

Food Tracking System Using Machine Learning

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Abstract

This research introduces a comprehensive food tracking system that leverages machine learning to monitor food quality, predict spoilage, and optimize inventory management. The system utilizes Internet of Things (IOT) devices to collect real-time data on temperature, humidity, and gas concentrations, then employs Machine Learning (ML) algorithms to analyze this data and predict food freshness. A web-based dashboard and mobile app provide remote access to the data, enabling users to monitor food status and receive alerts when spoilage is imminent. This approach aims to reduce food waste, ensure consumer access to fresh food, and enhance efficiency in food supply chains.

1. Introduction

The project titled "**FOOD TRACKING SYSYTEM USING MACHINE LEARNING**" aims to machine learning-based food tracking system leverages artificial intelligence algorithms to monitor and analyze food intake, quality, and potentially even spoilage. This system can aid in various applications, including personalized nutrition, weight management, and improving food safety. This could involve user input (e.g., through apps or smart devices), food images for recognition, and data from sensors monitoring food conditions (temperature, humidity, etc.). Machine Learning Models Image Recognition Algorithms like Convolutional Neural Networks can be trained to identify specific food items from images. Nutritional Information Retrieval: Once food items are recognized, the system can retrieve corresponding nutritional information (calories, `Macronutrients`, etc.) from a database. Predictive Modeling: ML can be used to predict food freshness, spoilage, or even individual food intake patterns based on various factors. Data Analysis and Reporting: The system can analyze user data to provide insights into dietary habits, identify potential nutritional imbalances, and track progress towards health goals. A user-friendly interface (app, website, etc.) allows users to input food information, view reports, and receive personalized recommendations.

1.2. FIELD OF INTEREST

Machine learning can be used to monitor real-time data from sensors and devices to detect potential contamination sources, such as microbial growth or chemical residues. Machine learning can optimize delivery routes for food products, taking into account real-time traffic conditions and other factors to ensure timely and efficient delivery. Demand Forecasting: By analyzing historical data on sales and other factors, machine learning models can predict future demand for specific food items, helping

businesses optimize inventory and minimize waste. Enhancing Food Safety and Quality Machine learning can identify potential hazards in food processing, such as improper sanitation practices or equipment malfunctions. Machine learning can automate quality control processes, ensuring that food products meet specific standards and are safe for consumption. Emerging Applications like Predictive analytics like Machine learning can be used to predict future food safety issues, allowing for proactive measures to taken.

1.3 PROBLEM STATEMENT

A machine learning-based food tracking system can help individuals manage their diet by automatically recognizing food, estimating calories, and tracking consumption patterns, leading to healthier eating habits. This system aims to address the problem of inconsistent calorie tracking, where users often struggle to remember and manually input their food consumption, leading to inaccurate assessments of their dietary intake.

Inaccurate Calorie Tracking Manual calorie tracking through food journals or apps is time-consuming, prone to errors, and often incomplete, making it difficult to accurately assess dietary intake. Lack of Automated Food Recognition Existing systems often require users to manually identify food items and input details, which can be cumbersome and inaccurate.

Many systems lack the ability to automatically track and analyze food consumption in real-time, hindering users from making immediate adjustments to their eating habits. The accuracy and security of stored food data are crucial, especially when dealing with sensitive health information.

1.4 MOTIVATION

The primary motivation for developing food tracking systems using machine learning is to improve food safety, reduce waste, and enable personalized nutrition recommendations. By leveraging artificial intelligence and machine learning, these systems can analyze vast amounts of data related to food production, distribution, and consumption to identify trends, predict risks, and provide actionable insights.

Artificial intelligence can be trained to recognize specific contaminants or allergens in food products, helping to prevent food borne illnesses and protect consumers. Machine learning can track food products from farm to table, providing a complete and auditable record of their journey, enhancing food safety and traceability.

In today's fast-paced world, maintaining a healthy diet is more challenging than ever. While people are increasingly aware of the importance of nutrition, the process of manually tracking food intake is tedious, time-consuming, and often inaccurate. Existing apps require users to search through databases or scan codes, which fails for homemade meals, fresh foods, or complex dishes from a restaurant. This creates a significant gap between the desire to eat healthily and the practical ability to do so.

By simply taking a picture of their meal, users can instantly identify the food items, get an accurate calorie count, and receive personalized diet advice tailored to their unique health goals, whether it's weight loss, managing a condition like diabetes, or building muscle. Ultimately, the motivation is to transform dietary management from a burdensome chore into a seamless, intelligent, and supportive experience, making healthy living accessible and sustainable for everyone.

OBJECTIVE

To develop an AI-based food recognition system: The primary goal is to design a system that can automatically identify different food items from images using advanced image processing and deep learning algorithms such as YOLO v8. This eliminates the need for manual food entry and makes calorie tracking faster and easier.

To accurately calculate calorie and nutrient values: Once the food items are recognized, the system aims to calculate their calorie content and nutritional composition (carbohydrates, proteins, fats, vitamins, and minerals) using a linked nutrition database for precise dietary assessment.

To provide personalized diet recommendations: The system is designed to generate custom meal plans based on each user's personal information — such as age, weight, dietary preferences, health conditions, and fitness goals (e.g., weight loss or muscle gain).

To enable real-time tracking of dietary intake: The project aims to help users track and monitor their daily, weekly, and monthly food consumption, giving them insights into their eating habits and helping them stay aligned with their health objectives.

To improve health awareness and lifestyle management: By offering instant feedback and personalized suggestions, the system motivates users to make better food choices, promoting a healthier and more balanced lifestyle.

2. LITERATURE SURVEY

The purpose of the literature survey is to obtain a clear understanding of the existing problem in the particular area of the domain. By clearly understanding all the previous development and their works will provide the best way to obtain the perfect problem statement existing in the present condition.

[1] Insightson Biofilm Management for Enhanced Food Safety and Quality

Author: Gisele LaPointe

Published year: 2020

Proposed method: Microbial Analysis, DNA sequencing, biofilm testing.

Sampling: Dairy farm, factory surfaces, milk storage & transport.

Parameter: Cleaning efficiency, sanitizer effectiveness, biofilm resistance. temperature, environmental effects.

Advantage: Enhanced Food Safety: Better biofilm control reduces contamination. Improved Dairy

Quality: Monitoring microbial communities ensures product integrity. Effective Sanitation: Identifies best cleaning

practices for dairy equipment. Early Detection tracks microbial changes to prevent spoilage and disease.

Limitation: Detection Challenges: Low microbial load in some samples affects accuracy.

High Costs: Advanced DNA sequencing and analysis require resources.

[2] Computer Vision and Deep Learning in Insects for Food and Feed Production

Author: Sarah Nawoya ,Frank Ssemakula ,Roseline Akol,Quentin Geissmann .

Proposed method: Computer Vision (CV) and Deep Learning (DL).

Proposed year: 2018.

Parameter: Size, growth stages, weight estimation, nutritional Content, analysis protein, fat, and moisture levels using spectroscopy.

Advantage: Enhances automation in insect farming, reducing labor costs. Improves efficiency and scalability in production. Enables real-time monitoring of insect growth and behavior. Supports sustainable protein production for food and feed.

Limitation: High computational costs for deep learning models. Variability in insect morphology affect accuracy.Need for large annotated datasets for training.

[3] Enhancing Optical Non-Destructive Methods for Food Quality and Safety Assessments with Machine Learning Techniques.

Author: Xinhao Wang, Yihang Feng, Yi Wang, Honglin Zhu

Proposed method: Integration of optical non-destructive techniques (RGB imaging, hyperspectral imaging, NIR spectroscopy) with machine learning (ML).

Proposed year:2015

Parameter: Optical Techniques: RGB imaging, hyperspectral imaging, NIR spectroscopy. Food Quality Indicators: Texture, color, chemical composition, microbial contamination.

Advantage: Non-destructive food analysis. Need for large annotated datasets for ML training. Preserving sample integrity. Faster and more accurate quality and safety assessments. Automation of grading, sorting, and contamination detection.

Limitation: High computational cost for processing large datasets. Variability in food matrices affects model.

[4] Improving Healthy Food Recommender Systems through Heterogeneous Hypergraph Learning

Author: Nidhi Sharma, Md Arafatur Rahman ,Jasni Mohamad Zain ,Md J.F.Alenazi.

Proposed method: Utilizes Heterogeneous Hypergraph Learning (HFRS-HHL) with Graph Neural Networks (GNNs), Hypergraph Convolution, and Attention Mechanisms

Proposed year:2022.

Parameter: User Preferences & Ratings Capturing food choices and user behavior. Food and Ingredient Relationships Understanding ingredient interactions. Hypergraph Weights & Similarity Scores, Dynamic adjustments for accuracy.

Advantage: Improves personalized food recommendations based on user behavior. Captures complex relationships between users, food, and ingredients. Leverages dynamic hypergraph learning for evolving food preferences. Enhances recommendation accuracy compared to traditional models.

Limitation: High computational complexity due to dynamic hypergraph adjustments. Scalability challenges for large datasets. Requires large, labeled datasets for accurate prediction.

2.1 COMPARISON TABLE OF LITERATURE SURVEY

TITLE	AUTHORS	PROPOSED METHOD	ADVANTAGES	DISADVANTAGES
Predicting Food Intake from Food Reward and Biometric Responses to Food Cues	Hanne Pedersen, Lars Jorge Diaz, Kim Katrine Bjerring Clemmensen	Mixed-Effects Random Forest (MERF) Approach using machine learning for food intake prediction	Combines biometric and food reward data, helps in personalized nutrition, provides objective insights	Low prediction accuracy, controlled setting may not reflect real-life behavior
Computer Vision and Deep Learning in Insects for Food and Feed Production	Sarah Nawoya, Frank Ssemakula, Roseline Akol, Quentin Geissmann	Computer Vision (CV) and Deep Learning (DL) for automated insect monitoring	Enhances automation in insect farming, real-time monitoring, supports sustainable protein production	High computational costs, requires large annotated datasets, variation in insect morphology affects accuracy
Enhancing Optical Non-Destructive Methods for Food Quality and Safety Assessments with Machine Learning	Xinhao Wang, Yihang Feng, Yi Wang, Honglin Zhu	Integration of optical non-destructive techniques with machine learning	on-destructive food analysis, faster & more accurate assessments, automation in food safety	High computational cost, variability in food matrices affects accuracy, need for large training datasets

3. PROPOSED METHODOLOGY

3.1 BLOCK DIAGRAM AND WORKING

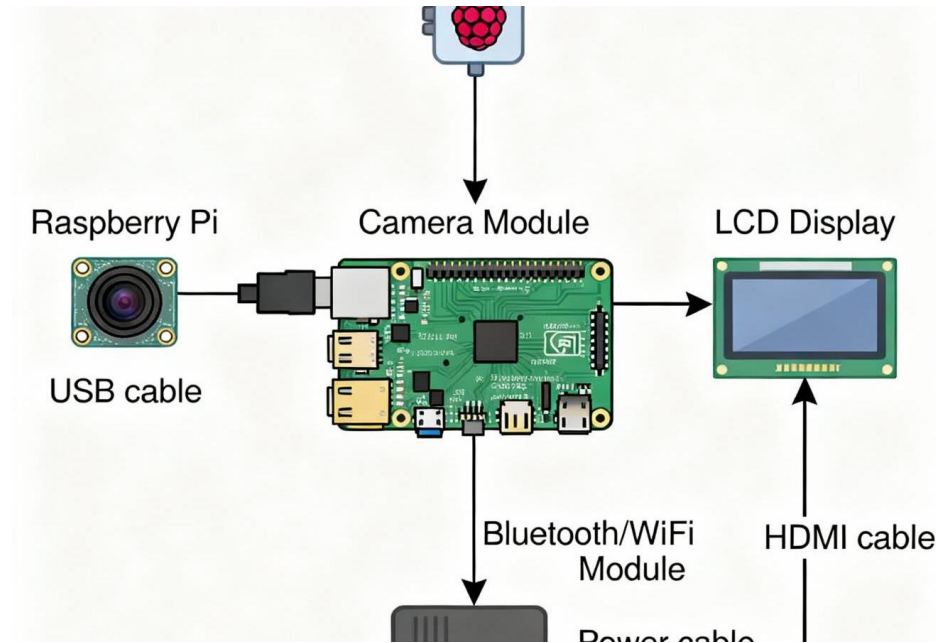


Figure 3.1 Block diagram

In a food tracking system like "NutriTrack," the **Raspberry Pi** serves as an integrated, all-in-one hardware platform that transforms the software concept into a functional physical device. It acts as the central hub, connecting and coordinating all the necessary components: a camera module is attached to capture images of meals, its processor runs the core artificial intelligence model (such as YOLO v8) to perform real-time food recognition and portion estimation directly on the device, and its computing capabilities are used to calculate nutritional information by cross-referencing identified foods with a database.

The Raspberry Pi Camera Module v2 serves as the "eye" of the food tracking system. It is directly connected to the Raspberry Pi via a dedicated ribbon cable. When a user places a food plate in view, the camera is triggered—either manually or automatically—to capture a high-resolution image of the meal.

A load cell amplifier is a critical component used to bring high accuracy to portion size estimation. In a food tracking system, a load cell (a weight sensor) is placed underneath a food platform or plate. When food is placed on it, the load cell generates a tiny electrical signal proportional to the weight. However, this signal is too weak and noisy for the Raspberry Pi to read directly.

The power supply is the fundamental component that provides the necessary electrical energy to operate the entire food tracking system. It acts as the system's "heart," delivering stable and consistent power to all critical hardware components. This includes powering the Raspberry Pi single-board computer, which acts as the system's brain the Camera Module that captures images of the food the Load Cell Amplifier and the load cell itself for precise weight measurement; and the Touchscreen Display that shows the results to the user.

The YOLO (You Only Look Once) model serves as the artificial intelligence "brain" for visual

recognition within the food tracking system. When an image from the camera is received, YOLO analyzes it in a single, fast pass to perform two critical tasks simultaneously: identification and localization. It identifies what each food item is (e.g., "banana," "slice of bread," "chicken breast") and draws a bounding box around each one, even in a plate with multiple items. This localization is crucial as it allows the system to estimate the portion size of each food item based on the dimensions of its bounding box. By instantly recognizing what the foods are and how much of each is present, YOLO provides the essential data that the system then uses to calculate accurate calorie and nutritional information.

The Micro SD card acts as the primary storage and "hard drive" for the food tracking system, particularly when it is built around a Raspberry Pi. It serves three essential functions: first, it stores the entire operating system (like Raspberry Pi OS) and all the necessary software, including the Python code, the YOLO AI model, and the nutritional database.

Flask is used as the lightweight web framework that creates the system's user interface and application logic. It acts as the "control center," handling all communication between the user and the underlying AI components. When a user accesses the system through a web browser, Flask serves the webpage that allows them to upload a food image.

3.2 FLOW CHART

3.2.1 FLOWCHART FOR FOOD TRACKING SYSTEM USING MACHINE LEARNING

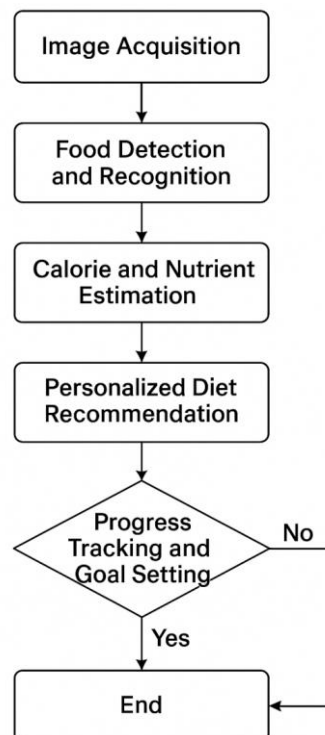


Figure 3.2.1: Flowchart for project

The operational flow of the NutriTrack system begins when a user, after logging into the application, captures or uploads an image of their meal. This image is first preprocessed to enhance its quality and is

then analyzed by the YOLO v8 deep learning model, which identifies each food item and estimates its portion size using bounding boxes. This data is passed to a nutrition calculation module, which cross-references the identified foods with a comprehensive nutritional database to determine the total calorie count and macronutrient breakdown for the meal. Simultaneously, the system retrieves the user's personal profile—including their health goals and dietary restrictions—from the user database.

This information is synthesized by a personalized recommendation engine, which generates tailored feedback and meal suggestions. The final results, including the identified foods, precise calorie information, and personalized advice, are displayed on the user's dashboard. Finally, all this data is logged into a tracking database, creating a historical record that enables progress monitoring and allows the system to refine its future recommendations, completing a continuous feedback loop for sustained dietary management.

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3.3. CIRCUIT DIAGRAM

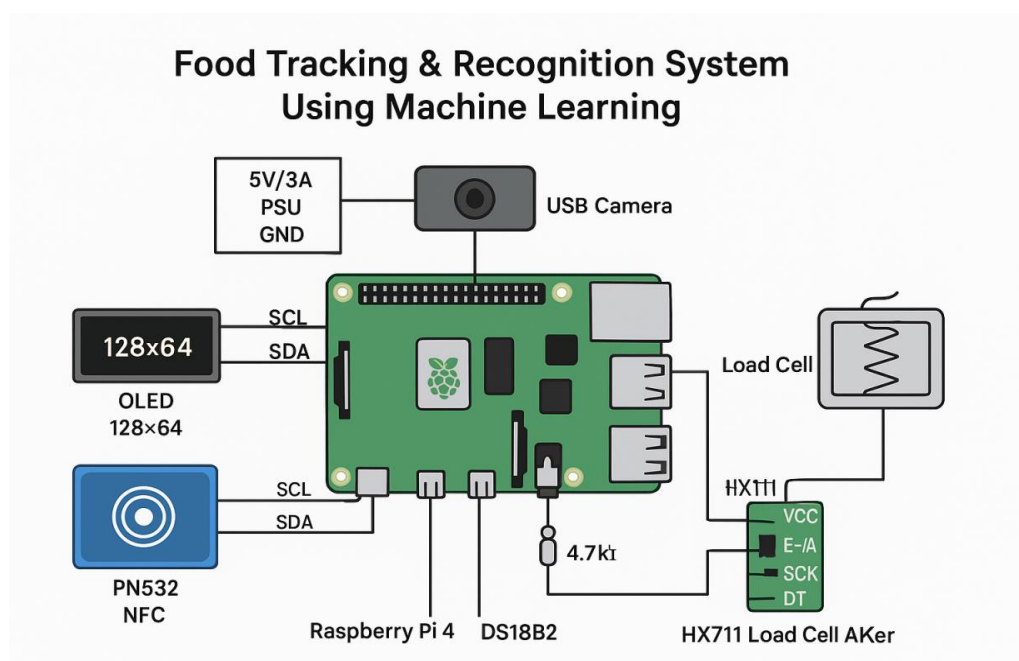


Fig 3.3: Circuit Diagram

The circuit diagram for the Foodtracking system illustrates how all hardware components are interconnected, with the Raspberry Pi 4 serving as the central processing hub. Power is supplied to the entire system via a 5V USB-C power adapter connected to the Pi. The Raspberry Pi Camera Module v2 is attached directly to the Pi's dedicated Camera Serial Interface (CSI) port, enabling high-speed image capture for food analysis.

For precise weight measurement, a load cell (placed under a food platform) is connected to an HX711 load cell amplifier, which then communicates weight data to the Pi via the General-Purpose Input/Output pins.

A touchscreen display is connected either through the Pi's HDMI and USB ports for displays with separate touch interfaces, or directly via the Display Serial Interface (DSI) for official Pi touchscreens, serving as the user interface for input and output.

All these components are powered through the Pi, either via its input/output pins (for the HX711) or their respective ports, creating an integrated circuit where the Raspberry Pi coordinates data flow from the camera and load cell, processes it, and presents the results on the display.

4. COMPONENTS REQUIRED

HARDWARE REQUIREMENTS:

3.4.1 Raspberry pi 4 model b



Fig 3.4.1 Raspberry Pi 4 Model

Raspberry Pi 4 Model B serves as the central computational and coordination hub, integrating all hardware and software components into a single, functional unit. Its powerful quad-core processor and substantial RAM (4GB or 8GB) are crucial for running the Python-based application and executing the YOLO v8 deep learning model with sufficient speed to identify food items and estimate portions from the images captured by the Raspberry Pi Camera Module v2, which is connected via the Pi's dedicated CSI port. The Pi's GPIO pins are used to read precise weight data from the HX711 load cell amplifier, allowing the system to combine visual analysis with accurate mass measurement for superior calorie calculation. Furthermore, the Pi's dual-band Wi-Fi enables it to fetch updated nutritional information from online databases.

After processing, the Pi leverages its connectivity features: its built-in dual-band Wi-Fi allows it to query cloud-based nutritional databases for the most up-to-date calorie and nutrient information, while its Micro-HDMI or DSI display output renders the complete user interface—showing identified foods, calorie counts, and personalized recommendations—on a connected touchscreen. By unifying control over the camera, sensor, AI processing, and display, the Raspberry Pi 4 transforms a collection of discrete components into a seamless, self-contained dietary analysis appliance, demonstrating a perfect application of edge computing in personalized health technology.

3.4.2 USB power supply



Fig 3.4.2 USB POWER SUPPLY

This communicate the information to the user, aiding in navigation or interaction with their environment. The power supply is a critical component that provides stable electrical power to the Raspberry Pi, which acts as the central brain of the entire food tracking system. Using a 5V USB-C power adapter, it delivers the necessary energy to boot the Raspberry Pi's operating system and run all its processes. Without this consistent power, the Pi cannot function, meaning it would be unable to receive data from the camera module for capturing food images, process information from the load cell amplifier for weight measurement, or drive the touchscreen display to show results to the user. Essentially, the power supply is the foundational element that energizes the Raspberry Pi, enabling it to coordinate all other hardware components and perform the complex tasks of food recognition, calorie calculation, and user interaction seamlessly.

3.4.3. Camara noir v2

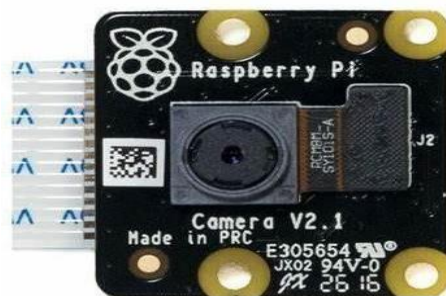


Fig 3.4.2 Camera module

The Raspberry Pi Camera Module V2 (Noir) is an 8-megapixel camera designed for use with Raspberry Pi. It uses a Sony IMX219 sensor, which allows it to capture high-quality images and videos. Unlike regular cameras, the Noir version doesn't have an infrared filter, making it ideal for low-light environments and night vision applications when paired with infrared lighting.

The Raspberry Pi Camera Module v2 serves as the "eye" of the food tracking system. It is directly

connected to the Raspberry Pi via a dedicated ribbon cable. When a user places a food plate in view, the camera is triggered—either manually or automatically—to capture a high-resolution image of the meal. This image is then instantly sent to the Raspberry Pi's processor, where the food recognition AI software (like the YOLO v8 model) analyzes it to identify individual food items and estimate their portion sizes based on visual cues. Essentially, the camera module is the critical input device that captures the raw visual data, enabling the entire automated process of food identification and subsequent calorie calculation.

3.4.4 LOAD CELL SENSOR

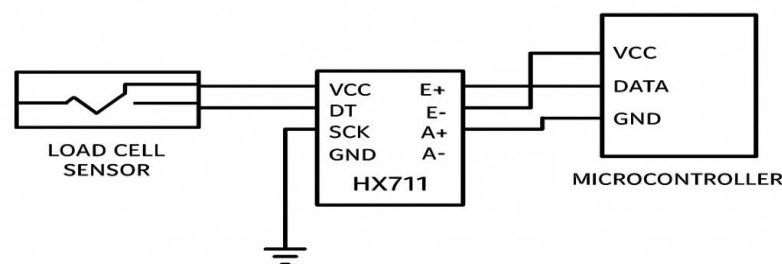


Fig 3.4.3 Load Cell Sensor

A load cell sensor is a type of transducer used to measure weight or force by converting mechanical pressure into an electrical signal. It works on the principle of strain gauge technology, where the strain gauge deforms slightly when a load or force is applied. This deformation changes its electrical resistance, which is then converted into a small voltage signal. Since this signal is very weak, it is amplified using an HX711 amplifier module before being sent to a microcontroller or processing unit such as a Raspberry Pi.

The Raspberry Pi uses a load cell sensor to bring precise, weight-based accuracy to portion size measurement. The load cell, which is a sensor that changes its resistance when force is applied, is placed under a food platform. When a plate of food is placed on it, the load cell generates a very weak electrical signal corresponding to the weight. This signal is too faint for the Pi to read directly. Therefore, an HX711 amplifier is used, which connects to the Raspberry Pi's GPIO pins. The HX711 amplifies and converts the load cell's analog signal into a clean digital signal.

The Raspberry Pi then reads this digital data via its GPIO pins, translating it into an exact weight in grams or ounces. By combining this accurate weight with the type of food identified by the camera and AI, the system can calculate a far more reliable calorie and nutritional value than by using visual estimation alone.

3.4.5 LOAD CELL AMPLIFIER

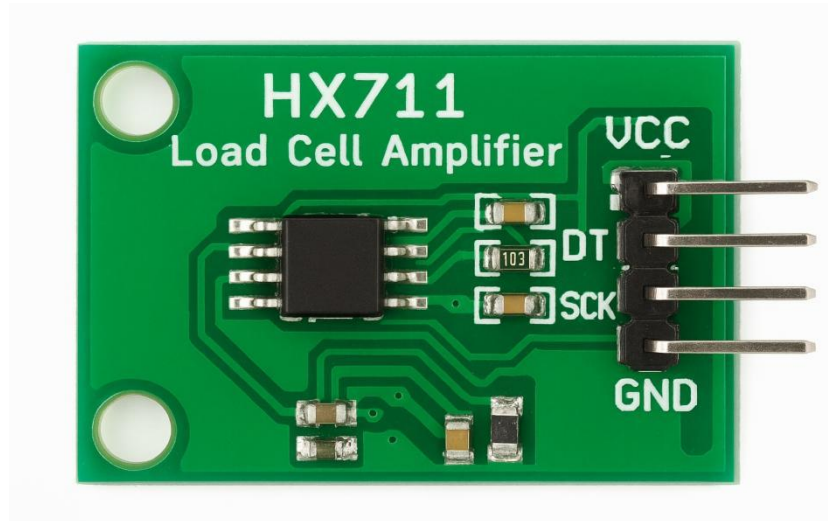


Fig 3.4.4 Load Cell Amplifier

A load cell amplifier, such as the HX711 module, is an essential electronic component used to amplify and convert the weak analog signal generated by a load cell sensor into a strong, readable digital signal. Since load cells produce output in the millivolt range, this signal is too small for most microcontrollers to detect directly. The amplifier boosts this signal while maintaining its accuracy and stability. The HX711, a popular 24-bit analog-to-digital converter (ADC), is specifically designed .

A load cell amplifier is a critical component used to bring high accuracy to portion size estimation. In a food tracking system, a load cell (a weight sensor) is placed underneath a food platform or plate. When food is placed on it, the load cell generates a tiny electrical signal proportional to the weight. However, this signal is too weak and noisy for the Raspberry Pi to read directly. The load cell amplifier bridges this gap: it takes this weak signal, amplifies it, and filters out the noise, converting it into a clean, strong, and readable digital signal. The Raspberry Pi can then read this precise weight data. By combining this exact weight from the load cell amplifier with the food type identified by the camera, the system can calculate a far more accurate calorie and nutritional value than by using image analysis alone.

SOFTWARE REQUIREMENTS:

[1] Operating system : Windows 10 Pro. /Mac Os:

The Operating System (Windows 10 Pro/macOS) serves as the fundamental software platform that manages all the hardware and software resources of the development and testing environment. It provides the essential foundation upon which the entire food tracking system is built and run. The OS is responsible for executing the Python programming language, which is used to code the core application logic, the YOLO v8 AI model for food recognition, and the Flask web framework that creates the user interface. It also manages the installation and operation of necessary libraries, drivers for hardware like cameras, and the connection to databases.

In essence, the operating system acts as the crucial intermediary layer that allows the developers to write, test, and run the application software that communicates with the hardware to deliver the complete food tracking functionality to the end-user.

[2] Coding Language: Python, HTML, CSS,JS:

Coding languages are tools used to create instructions that computers can understand and execute. The languages mentioned—**Python, HTML, CSS, and JavaScript (JS)**—each serve a distinct purpose in web development:

HTML (HyperText Markup Language): This is the fundamental language for creating web pages. It defines the structure and content of a page using tags, such as headings, paragraphs, links, and images.

CSS (Cascading Style Sheets): This language controls the presentation and visual styling of the content defined in HTML. It determines how elements look, including their colors, fonts, layout, and responsiveness on different screen sizes.

JavaScript (JS): This is a programming language that enables interactive elements on a web page. It handles dynamic behavior, such as responding to user clicks, validating form data, and communicating with servers without reloading the page.

Python: While versatile and used for many applications including backend web development, data science, and automation, within the context of the other listed languages, it is often used on the server-side to manage application logic, databases, and authentication, complementing the client-side technologies of HTML, CSS, and JavaScript

[3]Web Framework: Flask

Flask is a popular, open-source Python web micro-framework that provides the essentials for building web applications quickly and with a high degree of flexibility. Unlike full-stack frameworks like Django, Flask is minimalistic by design, offering a simple core that can be easily extended with third-party libraries. When a user accesses the system through a web browser, Flask serves the webpage that allows them to upload a food image.

Once an image is submitted, Flask's backend code coordinates the entire process: it takes the image, passes it to the YOLO model for food recognition, retrieves the results, calculates the nutrition by querying the database, and then dynamically generates a new webpage to display the final output (food labels, calories, and recommendations) back to the user. Essentially, Flask provides the structure to turn the complex AI and data processing into a simple, interactive web application.

4. IMPLEMENTATIONS**1. Overview**

The project implements an AI-powered system called NutriTrack that identifies food items from images, measures calories, and provides personalized diet recommendations. It uses deep learning (YOLO v8) for food recognition and Flask for web deployment.

2. Implementation Steps**a. Image Acquisition Module**

Users upload or capture food images using a camera or file upload interface. These images serve as the input for recognition.

b. Food Detection and Recognition

The system uses YOLO v8, a real-time object detection algorithm, to identify multiple food items in a single image.

The model is trained on a labeled food dataset containing various cuisines and ingredients.

YOLO detects each food item and draws bounding boxes around them.

c. Calorie Measurement Module

After recognition, the system queries a nutrition database (e.g., USDA or custom dataset) to find calories and nutrients (carbs, proteins, fats, vitamins).

YOLO's bounding boxes help estimate portion size, improving calorie estimation accuracy.

d. Personalized Diet Recommendation Module

Uses user data (age, weight, health conditions, goals) to recommend meal plans.

AI models analyze daily intake and suggest balanced diets for goals like weight loss or fitness.

The system continuously tracks and updates recommendations based on real-time data.

e. Progress Tracking and Goal Setting

Users can view their daily, weekly, and monthly reports.

The app adjusts targets and meal recommendations according to progress.

3. Technology Stack

Backend: Python

Frontend: HTML, CSS, JavaScript

Framework: Flask

Algorithm: YOLO v8 (for food recognition)

Database: Nutritional dataset or API integration

Hardware: i3 processor, 4 GB RAM minimum

4. Key Advantages

Real-time food detection and calorie feedback.

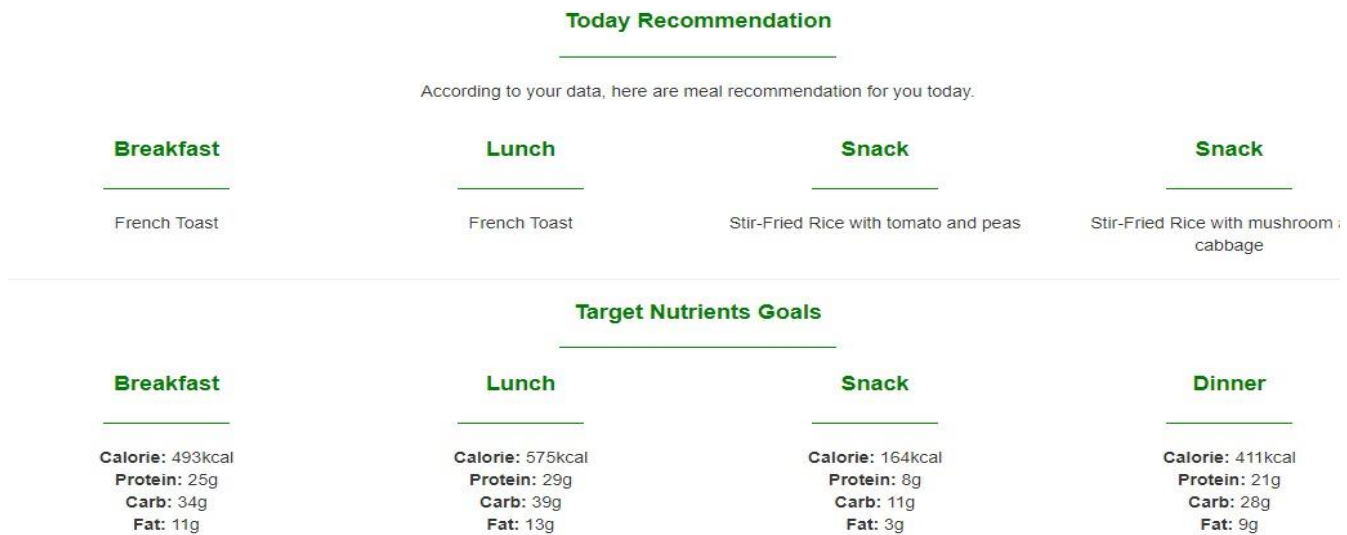
High accuracy in recognizing multiple food items.

Personalized meal recommendations based on user goals.

Works efficiently even on mobile or low-resource systems.

5. Outcome

The final system provides an automated, user-friendly diet tracking solution that recognizes food, calculates calories, gives personalized meal advice, and monitors progress — promoting healthy eating habits.



Food Recommendations



OUTPUT OF TESTED IMAGE

Reference

1. C. Liu, Y. Cao, Y. Luo, G. Chen, V. Vokkarane, and Y. Ma, “DeepFood: Deep learning-based food image recognition for computer-aided dietary assessment,” 2016 IEEE International Conference on Smart Data (SmartData), Chengdu, China, 2016, pp. 37–43, doi: 10.1109/SmartData.2016.18.
2. M. F. Vasiloglou, Y. Lu, and S. Mougiakakou, “An artificial intelligence-based system to assess nutrient intake for hospitalized patients,” IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 9, pp. 2550–2561, Sept. 2020, doi: 10.1109/JBHI.2020.2966998.
3. L. Bossard, M. Guillaumin, and L. Van Gool, “Food-101 – Mining discriminative components with random forests,” European Conference on Computer Vision (ECCV), Zurich, Switzerland, 2014, pp. 446–461, doi: 10.1007/978-3-319-10599-4_29.
4. R. Singh and P. Mehta, “Machine learning applications in nutrition and diet monitoring,” Journal of Artificial Intelligence Research, vol. 9, no. 3, pp. 45–52, 2020.
5. T. Lu, X. Zhang, and J. Zhao, “Automatic food recognition using deep convolutional neural networks with self-attention mechanism,” Human-Centric Intelligent Systems, vol. 4, no. 2, pp. 171–186, 2024, doi: 10.1007/s44230-023-00057-9.
6. S. Jayaraman and S. Karthikeyan, “Food image recognition using convolutional neural networks,” International Journal of Computer Applications, vol. 183, no. 2, pp. 25–30, 2021, doi: 10.5120/ijca2021921514.
7. A. A. Muhammad, N. H. Zakaria, and S. Abdullah, “A comprehensive survey of image-based food recognition and volume estimation methods for dietary assessment,” Healthcare, vol. 9, no. 12, pp. 1676, 2021, doi: 10.3390/healthcare9121676.

SDG REALTED TO PROJECT**SDG 2: Zero Hunger**

Helps in monitoring nutritional intake.

Can be extended to fight malnutrition and undernutrition. Supports balanced diets and food awareness.

SDG 3: Good Health and Well-being

Promotes healthy eating habits and lifestyle improvements.

Prevents obesity, diabetes, and cardiovascular diseases through diet tracking.

SDG 12: Responsible Consumption and Production

Encourages mindful eating and reduces food waste by portion estimation.

Helps individuals make sustainable food choices.

PROGRAM OUTCOMES (PO)	
PO1	Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
PO2	Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.
PO3	Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
PO4	Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO5	Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modelling to complex engineering activities with an understanding of the limitations.
PO6	The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
PO7	Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
PO8	Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
PO9	Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
PO10	Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11	Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
PO12	Life-long learning: Recognize the need for and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

PROGRAM SPECIFIC OUTCOMES (PSO)

PSO1	Develop the components for analog and digital systems, communication systems, control and signal processing systems using acquired knowledge of basic skills and various design tools.
PSO2	Formulatethe solution for interdisciplinary problems through acquired programming knowledge in the respective domain by complying real-time constraints.