Deep Learning-Based Food Recognition and Calorie Prediction Using Raspberry PI

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ABSTRACT: This paper presents automated food recognition and calorie estimation system implemented using a Raspberry Pi as the central processing unit. The system integrates a camera module to capture food images, which are processed in real time to identify food items and estimate their nutritional values. The captured images undergo pre-processing and feature extraction, followed by analysis using machine learning algorithms trained on diverse food datasets.The system classifies food types, estimates portion sizes, and calculates calorie content based on standard nutritional databases. The processed results are displayed on an LCD screen, providing instant feedback to users regarding their dietary intake. Designed as a standalone and portable solution, the system operates on a standard power supply, making it cost-effective and suitable for everyday use.This work demonstrates the practical implementation of computer vision and nutritional analysis on embedded platforms, offering an efficient and accessible approach for real-time dietary monitoring and calorie management.

*KEY WORDS:*Food Recognition, Calorie Estimation,RaspberryPi, Computer Vision,Deep Learning, Convolutional Neural Networks (CNN) ,Nutritional Analysis.

1. INTRODUCTION

Food object recognition has emerged as a significant research area due to its ability to provide objective analysis of dietary habits and eating behaviour. Monitoring food intake and understanding nutritional values play a crucial role in maintaining overall health, as diet directly influences metabolism, blood composition, and body condition. Traditionally, dietary assessment has relied on consultations with nutritionists and manual tracking methods, which can be time-consuming and subjective. However, the rapid advancement of multimedia technologies, internet accessibility, and artificial intelligence has led to the development of automated and on-demand dietary monitoring systems.With the growing use of smartphones and AI-based applications, food recognition technologies are becoming popular for tracking diet and managing health conditions. These systems help users monitor food intake and maintain a balanced diet by providing real-time nutritional insights.In this work, a food detection system is developed using a camera module with a Raspberry Pi and Python. The system captures food images and processes them using the YOLO deep learning algorithm, a fast CNN-based model for real-time detection and classification. The identified food items are then displayed on an LCD screen, enabling quick and efficient dietary monitoring.The proposed system is designed with two primary objectives: accurate detection and classification of food items, and estimation of their calorie content using visual features and pre-trained nutritional datasets. Despite challenges such as variations in food appearance, lighting conditions, occlusion, and complex backgrounds, the integration of deep learning, image processing techniques, and embedded hardware provides a scalable and automated solution. This approach facilitates real-time dietary monitoring, simplifies meal logging, and enhances user awareness of nutritional intake. Ultimately, AI-based food analysis offers an intelligent and practical tool for promoting healthier eating habits, effective weight management, and improved overall well-being.

2. LITERATURE SURVEY

YogeshvariMakwana, SaileshIyer, and SanjuTiwari: They developed a deep CNN-based system for food recognition and calorie estimation, achieving high accuracy in classification and improved calorie prediction. Their work highlighted the importance of large datasets and incorporated portion size estimation using bounding boxes, while also focusing on lightweight models suitable for real-world and mobile applications.

Banusharath K A, Karan Karthick R, Karthiban B, and Manimegalai C T: They proposed a CNN-based automated food recognition system with enhanced accuracy through optimized preprocessing and feature extraction techniques. Their model supports real-time analysis and focuses on both single and mixed food items, with improvements in calorie estimation and computational efficiency for practical dietary monitoring.

3. PROPOSED SYSTEM

The proposed food object identification system is designed using a Raspberry Pi controller, camera module, and Python programming environment integrated with the YOLO (You Only Look Once) deep learning algorithm for accurate and real-time food detection. In this system, the camera module connected to the Raspberry Pi captures images of food items placed in front of the camera. These images are then processed using Python-based image processing libraries and a pre-trained YOLO model. YOLO is a fast and efficient object detection algorithm that can detect and classify multiple objects in a single image with high accuracy. The Raspberry Pi acts as the central processing unit, where the captured images are analysed to extract important visual features such as shape, colour, and texture. The YOLO model compares these features with trained datasets to identify different types of food items. Once the food object is detected and classified, the system can estimate the approximate calorie value or provide information about the food item. The processed results are then displayed on an LCD screen or connected display for easy monitoring by the user. This system provides real-time food recognition and dietary monitoring, helping users track their eating habits and make healthier food choices. Compared to traditional systems, the proposed approach offers better accuracy, faster detection speed, and the ability to handle multiple food objects simultaneously. By combining deep learning, image processing, and embedded hardware like Raspberry Pi, the proposed system provides an intelligent and automated solution for food identification and nutritional awareness.

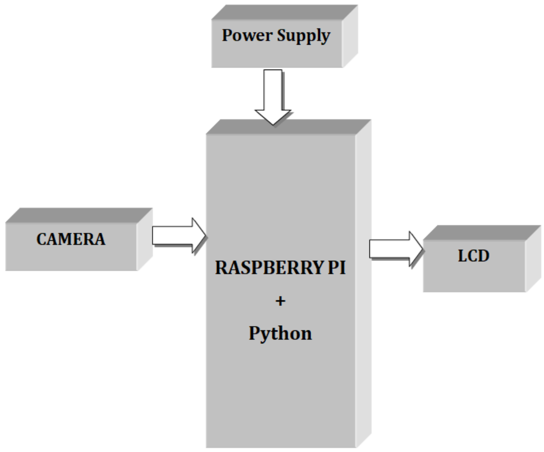

Fig 1: Proposed System

3.1 Block Diagram Expiation

The block diagram represents a Raspberry Pi–based image processing system using Python**. The** power supply provides the required electrical energy to the Raspberry Pi to ensure stable operation of all connected components. A camera module is connected to the Raspberry Pi to capture real-time images or video data from the environment. The Raspberry Pi acts as the central processing unit, where Python programming is used to process the captured images, perform analysis, or run computer vision algorithms. After processing the data, the output results are displayed on the LCD display, which provides visual information to the user. This architecture enables efficient image capture, processing, and display in real time, making it suitable for monitoring, surveillance, or smart automation applications. In this system, the Raspberry

Pi GPIOpins are used to interface with the camera and LCD display. The camera module is typically connected through the CSI (Camera Serial Interface) port of the Raspberry Pi, which allows high-speed image data transfer between the camera and the processor. The LCD display can be connected through the GPIO pins**,** I2C interface, or HDMI port, depending on the display type. The power supply provides 5V input to the Raspberry Pi through the micro-USB or USB-C power port**,** which powers the board and its peripherals. The GPIO pins also provide 3.3V and ground connections required for external devices. Through these pins, the Raspberry Pi communicates with external hardware components and controls the overall system operation while Python software processes the incoming data and sends the output to the display

I) Input: Cameras and sensors are installed along the farm boundaries, where sensors detect animal movement within a 30 m range and trigger the camera (50 m range) via a microcontroller. The camera, powered by battery and solar energy, captures images of the detected area and sends them for further processing.

II) Processing: The captured images are transmitted to a PC, where they are compared with a stored image database using indexing and retrieval functions. The system processes the query image to identify whether the detected object is a threat.

III) Food Recognition & Calorie Estimation:

Object detection techniques are used to identify food items based on visual features such as color, shape, and texture. The system employs the YOLO algorithm, a fast CNN-based model that detects and classifies food items in real time using bounding boxes. CNN layers extract important image features, and once the food is recognized, calorie values are estimated using a nutritional database. This integration enables accurate and real-time food recognition and calorie estimation.

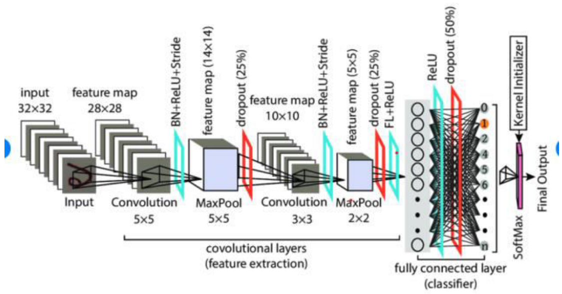

Fig 2: CNN Based YOLO Structure

3.2 Flow Chart

The flowchart of the Food Calorie Estimation System begins with capturing a food image using a camera. The captured image is then sent for image pre-processing**,** where noise is removed and the image is prepared for analysis. Next, the processed image is given to the YOLO-based Convolutional Neural

Network (CNN) model, which detects and identifies the food items present in the image. If the food item is successfully recognized, the system proceeds to estimate the calorie value by comparing the detected food with a predefined nutritional database. Finally, the calculated calorie information is displayed on the LCD screen for the user. If the food item is not detected, the system repeats the detection process until a valid identification is achieved. This process enables quick and automatic estimation of calorie intake from food images.

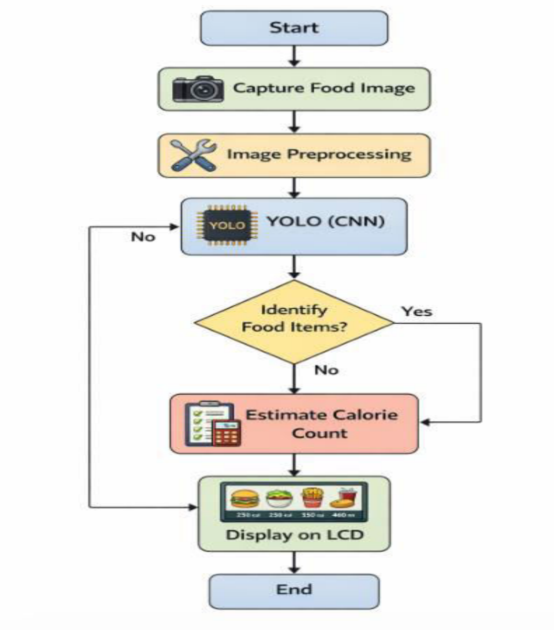

Fig 3: Proposed System flow chart

4. RESULTS AND DISCUSSION

The system successfully uses a Raspberry Pi and YOLO-based CNN to detect food items and estimate calories in real time. It achieves good accuracy and fast processing, especially under proper lighting conditions.The model extracts visual features to classify food and display calorie values, though performance may slightly decrease with complex backgrounds or overlapping items.

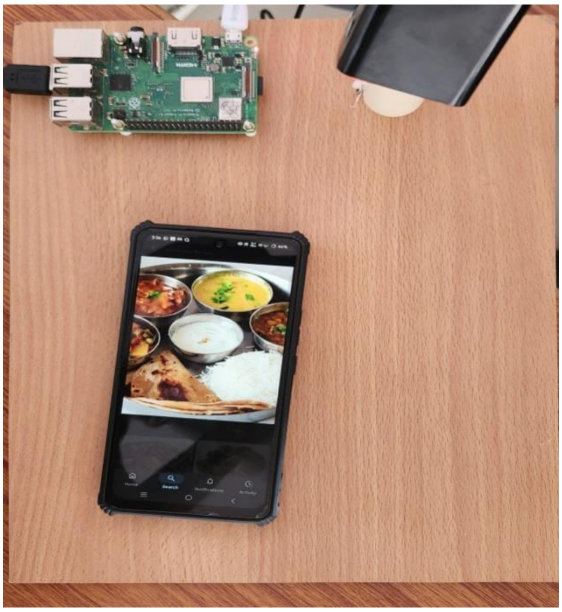

Fig 4: Hardware Implementation

The system uses a Raspberry Pi 3 with a USB webcam to capture real-time food images and process them using the YOLO model. It detects food items, estimates calorie values, and displays the results, enabling efficient and portable real-time dietary monitoring.

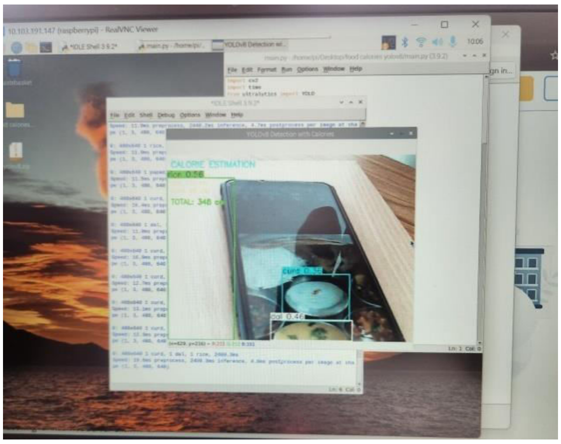

Fig5: Real-Time Detection Interface using VNC Viewer

The setup demonstrates real-time food recognition using a Raspberry Pi with output viewed remotely via VNC Viewer. The system detects food items from webcam input, displays bounding boxes with confidence scores, and estimates calorie values, allowing users to monitor results live from a connected laptop.

5. CONCLUSION

The food calorie estimation system using a camera, Raspberry Pi, and a YOLO-based Convolutional Neural Network (CNN) was successfully designed and implemented. The system captures images of food items and processes them using image pre-processing and deep learning techniques to identify the food type. After detection, the system estimates the calorie value by comparing the detected food item with a predefined nutritional database. The results are then displayed on an LCD screen for the user. The YOLO algorithm provides fast and efficient object detection, making the system capable of performing real-time analysis. Experimental results show that the system can detect and classify common food items with good accuracy under proper lighting conditions. Overall, the proposed system demonstrates that AI and computer vision techniques can be effectively used for automatic food recognition and calorie estimation, helping users monitor their daily dietary intake.

FUTURE SCOPE: The system can be enhanced by using larger and diverse datasets along with advanced deep learning models to improve food recognition accuracy. Integration with mobile apps, cloud platforms, and wearable devices can enable personalized diet tracking and health monitoring. Additionally, incorporating 3D imaging or weight sensors can improve portion estimation and provide more accurate calorie calculations.

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