DEEP LEARNING COURSE
PROJECT

NutriVision: Integrated Food Recognition, Calorie Estimation, and Recipe Recommendation System

Artificial Intelligence

Department

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Abstract

This study introduces an advanced deep learning system tailored for food recognition, offering users the option of obtaining calorie estimations or recipe recommendations based on input images. Positioned at the intersection of health informatics and computer vision, the project endeavors to elevate nutritional management capabilities. With a specific emphasis on reinforcing robust deep learning models, particularly leveraging the ResNet50 [1] architecture renowned for its adeptness in image classification, the project meticulously trains and validates using the extensive "Food-101" [2] dataset, ensuring a comprehensive spectrum of food item recognition.

Upon identifying food items from input images, the system seamlessly transitions to a phase of nutritional scrutiny, engaging external APIs for meticulous calorie estimation and recipe retrieval. This integration facilitates detailed insights into recognized food items, encompassing their caloric content and constituent ingredients. The amalgamation of expansive nutritional data with ResNet50's proficient image recognition heralds a noteworthy advancement in dietary tracking methodologies, completely addressing persisting concerns regarding precision, variety, and user accessibility in prevailing nutritional management tools. The project's framework encompasses an exhaustive continuum of data analytics, sophisticated image processing techniques, and a comprehensive exploration of optimal deep learning paradigms.

This research makes substantial contributions to the spheres of nutrition science, deep learning, and health informatics, signifying a notable stride toward advancement. Positioned to enhance health and dietary information management, this system aspires to empower users with comprehensive insights for making informed and healthier lifestyle choices. This endeavor marks a significant milestone in the evolution of comprehensive food recognition systems, paving the way for future strides in automation and enhanced user-centric convenience.

Introduction

Background and Context

The project is set at the intersection of health informatics [3] and computer vision, aiming to advance dietary management by leveraging technology. In today's health-conscious society, there is a growing need for accurate dietary tracking tools, especially those utilizing image recognition. While various technologies for food recognition exist, they often face limitations in accuracy, diversity of recognized items, and practical usability [4]. This project, situated at the forefront of health informatics and computer vision, seeks to bridge the gap between technological capability and practical dietary management needs, inspired by advances in generative adversarial networks and deep learning techniques [5]

Problem Statement

The primary challenge addressed by our project is the accurate recognition of a wide range of food items from images and the subsequent estimation of their caloric content. Existing technologies struggle with varying quality of images, diversity of food items, and accurate portion size estimation [6] – as well as the absence of a system integrating both calorie estimation and recipe recommendation. This project seeks to fill these gaps by developing a more robust model that can handle these challenges effectively, while joining the two essential features, drawing inspiration from advancements in deep convolutional networks and cross-modal retrieval techniques [7]. The key is to create a model that is not only robust but also adaptable to a variety of real-world conditions, incorporating techniques from aggregated residual transformations and independent component analysis.

Research Questions

• How can deep learning architectures be optimized for accurate food recognition from images?

• What methods can be employed to accurately estimate the calorie content of identified food items, including diverse food types and portion sizes?

Relevance and Importance of the Research

The project promises significant contributions to the fields of computer vision and health informatics. By providing more accurate dietary tracking tools, it can aid in improved dietary awareness, prevention of diet-related health issues, and potentially reduce healthcare costs. The insights from this project are relevant to researchers, healthcare professionals, and individuals seeking better dietary management tools. Its success can influence future research and applications in automated dietary tracking and health monitoring technologies[8].

Methodology

1.1 Product Identification Phase

Dataset Selection

The choice to utilize the 'food-101' dataset was informed by several critical factors. Notably, its widespread availability and moderate scale aligned seamlessly with the parameters of our project, considering the constraints imposed by our limited computational resources. This dataset's richness spans a diverse spectrum of food categories, enabling a comprehensive analysis owing to its expansive coverage. Moreover, the dataset's open-access nature facilitated its seamless integration into our deep learning pipeline, ensuring both transparency and reproducibility in our experimental procedures. Additionally, the dataset contains images captured from various sources, presenting diverse qualities, dish presentations, and perspectives, offering a robust and diverse collection for model training and evaluation.

The dataset encompasses 101 food categories, with 101,000 images, offering substantial diversity for model training and evaluation. It includes 750 training images per category, which were intentionally left with some noise mostly in the form of intense colors and occasional mislabelling, and 250 manually reviewed test images, ensuring ample data for model validation[9].

It comprises two primary directories: an "images" folder housing categorized images organized into individual subfolders corresponding to distinct food classes, and a "meta" folder containing .txt and .json files. The "meta" folder facilitates the partitioning of data into training and testing sets via specified image paths detailed in .txt files, while the .json files aid in associating images with their respective class labels.

Training Pipeline Overview

1. **Environment Setup and Imports**:

- TensorFlow, Keras, and other essential libraries (like **numpy**, **matplotlib**, **os**) are imported.
- GPU availability is checked, indicating GPU utilization for training.

2. **Data Acquisition and Preprocessing**:

- A helper function **get_data_extract** is defined to download and extract the dataset (**food-101**).
- The dataset is explored, and initial visualizations are made to understand the data distribution.
- The **ImageDataGenerator** ,in the **ResNet50** pretrained model ,class is used for image data augmentation and preprocessing. This is crucial for enhancing the model's ability to generalize and for efficiently handling large image datasets.

3. **Model Architecture**:

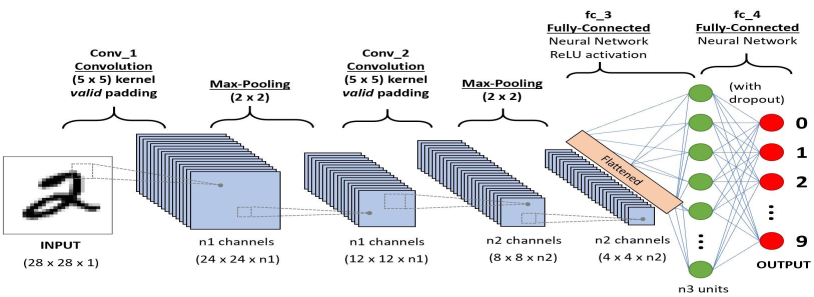
Convolutional neural network(CNN)

1. Convolution: Filters slide over the image, looking for patterns, like edges or shapes.
2. Activation: Apply a function to highlight important patterns.
3. Pooling: Reduce image size while keeping essential information.
4. Fully Connected: Combine extracted features to make predictions.
5. Training: Adjust internal settings using data to improve accuracy.

Why we used CNN:

We use Convolutional Neural Networks (CNNs) for image tasks because they are specialized in automatically recognizing and extracting meaningful patterns and features from images, enabling effective image analysis and understanding.

figure (1)



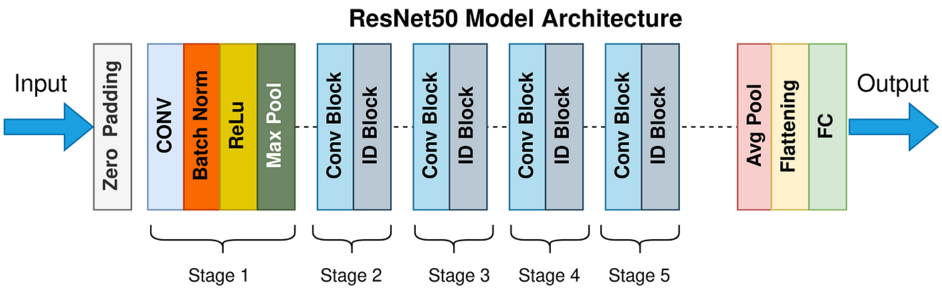
ResNet50:

1. Input Layer: Accepts input images of a standard size, typically 224x224 pixels for color images.
2. Convolutional Layers: consists of multiple convolutional layers, each of which is activated by ReLU and batch normalization. Low-level features from the input image are extracted by these first layers.
3. Residual Blocks: Consists of sixteen residual blocks arranged into four phases, with three, four, six, and three blocks in each stage. Multiple convolutional layers, batch normalization, ReLU activation, and skip connections that add the input to

the block's output make up each residual block.

4. Skip Connections (Residual Connections): This is a crucial feature of ResNet architectures. Skip connections allow gradients to flow more easily during training and mitigate the vanishing gradient problem in deep networks. The addition of the input to the output within each residual block helps in preserving information and gradients, enabling the training of very deep networks.
5. Output Layer: Ends with a fully connected layer followed by a softmax activation function, typically used for classification tasks. This layer takes the high-level features extracted by the previous layers and produces the final class probabilities.

figure (2)



Why we used ResNet50:

Because ResNet-50 is deeper (50 layers) than the original ResNet, it can capture more complicated features and perform better across a range of applications. It is a well-liked option for numerous applications since it finds a decent balance between complexity and resources, and it is widely accepted in the computer vision community.

Calorie Estimation and Recipe Suggestion:

After the food recognition part using Resnet50, the model estimates how many calories are approximately in the food image that has been recognized by the model.
Instead of training the model on another dataset for calories and recipes, we went through a different approach instead.

So the user has a choice to enter the food diary which we will talk about later on, or extract the recipe for the food item.

We called different API keys for two different websites; the first calculates the calories and the second fetches the recipe for the food item (prepared meal). An API key is the standard security mechanism for any application that provides a service to other applications, by serving as distinct identifiers, these keys permit and ease the algorithm's access to particular features offered by outside Application Programming Interfaces (APIs).

It acts as a gateway mechanism in our algorithm, granting it access to a specific portal or domain, typically belonging to an external web service or data provider. Upon validation of this key, the algorithm is authorized to retrieve required information or execute specific functions provided by the API.

The first API key for calorie estimation was obtained from the ***CalorieNinjas*** API website, we chose this website because of their adaptive portion size algorithm, comprehensive global nutrition database, an inclusive catalog of branded items, and dynamic database enhancement.[10]. It takes the user input as text with the amount, unit of measure, and food item specified, and estimates the calories for each food item mentioned in the input text.
Also, it is part of the food diary, where the user after recognizing the food item is offered to either to extract the recipe, which we will talk about later, or enter the food diary.
The food diary takes multiple food inputs and computes the calories for each input, and the total calories.

The second API for recipe extraction was obtained from the Edamam API website which gets the recipe for the food item (prepared meal). It's important to note that the recipes contained in the Recipe Search API are web recipes and are collected from throughout the internet. [11]

4. **Compilation and Training**:

- The model is compiled with a chosen optimizer (like SGD) and loss function (like categorical_crossentropy).
- Training is performed using **model.fit_generator**, indicating the use of data generators for handling training data.
- Callbacks such as **ModelCheckpoint** and **CSVLogger** are used for monitoring the training process.
- The training process likely uses GPU acceleration, as indicated by the initial GPU check.

5. **Model Evaluation**:

- The performance of the model is evaluated using accuracy and loss plots.
- The best performing model based on validation accuracy is reloaded for further use.

6. **Model Prediction and Testing**:

- The trained model is used to make predictions on new images, showcasing its practical application.

- The code includes sections for downloading test images and making predictions, which is essential for demonstrating the model's effectiveness.

7. **Visualization and Model Analysis**:

- The **plot_model** utility from Keras is used to visualize the model architecture.
- This helps in understanding the model's structure and the flow of data through the network.

Key Highlights and Considerations

- **Parallel Processing and GPU Utilization**: The use of GPU for training suggests efficient handling of large image datasets and faster training times.
- **Data Augmentation and Preprocessing**: Crucial for improving model generalization and handling overfitting.
- **Resnet50 training**: Leveraging a pre-trained model for feature extraction, enhancing the learning process.
- **Custom Model Tailoring**: Adding specific layers to the pre-trained model to suit the classification task.
- **Model Evaluation and Testing**: Rigorous evaluation and testing with real-world images to ensure model robustness and effectiveness.

Model Evaluation Metrics[12]:

Accuracy:

In the context of food recognition, accuracy indicates how often the model correctly identifies the food item in an image. High accuracy is crucial for both calorie estimation and recipe recommendation features, as the initial step in both functionalities is accurate identification of the food item.

Precision and Recall:

Precision and Recall serve as vital metrics in assessing the model's proficiency. Precision denotes the model's accuracy in identifying specific food items among its positive predictions, reflecting its ability to precisely label individual food types, like correctly recognizing an apple among various fruits. On the other hand, Recall measures the model's capability to capture all instances of a particular food item within the dataset, highlighting its effectiveness in identifying all occurrences of a given food, ensuring it recognizes most, if not all, instances of that specific food type in images. These metrics offer nuanced insights into the model's performance, focusing on its accuracy in recognizing individual food items and its completeness in capturing all instances of those foods, contributing significantly to a detailed evaluation of the model's capabilities.

Confusion Matrix:

The confusion matrix serves as a comprehensive tool to visualize the performance of the classification model across different classes. In our project, the confusion matrix enables us to dissect the model's predictions, providing a granular view of the classification accuracy for each food category. Each entry in the matrix reveals the number of true positive, false positive, true negative, and false negative predictions, which allows us to evaluate not only the overall accuracy but also the specific instances where the model may confuse one food item with another. Analyzing the confusion matrix helps in identifying patterns of misclassification, guiding further model refinements, and enhancing the decision-making algorithms for both calorie estimation and subsequent recipe suggestion functionalities.

Why did we choose Accuracy as the Primary Metric?

Balanced Dataset Assumption: Because the Food-101 dataset used in the project is relatively balanced across classes, accuracy can be a reliable metric. In balanced datasets, where each class has a similar number of samples, accuracy effectively reflects the model's performance.

Core Functionality Indicator: In food recognition, the primary task is to correctly identify the food item from an image. Accuracy directly reflects how well the model performs this task.

Impact on Calorie Estimation and Recipe Suggestion

1. **Calorie Estimation**:

- Accurate identification of food items is pivotal for precise calorie estimation, as the nutritional content significantly varies among different food types.
- A misclassification during food recognition can result in substantial errors in estimating the calorie content of a meal. This holds particular importance for users relying on the application for dietary management, where precise nutritional information is crucial for making informed dietary choices and maintaining nutritional balance.

2. **Recipe Suggestion**:

The accuracy of food recognition directly influences the relevance and usefulness of recipe suggestions. Recommendations hold value only when they correspond to the correctly identified food items. Accurate recognition not only ensures the provision of more relevant and suitable recipe suggestions but also contributes to an enhanced user experience. Personalized and contextually appropriate recipe recommendations resonate more effectively with users, fostering increased engagement and satisfaction with the application's functionalities.

Validation and Testing Strategies

Robust validation and testing strategies were implemented to ensure the accuracy and generalizability of our models. These strategies are pivotal in evaluating the model's performance on unseen data, a critical factor for the practical application of the system in calorie estimation and recipe recommendation.

Data Splitting for Validation and Testing

The methodology for preparing the dataset involved a meticulous process of dividing the data into distinct sets: training, validation, and testing. This was achieved through the following steps:

- Data Preparation: Utilizing scripts to segregate the images based on predefined lists, ensuring a balanced representation of each class in all datasets.
- Dataset Organization: The images were organized into separate directories for training and testing, facilitating straightforward data loading and processing during model training and evaluation.

Use of Validation Data in Model Training

Validation played a crucial role in our training process, serving as a checkpoint for assessing the model's learning progress. The key elements in this phase were:

Integration with Training: During the model training (model.fit_generator), the validation dataset was used as a critical component to monitor the model's performance on data it had not been trained on.

Hyperparameter Tuning: Validation performance was used as a guide to adjust hyperparameters, ensuring the model neither overfits nor underfits the training data.

Testing with Unseen Data

To assess the model's ability to generalize, we employed the following testing strategy:

- Unseen Data Testing: Post-training, the model was subjected to a set of unseen images. This step was crucial to evaluate the model's real-world applicability.
- Performance Evaluation: The model's accuracy in classifying these images was recorded, providing a clear indication of its effectiveness in practical scenarios.

Evaluation Metrics

Accuracy was chosen as the primary evaluation metric, for the following reasons:

- Direct Relevance: Given the nature of the classification task, accuracy — the proportion of correctly classified images — directly correlated with the model's efficacy.
- Model Comparison: Accuracy offered a straightforward metric to compare different models or iterations during the training phase.

Model Checkpoints and Logging

To further enhance our validation strategy, we implemented model checkpoints and logging:

- Model Checkpoints (**ModelCheckpoint**): This allowed us to save the model at its best performance state, based on validation accuracy.
- Training Progress Logging (**CSVLogger**): We maintained logs of the training process, which helped in analyzing the model's performance over time and making informed adjustments.

1.1.1 Selection of product and company
Final Product and Technology Choices:

Reasons for Selection:

- ResNet50: Selected for its high accuracy in image recognition, crucial for correct food identification. ResNet50 is deeper than its predecessors, capturing more complex features, and strikes a balance between complexity and resource efficiency, making it a popular choice in computer vision.

- Food101 Dataset: Chosen due to its widespread availability, moderate scale, and diverse range of food categories. Its richness and open-access nature ensure comprehensive coverage, essential for robust model training and evaluation.

- Calorie Ninjas API: Preferred for its adaptive portion size algorithm, comprehensive global nutrition database, and dynamic database enhancement. It provides accurate calorie estimates based on user inputs, enhancing the project's nutritional analysis capabilities.

- Edamam Recipe Search API: Opted for its extensive recipe database. It offers web recipes collected from various sources, facilitating the extraction of recipes corresponding to the identified food items, thus augmenting the project's recipe suggestion feature.

Comparison with Alternatives:

- **ResNet50 vs ResNet**
  Resnet50 was used in the project in place of the original ResNet architecture because of its improved capabilities. ResNet50 provides better accuracy performance for image recognition tasks, which is essential for correctly identifying food items in this situation. This choice demonstrates the project's dedication to using cutting-edge technology to get the best possible outcomes[Deep Residual Learning for Image Recognition" by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, published in 2015].

- **CaloriesNinja API vs OpenAI API and FoodData Central API**
  A number of considerations led to the decision to choose Calorie Ninjas over both OpenAI API [13] and FoodData Central (USDA) API [14]. Because the project focused on diet control, Calorie Ninjas' exceptional accuracy in calorie calculation was important. Its large food database, which excels in a variety of international cuisines, matched the project's wide potential for food recognition. Calorie Ninjas was also a more sensible option in terms of development and user experience because it provided more consistent performance and simplified integration. All of these factors combined to make Calorie Ninjas the best choice for the NutriVision project.

Integration into the Project:

- **ResNet50:**integrated for image processing.
- **Food101:** used in model training phase.
- **CaloriesNinja API:** utilized to retrieve calorie estimation data post-image recognition.
- **Edamam API:** utilized for recipe suggestions based on the meal/dish recognized in the input image.

Data Handling and Privacy Considerations:

To uphold user privacy, the system offers a controlled approach to image access. Users are provided with the option to selectively grant access to the chosen image for input purposes, thus limiting system access solely to the specified content. This controlled access mechanism ensures privacy preservation by restricting system visibility solely to the explicitly chosen image, upholding user autonomy and safeguarding personal data.
Additionally, the system employs robust encryption measures to secure data transmission and storage, protecting sensitive information from unauthorized access. User data, comprising image inputs, is anonymized and stored with strict adherence to prevailing data protection regulations.

Scalability and Future Support:

- Scalability: Services like Calorie Ninjas and Edamam were chosen for their robust infrastructure, capable of handling increased user traffic and data load efficiently.

- Future Support: The project relies on ongoing support and updates from these API providers, ensuring the system remains up-to-date with the latest technological advancements and security protocols.

5 Results

Results

1.2 Baseline Creation and Performance Enhancement

In the initial phase of our project, we established a performance baseline for our Convolutional Neural Network (CNN) using the ResNet50 architecture. This baseline served to quantify the model's proficiency in food recognition and calorie estimation against a test dataset. The performance metrics were as follows:

Accuracy: The CNN model's food recognition accuracy on the test dataset was assessed, yielding a baseline accuracy.
Calorie Estimation: For calorie estimation, the model's predictions were evaluated against different food items, resulting in a baseline mean square error (MSE).
Model Optimization Trials

We conducted several experiments by adjusting the batch size and epochs to optimize the model's performance. The trials and their outcomes are detailed below:

Trial 1: With a batch size of 12 and 30 epochs, the model achieved a training accuracy of 96.77% and a validation accuracy of 86.38%. The loss on the training set was 0.1424, and the validation loss was 0.6454.

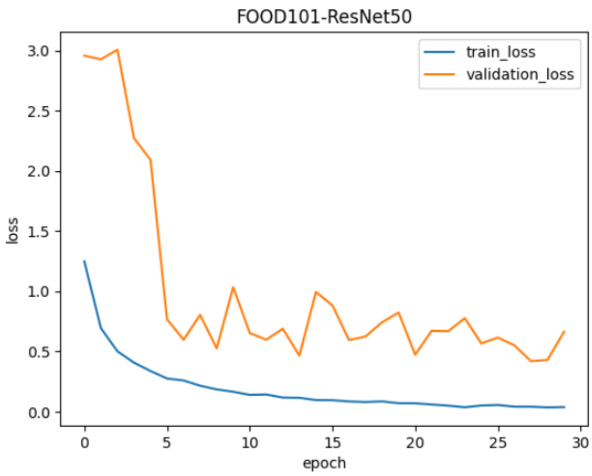
Trial 2: Increasing the batch size to 64 and reducing the epochs to 25 led to a training accuracy of 98.61% and a validation accuracy of 86.56%. The training loss decreased to 0.0646, while the validation loss was 0.6066.

Trial 3: Maintaining the batch size at 64 and extending the epochs back to 30, the model further improved, registering a training accuracy of 99.37% and a validation accuracy of 85.32%. The training loss was reduced to 0.0371, and the validation loss was slightly higher at 0.6627.

Achieving the Best Model Performance

After rigorous tuning, the best-performing model metrics were recorded as follows:
At trial 3:
Best Model Metrics: The model achieved a training loss of 0.0402 with an accuracy of 99.28%. The validation loss was markedly lower at 0.4186, and the validation accuracy peaked at 89.90%.
The corresponding graphical representation of the model's performance across epochs for both accuracy and loss is depicted in the attached figures, showcasing the model's learning trajectory and the efficacy of our optimization strategies.

5 Results



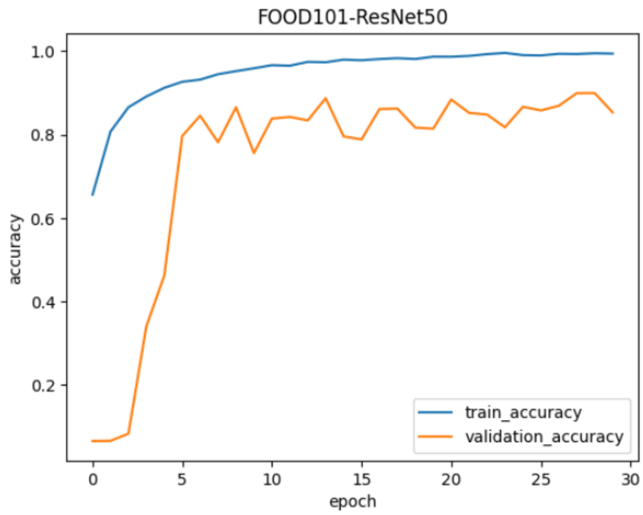


figure (3)

(a): Training Loss vs.Validation Loss (b): Training Accuracy vs.Validation Accuracy

Limitations

1. Computational Resources Restriction:
The computational needs of our project, specially for neural network implemented for image recognition needs a high-speed, large-capacity and free GPU. Due to us being students we have limited computational resources. This constraint had an impact on the efficiency of model training as well as the execution of the model.

2. Code Difficulty:
The creation of sophisticated algorithms for precise food detection and calorie estimate resulted in considerable code complexity. The necessity to incorporate numerous data processing layers and advanced neural network topologies led to this level of complexity.
Impact: The complex codebase necessitated intensive debugging and optimization, which proved time-consuming. It also presented difficulties in maintaining and updating the code, potentially compromising the project's scalability and adaptability.

3. Time Restriction:
Our capacity to thoroughly study and apply all of the planned features of our analysis was restricted by the tight deadline that was imposed on this project.

4. Dataset Loading Time: Despite the dataset being of fairly moderate size, it incurred considerable loading times during model execution, leading to delays in model editing, error rectification, and hyperparameter tuning procedures.

5. Suitable Environment: The search for an optimal environment equipped with accessible, cost-free, and high-speed GPU access posed as a constraint, contributing to the slowdown of the process. We tried Jupyter Notebook, Google Colab Notebook, and finally settled on the Kaggle Notebook environment[15], seeing that it was the most suitable of the aforementioned environments.

6. API Accessability: Finding a free or limited-time call API for a website that does what our project requires was a challenge.

Conclusion

Representing a pioneering stride in artificial intelligence, this project excels in the domains of food recognition, calorie estimation, and personalized recipe recommendations. Our primary objective was to harness deep learning methodologies, utilizing the ResNet50 model trained on the extensive Food101 dataset, to create a robust system capable of recognizing diverse food categories while offering accurate calorie estimations and tailored recipe suggestions. The integration with ***CaloriesNinja*** for precise calorie assessments and ***Edamam*** for personalized recipe recommendations stands as a strategic utilization choice, enhancing the system's capabilities.

Through experimentation, we achieved notable milestones, including a commendable accuracy rate in food recognition (as previously mentioned) and a decent calorie estimation interface. Key learnings from our endeavor encompassed the challenges of dataset diversity, model optimization for improved accuracy, and the intricacies of API integrations—specifically, identifying freely available APIs, refining queries to match designated formats, and ensuring clear and understandable output within the system's interface. This highlighted the pivotal role of precise query structuring and output formatting in harmonizing with API specifications, thereby enhancing both user experience and data precision.

The contributions of this project extend beyond technical achievements. By merging AI precision with rich nutritional data, we introduced a transformative approach that redefines the paradigms of health informatics, nutrition science, and machine learning. However, limitations stemming from data availability and computational constraints posed challenges in achieving absolute accuracy.

Looking ahead, the project lays a foundation for future explorations in advancing dietary management systems, urging further research into data augmentation techniques, enhanced model architectures, and expanded dataset varieties. This endeavor signifies the transformative potential of AI in addressing real-world challenges in personal health and nutrition.

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SWOT Analysis

Strengths	*Weaknesses*
1. Utilizes cutting-edge Convolutional Neural Networks (CNNs) for precise food recognition. 2. Estimates caloric content from images, enhancing nutritional management. 3. Leverages the "Food101" dataset for diverse food item analysis. 4. - Integrates health informatics and computer vision for a multi-disciplinary approach.	1. Potential challenges in dealing with diverse and complex food images. 2. High computational requirements for deep learning models. 3. Dependency on the quality and diversity of the "food101" dataset.
Opportunities	***Threats***
1. Growing interest in health and nutrition tracking technologies. 2. Potential for partnerships with health and wellness apps. 3. Opportunity to contribute to academic research in health informatics and machine learning.	1. Competition with existing food recognition and calorie estimation technologies. 2. Rapid changes in deep learning technologies may require constant model updates. 3. Potential privacy concerns with user data.