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Fruit Identification and Calorie Estimation Technology based on Deep Learning (November 2024)

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ABSTRACT With the advent of an aging society, there is a growing emphasis on health and nutrition, particularly in the importance of calorie control. The recommended daily calorie intake is 2,500 kcal for men and 2,000 kcal for women, with varying requirements based on age and health conditions. For instance, children's daily caloric needs depend on their age, elderly individuals require approximately 30 kcal per kilogram of body weight, and long-term bedridden patients need around 25 kcal per kilogram. Precise calorie calculation is essential for individuals aiming to maintain an ideal physique or manage conditions such as hypertension, hyperlipidemia, and hyperglycemia. Addressing this need, this study develops a system integrating image recognition and weight sensing, utilizing a Raspberry Pi 4B-driven camera and an HX711 electronic scale to identify fruit types, measure weight, and calculate calorie content. The study evaluates the performance of five pre-trained models (MobileNet-v2, MobileNet-v3, DenseNet-201, DenseNet-121, Inception-v3) using metrics such as accuracy, recall, and F1 Score to select the optimal model for fruit recognition. By incorporating user-specific data such as gender, age, height, and weight, the system provides daily calorie recommendations to assist users in aging societies in improving dietary habits and achieving health management goals.

INDEX TERMS Image recognition, weight sensing, calorie calculation, pre-trained models

1. INTRODUCTION

In an era of rapid technological advancement, smart living has become a key aspiration for modern society. As living standards improve, public awareness of health has steadily increased, with dietary management receiving particular attention. Fruits, being rich in nutrients and low in calories, are an essential component of a healthy diet. However, the challenge of controlling calorie intake while ensuring adequate nutrition has become a pressing issue for many individuals.

To address this need, this study proposes a smart system based on image recognition and weight sensing to identify fruit types and calculate their calorie content. Five mainstream pre-trained models (MobileNet-v2, MobileNet-v3, DenseNet-201, DenseNet-121, Inception-v3) were adopted and fine-tuned to meet the specific requirements of fruit recognition. These models were evaluated using accuracy, recall, and F1 Score metrics to determine the optimal model for practical implementation.

The proposed system integrates a Raspberry Pi-driven camera with an HX711 electronic scale to enable automatic fruit identification and weight measurement through image recognition technology. By incorporating user-specific parameters such as gender, age, height, and weight, the system calculates recommended daily calorie intake and provides personalized dietary suggestions. This approach not only helps users manage their daily calorie consumption with precision but also contributes to fostering healthier dietary habits among elderly individuals in aging societies, thereby enhancing their quality of life.

1. Related Works

In recent years, deep learning has significantly advanced applications in image recognition, object detection, and health monitoring. The integration of pre-trained models, such as MobileNet and DenseNet, with sensors like HX711 for weight detection has enabled precise calorie estimation systems. Table I summarizes key related works that explore various approaches to image recognition, object detection, and calorie estimation, highlighting their technologies, models, datasets, and applications.

Table 1. Summary of Related Works

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **No.** | **Reference ID** | **Technology** | Model | Dataset | **Problem** |
| 1 | |  | | --- | |  |   [DXG+20] | Face Recognition | SSD | Custom Dataset | Face Recognition in complex conditions |
| 2 | [LXK+19] | Object Detection | SSD-ResNet | ImagNet2011 | |  | | --- | | Real-time Object Detection |  |  | | --- | |  | |
| 3 | [MMA+24] | Face Recognition | Faster R-CNN | ORL | High-accuracy Face Recognition |
| 4 | [LZ20] | Flower Classification | DenseNet + SVM | Oxford-17, Oxford-102 | Flower Classification |
| 5 | [GGL21] | Low-Quality Defect Recognition | GAN + Deep Learning | NEU | |  | | --- | |  |   Low-Quality Defect Reconstruction |
| 6 | [ZAW20] | UAV Remote Sensing | Faster R-CNN | Custom UAV Dataset | Building Recognition |
| 7 | [CYF+22] | Human Action Recognition | FCN + STN | UCF-101, HMDB-51 | Human Action Recognition |
| 8 | [TT19] | Handwritten Recognition | LeNet-5 | MNIST | Handwritten Numeral Recognition |
| 9 | [CLW20] | Face Recognition | Image Fusion | LFW | Occluded Face Recognition |
| 10 | [KYS+23] | Livestock Surveillance | YOLO | MS COCO | Livestock Monitoring |
| 11 | [YS23] | Biometric Systems | Alex Net | Custom Biometric Dataset | Multimodal Biometric Recognition |
| 12 | [WGL+23] | Object Detection | Mask R-CNN | FriesianCattle2017 | Cattle Recognition |
| 13 | [QPWR17] | Human Target Recognition | Fast-RCNN | Custom Service Robot Dataset | Human Target Recognition in robots |
| 14 | [TTL+22] | Emotion Recognition | GoogleLeNet | TESS | Speaker Emotion Recognition |
| 15 | [RYD+24] | Polyp Segmentation | SPPNet | CVC-ClinicDB | Medical Polyp Segmentation |
| 16 | [XYL20] | Text Image Recognition | SRR-GAN | IIIT5K | Low-Resolution Text Recognition |
| 17 | [WZ18] | Building Recognition | Faster R-CNN | PASCAL VOC2007 | Urban Building Recognition |
| 18 | [AB18] | Object Detection | DPM | KITTI | Driver Assistance Object Detection |
| 19 | [LLJ+24] | Visual Prosthesis Recognition | VGG | CIFAR-10 | Visual Prosthesis Recognition |
| 20 | [MCC+24] | Masked Face Recognition | CNN | LFW | Masked Face Recognition |

PROPOSED APPROACH

1. System Architecture

The proposed system integrates deep learning-based image recognition, weight sensing, and personalized calorie estimation. The overall architecture consists of four main components:

1. Image Recognition Module: Utilizes pre-trained deep learning models to identify fruit types from images.
2. Weight Measurement Module: Measures the fruit's weight using an HX711 electronic sensor.
3. Calorie Estimation Module: Calculates the calorie content of the identified fruit and determines the user's Total Daily Energy Expenditure (TDEE).
4. User Interface Module: Displays the fruit type, calorie information, and personalized dietary recommendations.

一張含有 黑色, 黑暗 的圖片

自動產生的描述

1. Model Selection and Evaluation

Five pre-trained models were evaluated to identify the best-performing architecture for fruit recognition:

1. MobileNet v2 and MobileNet v3: Known for their lightweight design, suitable for resource-constrained environments.
2. DenseNet121 and DenseNet201: Feature reuse capabilities allow for robust classification performance.
3. Inception v3: A computationally efficient model optimized for large-scale image datasets.

The models were compared based on:

* Accuracy: Measures the percentage of correctly identified fruit types.
* Recall: Assesses the ability to identify all relevant instances.
* F1 Score: Balances precision and recall to provide a comprehensive evaluation.

1. Calorie Estimation Process

The calorie estimation process integrates the fruit recognition and weight measurement modules to provide precise dietary information. The steps involved are detailed below:

1. Weight Measurement: The HX711 sensor captures the fruit's weight in grams. This value is crucial for determining the fruit’s calorie content.
2. Calorie Calculation: Each fruit type has a predefined calorie density (kcal/g) based on nutritional data. The calorie content is calculated as:

1. TDEE Calculation:

* The Total Daily Energy Expenditure (TDEE) is calculated using the Mifflin-St Jeor Equation:
  + BMR (Basal Metabolic Rate) is computed as:
  + Activity Factor values range from 1.2 (sedentary) to 1.9 (very active).

1. Remaining Calorie Calculation:
   * After consuming the fruit, the system calculates the user's remaining calorie allowance:
2. Workflow and User Interaction

The proposed system follows an intuitive and user-friendly workflow, as outlined below:

1. Fruit Placement:
   * The user places the fruit on the HX711 electronic scale. The system detects the fruit’s weight in real-time.
2. Image Capture:
   * A Raspberry Pi-driven camera captures an image of the fruit. The image is preprocessed (resized, normalized, and augmented) before being fed into the deep learning model.
3. Fruit Recognition:
   * The selected deep learning model processes the image to identify the fruit type with high accuracy.
4. Calorie and TDEE Calculation:
   * The system calculates the fruit’s calorie content and the user's TDEE based on the input parameters (age, gender, height, weight, and activity level).
5. Output Display:
   * The user interface provides:
     + Recognized fruit type and weight.
     + Calorie content of the fruit.
     + Remaining daily calorie allowance.

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