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Advanced Deep Learning Model for Food Recognition and Personalised Diet Planning

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Abstract
Technology is becoming an important partner when the awareness grows about how our diet & lifestyle affect health. It helps people make better food choices—choices that are more informed. One of the most exciting advancements is using AI to identify the foods we eat and create personalized nutrition plans. Models like VGG16 have been used for food recognition, but they often fall short in accuracy. They do not have the data for tailored dietary suggestions. This shortcoming stops them from offering the best health solutions to users.To overcome these issues, we recommend the Inception V3 deep learning model. It is widely recognized for its outstanding performance in image classification tasks. Inception V3 has a smart design that employs different filter sizes and pooling methods. This feature allows it to notice more complex patterns in food images. As a result, food recognition accuracy improves, making it easier for the system to identify a wider variety of foods & dishes. Beyond accurate food recognition, our system also includes a personalized diet planning feature that considers factors such as age, weight, gender, blood pressure, and Body Mass Index (BMI). By evaluating these factors, the model creates personalized diet plans that match users' health goals and nutritional requirements. This dual approach—improving food recognition and offering tailored diet plans—helps users make healthier dietary choices, ultimately leading to better health outcomes and lifestyle improvements.

Keywords: *Body Mass Index (BMI), deep learning model, VGG16.*

1. Introduction
Nourishment is exceptionally imperative in human life. It's crucial for survival and makes a difference to meet numerous needs. These needs incorporate sustenance, taste, wellbeing, and social social occasions. With growing health concerns like diabetes and obesity, making healthy dietary choices has become more important than ever.According to the Universal Diabetes Alliance, 415 million individuals have diabetes. Also, the Worldwide Burden of Illness Think about appears that awful diets lead to lack of healthy sustenance, weight, and early passings. To handle these issues, nourishment computing has come up as a modern region. One key portion of typically nourishment proposal frameworks that offer assistance clients select more beneficial options.A adjusted slim down is truly vital; in any case, everyone's needs are diverse. Your wellbeing issues, likes, and way of life play a enormous portion. Personalized nourishment proposal frameworks are required. They see at things like age, action levels, and wellbeing metrics.The quick development of web administrations and smartphones has made a parcel of nourishment substance accessible. But it too brings a challenge: how can clients discover the proper nourishments from so numerous choices? Nourishment suggestion frameworks ought to not as it were consider conventional things like taste but moreover see at other setting data. This takes into account factors like time, location, and real-time body signals such as

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heart rate, steps, and sleep quality, which can be tracked by wearables. [1]

2. Related Work

Effective food recommendation systems are becoming more and more necessary to encourage healthier eating habits as obesity rates rise and associated health risks including diabetes, heart disease, and cancer increase. These health problems are mostly caused by unhealthy diets that are high in fatty and energy-dense meals. Food suggestion is still in its infancy, despite the fact that recommendation systems have advanced significantly in fields like movies and locations of interest. This article offers a cohesive framework that addresses the main issues in food recommendation, such as incorporating contextual data, building customized models, and examining the properties of food items. Additionally, it examines existing solutions, pointing out drawbacks such the lack of data, changing dietary preferences, and the requirement for recommendations that are culturally appropriate. In order to improve health outcomes and help people make better dietary choices, the article highlights the significance of creating more reliable methodology and technology to strengthen food recommendation systems. (Food Recommendation: Framework, Existing Solutions and Challenges [1] Ramesh Jain [1],2019) Automatic food analysis is becoming more and more popular, particularly at self-service restaurants, as people become more conscious of their eating habits. This technology not only helps with operational problems, such as reducing cashier traffic during peak hours, but it also enables the collection of nutritional information from consumers' meal selections. Restaurants can increase customer happiness and service efficiency by automating food tray analysis. This paper presents a novel approach, Semantic Food Detection, that uses convolutional neural networks (CNNs) to integrate food localization, recognition, and segmentation into a unified framework.This method provides a comprehensive understanding of the food composition on a tray, which facilitates the identification and processing of specific items. On the UNIMIB2016 public dataset, experiments show that Semantic Food Detection works better than current techniques, with an F-measure of almost 90%. This innovation contributes to more effective eating experiences by marking a major advancement toward automatic restaurant invoicing systems. This approach helps people eat healthier and get better at recognizing different (Grab, Pay and Eat :Semantic Food Detection for Smart Restaurants [2] EduardoAguilar, Beatriz Remeseiro [2],2018) This study suggests a novel Internet of Things (IoT)-based framework for nutritional assessment that makes use of edge computing to increase efficiency and deep learning for precise food recognition. By recognizing food items using sophisticated algorithms, lowering latency, and preserving battery life, this system improves accuracy over traditional self-reported dietary techniques, which can be unreliable. According to experiments, the system works better than current techniques in terms of recognition accuracy, response time, and energy usage. These developments support more precise dietary assessments, which aid in weight loss and promote healthier eating habits (A New Deep Learning-based Food Recognition System for Dietary Assessment on An Edge Computing Service Infrastructure [3] Chang Liu, Yu Cao [3],2017) A cross-region recipe analysis framework that incorporates recipe ingredients, food photos, and characteristics like cuisine type and course is presented in this study. Finding cultural insights from diverse culinary cultures is the aim. While a manifold ranking algorithm incorporates deep visual features for improved retrieval and presentation of related food photos, a probabilistic topic model is introduced to uncover ingredient patterns particular to various cuisines and courses. Multi-modal cuisine summarization, cuisine-course pattern analysis, and personalized cuisine recommendation systems are the three main domains in which the framework is utilized. Assessments utilizing a dataset of 66,615 recipes from ten different cuisines demonstrate how the framework can improve knowledge of culinary cultures and provide insightful information for culinary applications (You Are What You Eat: Exploring Rich Recipe Information for CrossRegion Food Analysis [4] Weiqing Min, Bing-Kun Bao [4],2017) With an emphasis on the use of food photos for real-time

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nutrient content analysis in smartphone applications, this paper examines cutting-edge techniques for automatic food detection and volume estimate. It discusses methods for segmenting, classifying, and calculating the volume of food images while evaluating how various food picture databases affect these techniques' efficacy. Along with pointing up areas for more research and offering answers to current problems, the review also highlights the advantages and disadvantages of current methodologies. Enhancing dietary assessment systems is the ultimate objective in order to enable more precise and intuitive applications that support better public health outcomes and healthier eating habits (A Review of Image-Based Food Recognition and Volume Estimation Artificial Intelligence Systems [5] Fotios S. Konstantakopoulos , Eleni I. Georga [5],2024)

3. Proposed System

In order to provide individualized diet programs based on user profiles, we suggest a revolutionary deep learning model that will greatly increase the accuracy of food detection and calorie estimate. Our methodology improves the capacity to precisely identify food items and their nutritional content by integrating crucial variables including age, weight, gender, blood pressure, and body mass index (BMI). Users can obtain more accurate dietary evaluations thanks to this all-inclusive method, which also helps them better understand how their eating patterns relate to their health objectives. Furthermore, our model's customized dietary recommendations enable users to make well-informed food choices that suit their particular lifestyle preferences and health requirements. We make sure the nutritional suggestions are not only correct but also pertinent to each individual by combining user-centric data with cutting-edge deep learning techniques. By encouraging healthier eating habits and enabling better management of dietary-related illnesses, this customized approach can enhance health outcomes and ultimately contribute to a more comprehensive understanding of nutrition and wellbeing.

4. System Architecture

4.1. ROI Pooling (Region of Interest Pooling)

A popular technique in object identification models like Faster R-CNN is ROI pooling. In these models, the goal is to identify specific regions in an image and classify the objects within those regions. ROI Pooling extracts fixed-size feature maps from these regions of interest, regardless of their original size. This is achieved by dividing the region into grid cells, applying spatial transformations, and pooling the maximum or average values within each grid cell. ROI Pooling ensures compatibility between the regions of interest and subsequent layers in the neural network. (Figure 1)

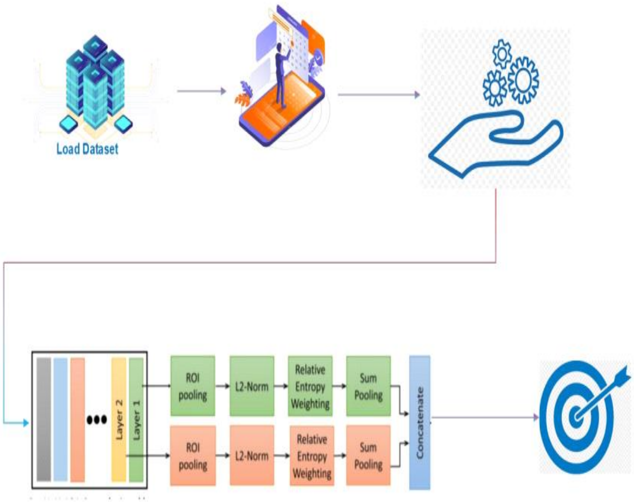

Figure 1 Architecture Diagram of Inception V3 Model

4.2. L2-Norm

The L2-Norm, sometimes referred to as the Euclidean norm, is a vector magnitude measurement in mathematics. Normalization is one of the most common uses in machine learning. L2-Norm helps to stabilize learning and enhance convergence during training by scaling features to guarantee they have a unit norm (length = 1). When it comes to algorithm optimization and avoiding numerical instability, this method is quite helpful.

4.3. Relative Entropy Weighting

Entropy Relative Assigning weights to characteristics or components according to relative entropy—also referred to as Kullback-Leibler divergence—is most likely what is meant by weighting. Relative entropy, which is

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frequently employed in feature selection or regularization, quantifies the difference between two probability distributions. By incorporating weights derived from relative entropy, models can prioritize important features while reducing the influence of redundant or less informative ones.

4.4. Sum Pooling

Sum pooling is a straightforward pooling procedure in which the total of all the elements in a pooling zone is the output value for that region. Sum Pooling places more emphasis on the cumulative information in the pooling region than either Max Pooling, which chooses the maximum value, or Average Pooling, which determines the mean. When the overall density or magnitude of features matters more than the values of individual features, it may be useful. [2]

4.5. Concatenate

Multiple feature vectors, tensors, or outputs from different layers are combined into a single, coherent tensor using a straightforward procedure known as concatenation. In neural network topologies, this method is commonly used to integrate data from multiple sources or processing routes. For example, you can leverage both low-level and high-level information for additional analysis by concatenating features that were extracted from Layers 1 and 2 of your diagram. [3]

4.6. The Layers and Operations

The neural network's workflow is formed by the interactions between these layers and operations. Layers 1 and 2 are the stages where various feature types are collected or processed "Concatenate" and other operations aid in integrating these aspects for a more thorough depiction. Whether the model's goal is object identification, categorization, or another task, these elements cooperate to accomplish it. [4]

5. Module Description

5.1. Data Collection

To begin developing a successful food recognition system, a representative and varied dataset must be gathered. The process of gathering data entails gathering a sizable collection of food photos and the nutritional data that goes with them, including the number of calories, macronutrients (such as proteins, lipids, and carbs), and micronutrients. The model must be trained using these datasets in order to correctly identify various foods and associate them with their nutritional information. The algorithm may be trained to recognize items from different cuisines, dietary practices, and meal kinds by gathering high-quality, properly labeled data, which lays the groundwork for precise predictions. [5]

5.2. Data Pre-Processing

One of the most important steps in getting the raw data ready for model training is data pre-processing. The gathered food photos and labels must be cleaned and converted into a format that can be fed into the deep learning model. To improve variety and prevent overfitting, this involves operations like scaling and normalizing photos, handling missing or inaccurate labels, and enhancing the dataset with methods like rotation, flipping, and cropping. Effective pre-processing guarantees that the model can effectively learn from the data and increase its precision in calorie calculation and food recognition. [6]

5.3. Feature Extraction

Feature extraction is the process of locating significant patterns or attributes in the previously processed food photos. When it comes to deep learning, this is usually accomplished with a pre-trained Convolutional Neural Network (CNN), such as Inception V3, which can extract hierarchical characteristics from pictures. The texture, shape, and color of the food products are represented by these characteristics, which are important for distinguishing between different food categories. The system can learn to identify and categorize food items more precisely by utilizing Inception V3's deep layers, which will enable more precise calorie estimations. [7]

5.4. Model Creation Using Inception V3

One of the best deep learning models for picture classification is Inception V3. The Inception V3 model, fine-tuned on a food dataset, is used to categorize food items into specified categories after the images have been pre-processed. Through the use of its intricate architecture, which consists of several layers of convolutional processes and pooling, the model is trained to identify a broad variety of food categories. Inception V3 is ideally suited for real-time food recognition applications because of its capacity to strike a compromise between depth and

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computing efficiency, which enables quicker and more precise predictions. [8-9]

5.5. Prediction of Calorie

The Inception V3 model can identify the food items and then predict how many calories they contain. This is accomplished by linking every food item to the relevant nutritional data from the dataset. This information may then be used by the model to calculate the number of calories in any particular food image, providing users with a more realistic picture of how many calories they consume each day. Through the use of the food's classification results and their correlation with extensive nutrition data, the system is able to provide precise calorie estimates. This is crucial for users who want to control their diet and uphold healthy eating practices. [10-12]

5.6. Recommend The Diet Plan

Once the food items have been identified and their calorie content estimated, the system may produce a customized diet plan. This entails making specific food recommendations based on the user's dietary restrictions, tastes, and health goals. Together with dietary advice, the system can prescribe an exercise program based on the user's fitness level and goals, including overall fitness, muscle gain, or weight loss. Additionally, the system can offer a water reminder function that, depending on the user's activity level, body weight, and ambient conditions, can encourage them to stay hydrated throughout the day. The system provides a thorough, personalized strategy that encourages healthy living and assists users in reaching their exercise and dietary objectives by combining all of these components. [13]

6. Result and Discussion

The evaluated research' findings reveal notable advancements in food recognition and volume estimate techniques; deep learning-based approaches hold the greatest potential for precisely identifying food items and calculating portion sizes. Food identification has become more dependable thanks to advancements in segmentation and classification brought about by Convolutional Neural Networks (CNNs) and other sophisticated image processing models. There are still issues, though, especially with the precision and consistency of food recognition in a variety of lighting settings and cuisines. Furthermore, when food products have complicated geometries or when numerous ingredients are included in a single photograph, the volume estimate algorithms frequently have trouble performing accurate calculations. The effectiveness of these techniques is also greatly influenced by the quality of the dataset; several models exhibit limits when trained on datasets that are smaller or less varied. Despite these challenges, the accuracy and usefulness of these systems could be enhanced by integrating multi-modal data, such as food photos paired with user inputs or environmental parameters. Enhancing algorithm robustness, creating bigger, more varied datasets, and investigating useful real-time applications in daily nutritional monitoring should be the main goals of future study. [14-16]

6.1. Accuracy

A classification model's overall performance is assessed using its accuracy. The percentage of accurate predictions—both true positives and true negatives—among all the predictions made is measured. (Figure 1)

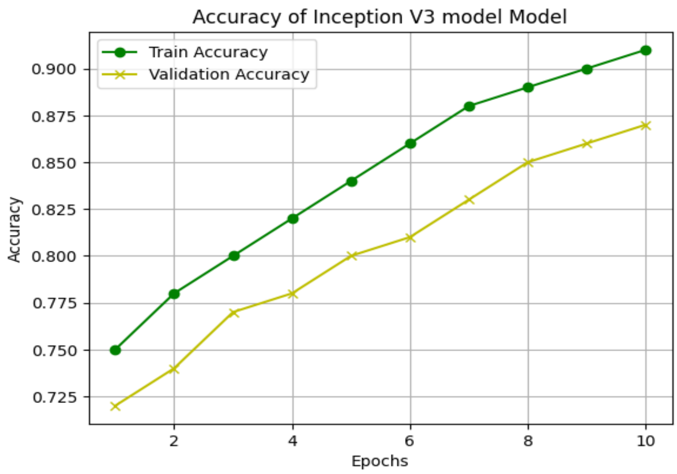

Figure 2 Accuracy of Inception V3 Model

Accuracy is the proportion of correctly classified instances (both true positives and true negatives) among all instances in the dataset.

$$Accuracy = \frac{TP}{TP + TN + FP + FN}$$

Where:

- **TP:** True Positives (correctly predicted food items)

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- **TN:** True Negatives (correctly predicted non-food items)
- **FP:** False Positives(incorrectly classified non-food items as food)
- **FN:** False Negatives(incorrectly classified food items as non-food)
- Regardless of the specific type of food, accuracy measures the overall ability of the model to identify food items correctly In food prediction. [17]

6.2. Precision

The ratio of accurately anticipated positive observations to all predicted positives is known as precision. It illustrates the model's capacity to prevent incorrectly categorizing non-food items as food in the context of food prediction. When the repercussions of false positives (such as mislabeling food items) are severe, like in health applications where precise identification is necessary for nutrient analysis, it is crucial. [18]

Precision=TP/(TP+FP)

Where:

- **TP:** True Positives (correctly predicted food items)
- **FP:** False Positives (incorrectly classified non-food items as food)

6.3. Recall

The ratio of accurately predicted positive observations to all actual positive observations is called recall, sometimes referred to as sensitivity. Recall in food prediction quantifies the model's capacity to accurately identify every real food item, emphasizing its ability to reduce false negatives. To ensure that every food item is recognized in dietary tracking systems, a high recall is necessary.

Recall=TP/(TP+FN)

Where:

- TP: True Positives (correctly predicted food items)
- FN: False Negatives (incorrectly classified food items as non-food) [19]

6.4. F1 Score

The F1 score offers a fair assessment of the model's performance since it is the harmonic mean of precision and recall. When there is an unequal distribution of classes in the dataset—for example, when food items are less common than non-food items—it is quite helpful. By integrating the model's precision (avoidance of false positives) and recall (recognition of food items) into a single grade, the F1 score offers a more comprehensive evaluation.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The F1-score is a number between 0 and 1, where 1 denotes flawless recall and precision. It is particularly useful in fraud detection, where reducing false positives and detecting fraud are both crucial. (Figure 3) [20]

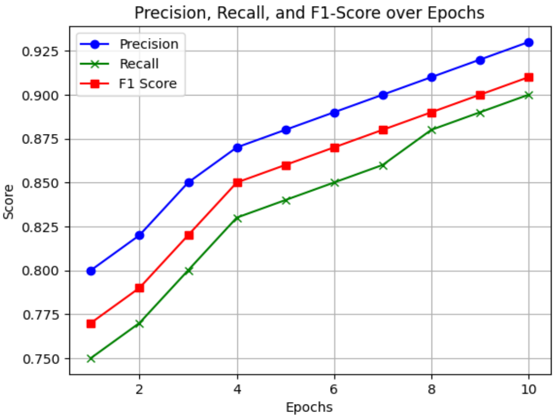

Figure 3 Comparison of Precision, Recall, F1-Score Over Epochs

Conclusion

In conclusion, a promising way to overcome the difficulties of encouraging healthy eating habits in today's health-conscious society is to combine individualized diet planning with sophisticated deep learning models, such as Inception V3, for food recognition. Our method greatly increases food identification accuracy by leveraging the advanced architecture of Inception V3, setting the stage for more accurate nutritional analysis. Together with the capability to create customized diet plans using personal health information like age, weight, gender, blood pressure, and BMI, the system offers dietary suggestions that are particular to each user's needs and health objectives. This all-encompassing strategy not only improves food recognition efficiency but also gives users the ability to make more informed dietary decisions, which eventually promotes better health outcomes and long-term wellbeing. [21]

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