Food Image Recognition and Calorie Estimation Using Transfer Learning and Multi-Task Learning Approaches

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Overview

Introduction to Problem and Application

Mathematical View:

The model is fine-tuned by modifying the weight matrix W_t for specific food classification tasks:

$$L = L_0 + \alpha \cdot L_{\text{fine-tune}}$$

Where:

- L_0 is the original loss from ImageNet,
- $L_{\text{fine-tune}}$ is the loss for the food classification task. The model is optimized by minimizing the total loss.

Challenges:

- **Food Image Recognition:** High variability in food appearance (e.g., lighting, angles, overlapping items).
- **Calorie Estimation:** Estimating calories from a single image requires understanding portion sizes, ingredients,

Objective and Application

We aim to improve the accuracy of food image recognition and calorie estimation by utilizing Transfer Learning for better feature extraction and Multi-Task Learning (MTL) to handle both tasks in a single model.

Application: This project can be used in mobile health apps for automatic calorie tracking, making dietary management easier for users.

Contribution: By improving both tasks in a single, cohesive model, we provide a system that can analyze food images with high accuracy and deliver calorie estimations simultaneously.

State-of-the-art Literature related to the work

- **Dataset Preparation and Preprocessing:**
  - Download and clean the FoodX-251 dataset for food classification.
  - Custom dataset creation for calorie estimation, including calorie labeling.
  - Data Augmentation (Rotation, Cropping, Scaling).

Dataset	Classes	Total Images	Source	Food-type
ETHZ Food-101 [7]	101	101,000	foodspotting.com	Misc.
UPMC Food-101 [26]	101	90,840	Web	Misc.
Food50 [16]	50	5000	Web	Misc.
Food85 [15]	85	8500	Web	Misc.
CHO-Diabetes [4]	6	5000	Web	Misc.
Bettadapura et al. [5]	75	4350	Web, smartphone	Misc.
UEC256 [18]	256	at least 100 per class	Web	Japanese
ChineseFoodNet [10]	208	185,628	Web	Chinese
NutriNet dataset [22]	520	225,953	Web	Central European
Food-251	**251**	**158,846**	**Web**	**Misc.**

Figure: Datasets for food recognition
Source: IEEE 2019 FoodX-251: A Dataset for Fine-grained.

Multi Image-Based Estimation of Real Food Size for Accurate Food Calorie Estimation

Key Contributions:

- It focuses on 5 approaches for food calorie estimation methods like CalorieCam, AR DeepCalorieCam V2 and DepthCalorieCam .
- They achieved a 10% or less estimation error in food calorie estimation using stereo cameras and reference objects.

Limitation's:

- Hardware Dependency: The accuracy of calorie estimation is heavily reliant on specific hardware like stereo cameras and AR-based technologies. This makes the approach less accessible for users without such hardware.
- Reference Object Accuracy: Estimation depends on having reference objects like rice grains for calibration, which can be impractical in real-world scenarios.

Sharing Food with FoodLifeSavr Smartphone App

Key Contributions:

- The paper addresses food waste by developing a smartphone app that allows people to donate excess food to those in need.
- The focus is on the social impact of reducing food waste through real-time tracking and mobile app-based food sharing.

Limitation's:

- Focus on Social Impact: While the solution addresses food waste and sharing, it does not provide technical innovation in terms of food recognition or calorie estimation.
- Not Individualized: The approach does not deal with personalized food tracking or health improvements, which limits its application in individual nutrition.

Optimizing Food Allocation in Food Banks with Multi-agent Deep Reinforcement Learning

Key Contributions:

- The research focuses on optimizing food allocation in food banks using multi-agent deep reinforcement learning.
- It addresses food waste and inefficiencies in the food supply chain by applying reinforcement learning to allocate resources in food banks.

Limitation's:

- Focus: Optimizes large-scale food distribution, not image recognition or calorie estimation.
- Applicability: Effective for logistics, not for individual nutrition or food image analysis.

A Deep Learning NOVA Classifier for Food Images

Key Contributions:

- The paper introduces an approach to detect and classify food items into NOVA groups based on their level of processing.
- The deep learning model achieved a mAP of 0.90 for food detection and F1-score of 0.86 for NOVA classification.

Limitation's:

- Limited Detail: NOVA classifies foods as processed or unprocessed but lacks detailed nutritional info.
- Focus Issue: It doesn't analyze ingredients, which is crucial for accurate nutrition and calorie counts.
- Our Edge: We offer detailed ingredient recognition and calorie estimation, enhancing personalized health

A Dataset for Fine-grained Food Classification (2019)

Focus:

- Introduced the FoodX-251 dataset with 251 fine-grained food categories and 158k images, focusing on distinguishing visually similar foods.

Solution:

- Applied deep learning models and convolutional neural networks to train fine-grained classifiers.

Relevance:

- Building using transfer learning techniques to achieve higher accuracy.
- Combining fine-grained classification with calorie and nutritional estimation using multi-task learning for a more comprehensive recognition process.

Summary: How Our Work Stands Out

- **Multi-task Learning:** Many studies focus on calorie estimation or food classification in isolation. Our approach predicts calories and nutritional components simultaneously, offering more comprehensive insights.

- **Transfer Learning:** Using pre-trained models can improve accuracy with less training data, an advantage over earlier works that depend on large datasets.

- **Scalability and Flexibility:** Our approach can be implemented without reliance on specific hardware (e.g., stereo cameras), making it more applicable across a variety of devices.

Gaps in Current Literature

Limitations:

- Most models focus on either food recognition or calorie estimation, not both.
- Existing methods often rely on hardware like stereo cameras.

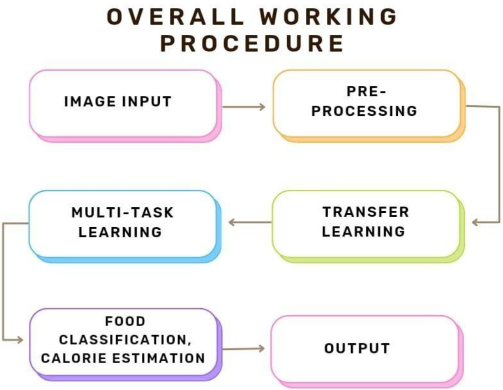
Our Contribution:

- Transfer Learning allows fine-tuning pre-trained models for higher accuracy.
- Multi-Task Learning combines both tasks, improving overall efficiency.

Proposed Methodology

Overview of the Methodology:

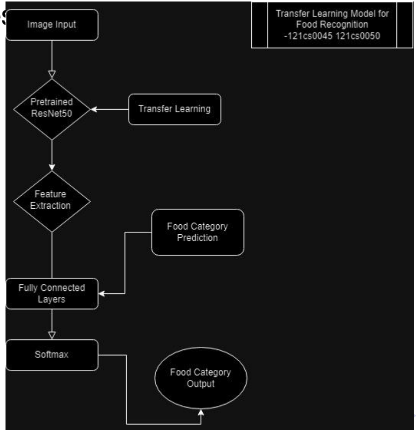
- Transfer Learning for food recognition.
- Multi-Task Learning for food category prediction and calorie estimation.



Transfer Learning Model (Food Recognition)

Model Architecture:

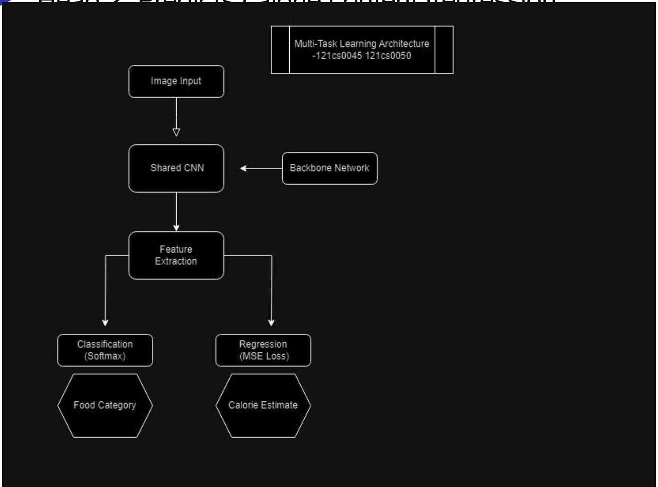
- Fine-tune a pre-trained ResNet50 model. On large datasets like ImageNet and fine-tuning them for specific tasks like food recognition.
- Dataset: FoodX-251 (158,000 images, 251 categories



Multi-Task Learning Architecture

Shared Architecture:

- Backbone: CNN (e.g., ResNet).
- Two Heads:
  - Head 1: Predicts food category (softmax).
  - Head 2: Predicts calorie content (regression



Multi-Task Learning in Computer Vision

Overview:

- Task 1: Food Classification
- Task 2: Calorie Estimation

Total loss is optimized by minimizing:

$$\min(L_{\text{classification}}(\theta_{\text{shared}}, \theta_{\text{food}}) + L_{\text{calorie}}(\theta_{\text{shared}}, \theta_{\text{calories}}))$$

Lclassification : Loss for food classification (cross-entropy loss).

Lcalorie : Loss for calorie estimation (mean squared error).

θshared: Shared model parameters.

θfood and θcalories : Task-specific parameters for food classification and calorie estimation respectively.

Calorie Estimation Methods

Deep Learning-Based Calorie Estimation (2022):

- Used CNNs to estimate calorie content by capturing food volume and contour from stereo images.
- Our method avoids specialized hardware, using standard 2D image inputs.

For calorie estimation:

$$\hat{y} = W \cdot f(x) + b$$

Loss function:

$$L = \frac{1}{n} \sum_{i} (y_i - \hat{y}_i)^2$$

Training and Evaluation

Training Details:

- For food recognition: Cross-entropy loss.
- For calorie estimation: Mean Squared Error (MSE).
- Adam optimizer with learning rate 1×10^{-4}.
- Dataset split: 80% training, 10% validation, 10% testing.
- Train for 50 epochs with early stopping.

Results

Expected Results:

- Data Augmentation: Applying data augmentation techniques (like rotation, scaling, and flipping) to improve model robustness.
- 5-10% improvement in food classification accuracy.
- Reduce's error in calorie prediction through MTL.

Plan for the Next 2 Months

Month 1:

- Data collection,Label Expansion and preprocessing.
- Fine-tune ResNet50 for food classification.

Month 2:

- Set up Multi-Task Learning architecture.
- Train and evaluate the model.

Till Now

Problem Statement Formulation:

- Finalized the problem statement and got approval from supervisor.

Literature Review:

- Reviewed relevant papers to understand state-of-the-art techniques.

Dataset Exploration:

- Evaluated and selected the FoodX-251 dataset.

Planning:

- Created a detailed project plan with objectives and methodologies.

Initial Work on Dataset:

- Preprocessed the dataset (data cleaning and preparation).
- Applied data augmentation techniques (rotation, scaling, flipping).

Future Work

Summary:

- This project improves food image recognition and calorie estimation using Transfer Learning and MTL.
- Future work may extend to predicting additional nutritional information or health-based recommendations.

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