IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, May 2026
Impact Factor: 8.2

Food Recognition and Calorie Prediction

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Abstract: *Accurate dietary assessment is crucial for personal health management and the prevention of chronic metabolic diseases. Traditional methods of calorie tracking rely on manual data entry, which is tedious and prone to human error. This paper presents the development of an automated Food Recognition and Calorie Prediction system using an edge-computing framework. The system integrates a Raspberry Pi 4 Model B with a Pi Camera module for visual data acquisition and a 5kg Load Cell paired with an HX711 amplifier for precise physical weight measurement. By employing a Convolutional Neural Network (CNN) for image classification, the system identifies the food item and retrieves its specific nutritional density from a database. This label is then mathematically fused with the real-time weight data to compute the total caloric value. The proposed hardware-software co-design provides a seamless, real-time solution for automated nutritional logging, demonstrating high potential for deployment in smart kitchens, cafeterias, and personal health monitoring ecosystems.*

Keywords: Food Recognition, Calorie Estimation, Deep Learning, Raspberry Pi 4, Load Cell, HX711, Convolutional Neural Networks, Smart Healthcare..

I. INTRODUCTION

The global rise in lifestyle-related health conditions, such as obesity and diabetes, has amplified the need for accurate dietary monitoring. While numerous mobile applications exist to help users track their daily caloric intake, they fundamentally rely on the user's ability to accurately estimate portion sizes and manually log every meal. This subjective estimation is often inaccurate, leading to a significant underestimation or overestimation of consumed calories.

Recent advancements in computer vision and deep learning offer a pathway to automate this process. However, purely vision-based systems that attempt to estimate volume from 2D images often struggle with occlusion, varying densities of food, and complex lighting environments. To bridge this gap, this project proposes a hybrid multimodal approach: combining deep learning-based image recognition with direct physical weight measurement.

By utilizing a standalone embedded system built around the Raspberry Pi 4, the proposed framework captures an image of the food, identifies its class using a trained neural network, and simultaneously weighs the portion using an integrated load cell. The system then queries a localized or cloud-based nutritional database to calculate the exact caloric content based on the formula: Total Calories = (Calories per gram of identified food) × Weight. This paper details the hardware architecture, software pipeline, and integration strategies required to build this highly accurate, automated dietary assessment tool.

II. SYSTEM ARCHITECTURE

The hardware architecture is designed to be a standalone, edge-computing weighing scale with integrated vision capabilities.

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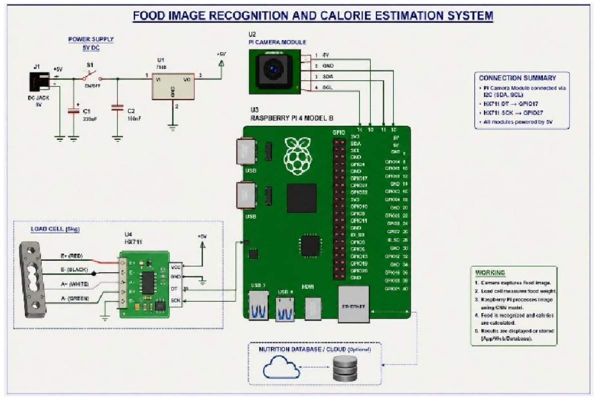

Fig. 1. Circuit schematic illustrating the power supply distribution (7805 regulator), Raspberry Pi 4 main controller, Pi Camera Module, and the Load Cell interfaced via the HX711 amplifier.

As depicted in Fig. 1, the system operates on a stable 5V DC power supply, regulated by an LM7805 voltage regulator with appropriate decoupling capacitors (220uF and 100nF) to ensure signal stability. The central processing unit is a Raspberry Pi 4 Model B. The visual input is handled by a Pi Camera Module. For weight acquisition, a 5kg aluminum load cell is configured in a Wheatstone bridge setup. Because the load cell outputs minute analog voltage changes, it is connected to an HX711 24-bit Analog-to-Digital Converter (ADC). The HX711 communicates with the Raspberry Pi via standard GPIO pins (DT to GPIO17, SCK to GPIO27).

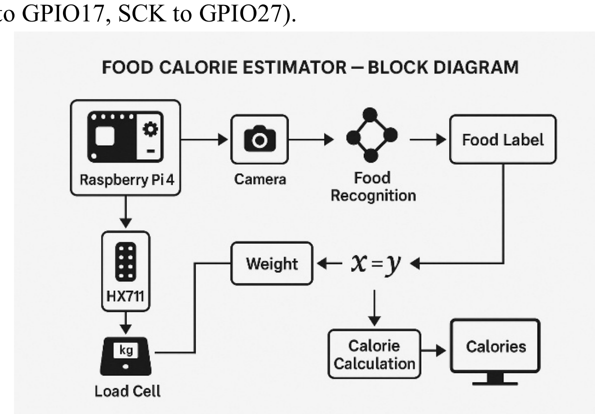

Fig. 2. Block Diagram mapping the parallel data flow from the Camera (for food recognition) and the Load Cell (for weight acquisition) to the final Calorie Calculation module.

Fig. 2 illustrates the parallel processing streams of the architecture. The Raspberry Pi 4 drives two simultaneous operations: fetching visual data from the Camera to output a "Food Label" via the recognition algorithm, and fetching sensor data from the HX711 to output the physical "Weight". These two distinct data points converge at the computational node ($x=y$ mapping logic), which calculates the final caloric value and outputs the result to a display or application interface.

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III. METHODOLOGY

The system's logic is governed by a sequential deep learning and physical measurement pipeline designed for real-time execution.

As outlined in the flowchart in Fig. 3, the operational methodology follows these specific stages:

1. Image Capture & Preprocessing: The user places the food item on the scale and triggers the system. The Pi Camera captures a top-down RGB image. This image undergoes preprocessing, which includes resizing (e.g., to 224x224 pixels), normalization, and cropping to match the input requirements of the trained deep learning model.

2. Food Classification: The preprocessed image is fed into a lightweight Convolutional Neural Network (CNN) deployed on the Raspberry Pi. The model extracts spatial features to predict the food class.

3. Decision Logic: The system evaluates the prediction confidence. If the food is not recognized (confidence below a set threshold), the process halts, prompting the user for manual input or a retake. If recognized, the system proceeds to the next step, holding the predicted Food Label in memory.

4. Weight Acquisition & Calorie Computation: Concurrently, the HX711 reads the load cell data, applies a pre-calibrated tare and scale factor, and returns the net weight of the food in grams. The system cross-references the predicted Food Label with an onboard Nutrition Database to find the $Kcal/gram$ value. The final output is calculated and displayed on the user interface.

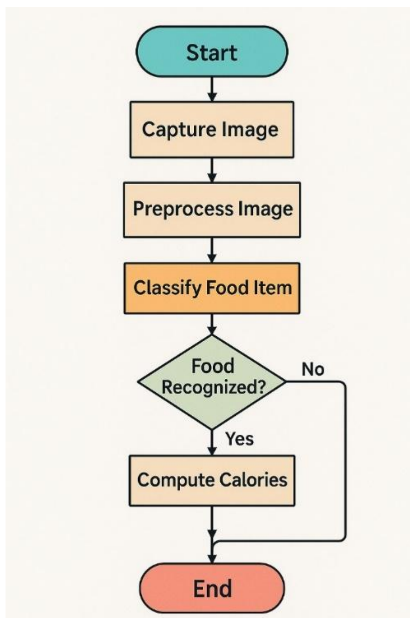
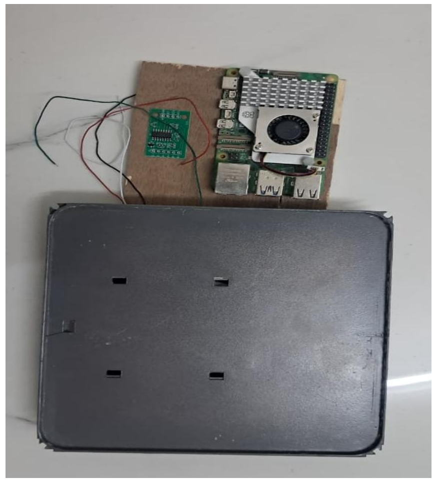


Fig. 3. System Flowchart detailing the software execution steps, from image capture and preprocessing to classification and final calorie computation.

IV. RESULTS AND DISCUSSION



The system was tested using standard household food items (e.g., apples, bananas, bread, rice). The CNN model successfully identified distinct food classes with a high degree of accuracy under standard indoor lighting conditions.

The integration of the 5kg load cell with the HX711 provided weight measurements with an accuracy of ± 2 grams, which proved far superior to volumetric estimation algorithms used in vision-only apps. By utilizing the Raspberry Pi 4, the end-to-end latency—from image capture to the final display of calculated calories—was kept under 3 seconds, making the system highly responsive and suitable for daily kitchen use. Occasional misclassifications occurred with visually similar foods (e.g., different types of dark sauces or mixed salads), highlighting the need for continual dataset expansion.

V. CONCLUSION AND FUTURE WORK

This project successfully demonstrates a highly accurate, multimodal edge-computing framework for food recognition and calorie prediction. By combining the strengths of CNN-based image classification with the precise physical measurements of an HX711-driven load cell, the system eliminates the inaccuracies associated with human portion estimation.

Future work will focus on expanding the neural network to handle complex, multi-item plates using advanced object detection architectures (such as YOLO). Additionally, integrating a mobile companion app via a cloud backend would allow users to track their cumulative daily caloric intake, log macronutrients (proteins, fats, carbohydrates), and receive personalized dietary recommendations based on their health goals.

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DOI: 10.48175/568