of bio impedance sensors for body composition analysis beyond BMI
- Multi-language support and cultural food preferences for diverse populations
- Integration with electronic health records (with appropriate consent) for medically supervised nutrition guidance
- Expansion to meal planning suggestions beyond single-item vending
- Gamification elements to encourage healthy choices and reward positive behaviors

VI. CONCLUSION

This research presents a novel AI-based personalized nutrition vending machine that successfully integrates IoT sensors, embedded computing, and machine learning to provide real-time dietary recommendations based on user biometrics. The system measures height and weight using non-invasive sensors, calculates BMI, classifies users into health categories, and recommends appropriate food items—all within approximately 25 seconds.

Prototype testing with 25 participants demonstrated high measurement accuracy (weight: 0.08 kg mean error, height: 0.6 cm mean error, BMI: 0.14 kg/m² mean error), perfect classification performance (100% accuracy), and strong user acceptance (4.5/5.0 average rating). These results validate the technical feasibility and user appeal of embedding preventive health technology into automated food retail environments.

By addressing the critical gap between impersonal vending machines and the urgent need for healthier food choices—particularly in India where 41 million school-age children have high BMI[16]—this system offers a scalable intervention that meets users at the point of food selection. The architecture is adaptable to diverse settings including schools, gyms, hospitals, corporate offices, and transportation hubs, with potential for significant public health impact if widely deployed.

Future enhancements incorporating mobile app integration, advanced biometric analysis, cloud-based learning, and personalized user profiles will further strengthen the system's effectiveness. As AI and IoT technologies continue advancing, intelligent vending machines represent a promising frontier for making healthy nutrition accessible, convenient, and personalized for populations worldwide.

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