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CALORIE ESTIMATION OF FOOD AND BEVERAGES USING DEEP LEARNING

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Abstract: The utilization of deep learning techniques in "Deep Learning-driven Food Recognition and Calorie Estimation for Intelligent Diet Monitoring" offers a unique method to improve diet monitoring and encourage healthy eating habits. The main goal of this initiative is to accurately identify various food items and estimate their calorie content in real-time, granting users access to intelligent and tailored diet monitoring features. By utilizing the Python programming language and the MobileNet architecture model for food recognition and calorie estimation, this project has achieved a remarkable level of precision in recognizing and categorizing different food items. Through the use of deep learning algorithms, the system can swiftly analyze input images on the web framework to pinpoint the specific food item within seconds. Additionally, the system can estimate the calorie content of the identified food, equipping users with essential information to effectively monitor their dietary intake. The intelligent diet monitoring capabilities of SmartBite empower users to make well-informed decisions regarding their food selections. By monitoring and evaluating their daily food consumption, users can gain valuable insights into their nutritional patterns, establish personalized objectives, and make necessary adjustments to attain a well-rounded and healthy diet.

Index Terms – Early Detection, Deep learning,CNN Algorithm, Image Processing.

I. INTRODUCTION

The utilization of deep learning for calorie estimation in food and beverages represents a state-of-the-art application of artificial intelligence that caters to the increasing need for precise and convenient nutritional details. Through the utilization of deep learning capabilities, this innovative method strives to offer accurate calorie approximations for a diverse range of food items and drinks. By integrating image recognition, nutritional databases, and calorie estimation, deep learning models can identify and measure the nutritional value of food items from images, presenting a promising solution for individuals looking to manage their dietary intake and overall well-being. The model is constructed using the MobileNet Architecture, a convolutional neural network specifically designed for mobile and embedded vision applications. Obesity is typically identified when an individual's Body Mass Index (BMI) exceeds 30 kg/m2, with a high BMI being linked to an elevated risk of various health conditions. The primary cause of obesity is the disparity between food consumption and energy expenditure. Effective obesity management necessitates the consumption of nutritious foods and a reduction in daily calorie intake, requiring individuals to monitor and calculate their calorie intake regularly. Poor dietary habits and the consumption of foods with high caloric content and low nutritional value are key contributors to obesity. Obesity is associated with a range of health issues such as hypertension, diabetes, cardiovascular problems, and respiratory difficulties. Excessive body weight resulting from obesity can lead to ligament damage in the knees and other joints. This system can be utilized by individuals aiming to gain weight or those with low white blood cell counts below 150,000 to increase their calorie intake by consuming foods with high caloric content.

II. OBJECTIVE

This project aimed to estimate calories accurately in order to reduce the health hazards associated with obesity and encourage healthy eating, especially in young people.

III. EXISTING SYSTEM

The accuracy of the existing system was 93.29% during training and 78.7% during testing. Users and medical professionals may be able to identify eating habits and food selections linked to health issues more quickly by utilizing software that is intended to precisely calculate food calories from still photographs. Although it is challenging, it has been possible to calculate calories using photographs. As of right now, no publicly accessible tool combines the ability to estimate food intake from images with the ability to offer personal health data.

IV. LITERATURE REVIEW

Haiyan H U, [1] The accurate calculation of calorie consumption plays a crucial role in managing human diet and health. Currently, most solutions rely on image-processing techniques to identify food types and refer to nutrition tables to calculate total calories. However, this approach faces difficulties in distinguishing between foods that appear similar but have significantly different calorie quantities. To overcome this challenge, we propose utilizing near-infrared spectroscopy (NIRS) to determine nutrient concentrations based on the distinctive absorption spectrum of foods..

Sirichai Turmchokkasam explains, [2] In order to determine the calorie content of food, which can vary depending on its ingredients and portion size during cooking, it is necessary to calculate the calories before consuming it. This study presents a novel approach to estimating the calorie content of food based on its ingredients using nutrition knowledge and thermal information. The first step of this method involves recognizing the type of food from an image, and then retrieving the corresponding ingredients from a database along with their nutritional information and thermal patterns. Simultaneously, the image is segmented to identify the boundaries of the ingredient candidates, and these boundaries are classified into specific ingredients using fuzzy logic based on their heat patterns and intensities. Finally, the classified ingredients are used to calculate the total calorie content based on the area ratio and nutrition knowledge.

Berker Arslan in this paper, [3] The automatic food recognition system has various practical applications, such as waste food management, advertising, calorie estimation, and daily diet monitoring. Despite the significance of this topic, there is a limited number of related studies. Additionally, the comparison in existing literature has focused on the best-shot performance without considering the common method of averaging over multiple trials. This paper examines the prevalent deep learning techniques for food classification, provides information on publicly available food databases, presents benchmark results for food classification experiments averaged over five trials, and surpasses the current best-shot performance experiment by achieving a state-of-the-art accuracy of 90.02% on the UEC Food-100 database.

Takumi Ege proposes, [4] comprehensive review of our research on accurately estimating the real size of foods using image-based techniques for precise food calorie estimation. The review includes three existing works and two new works. The first work, called "CalorieCam," utilizes a reference object to estimate the real food size.

Kaoyu, [5] Over the past few decades, there has been a prevailing trend in China where individuals are increasingly focusing on enhancing their health and monitoring their calorie consumption for each meal. As a response to this concern and driven by our keen interest, we developed a calorie estimation model specifically for Chinese cuisine. By utilizing object detection, we aimed to estimate the calorie content of popular Chinese and Western dishes. Leveraging food images and existing calorie data, we created image-based calorie estimation models to accurately recognize the names of these dishes, provide their calorie content and recipes, and ultimately offer dietary advice tailored to different groups of individuals.

V. METHODOLOGY

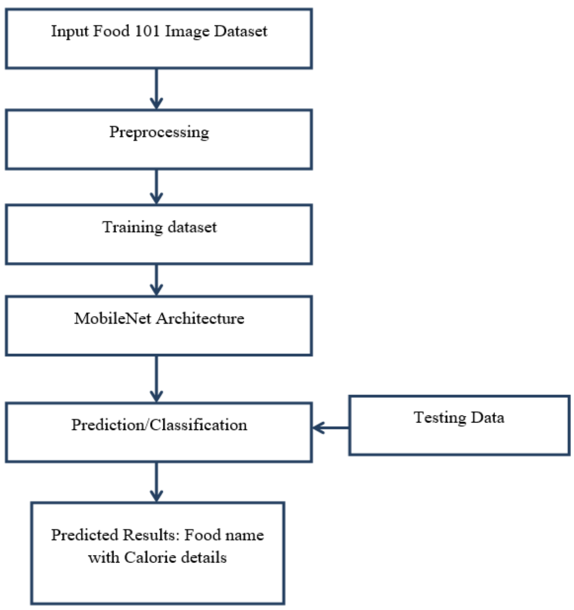

Fig: Data flow diagram

Input Food 101 Image Dataset:

The Food 101 dataset is supplied as input in this first stage. - Images of different food products divided into 101 classes can be found in the Food 101 dataset.

Preprocessing:

The Food 101 dataset's photos go through preprocessing in this step. Resizing photos to a defined size, normalization (scaling pixel values to a range), data augmentation (performing transformations like rotation, flipping, etc., to increase the diversity of the dataset), and other methods to enhance model performance are examples of preprocessing steps.

Training Dataset:

The dataset is split into training and testing subgroups following preprocessing. The model is trained using the training dataset. It includes many photos from the dataset along with the labels that go with them.

MobileNet:

Convolutional neural network (CNN) architecture MobileNet is pre-trained and optimized for mobile and embedded devices.

- Here, MobileNet serves as the foundational paradigm for transfer learning.
- Transfer learning is the process of optimizing a previously trained model for a particular task or dataset. Because MobileNet was pre-trained on a sizable dataset (like ImageNet), it already knows how to extract characteristics from photos that are helpful.

Training:

The training dataset is used to train the MobileNet model. The model picks up elements and patterns in the photos linked to various meal classes throughout training.

- In order to make predictions, this method entails both forward propagation, in which input data is sent through the network, and backward propagation, in which the model's predictions are compared to the actual labels and its parameters are changed to minimize error.

Prediction (Testing Data):

The testing dataset is used to assess the model once it has been trained.

- Images not seen by the model during training are included in the testing dataset.
- The performance of the training model is evaluated by comparing its predictions with the ground truth labels on the testing dataset.

Architecture:

MobileNet utilizes depthwise separable convolutions to create efficient deep convolutional neural networks suitable for mobile and embedded vision applications. The architecture is structured around depthwise separable filters, which consist of depthwise convolution filters and point convolution filters. The depthwise convolution filter processes each input channel individually, while the point convolution filter combines the results of the depthwise convolution with 1 * 1 convolutions. Global Average Pooling is a pooling technique that replaces fully connected layers in traditional CNNs by generating a feature map for each category in the classification task. Instead of adding fully connected layers, the average of each feature map is calculated and fed directly into the softmaxlayer.

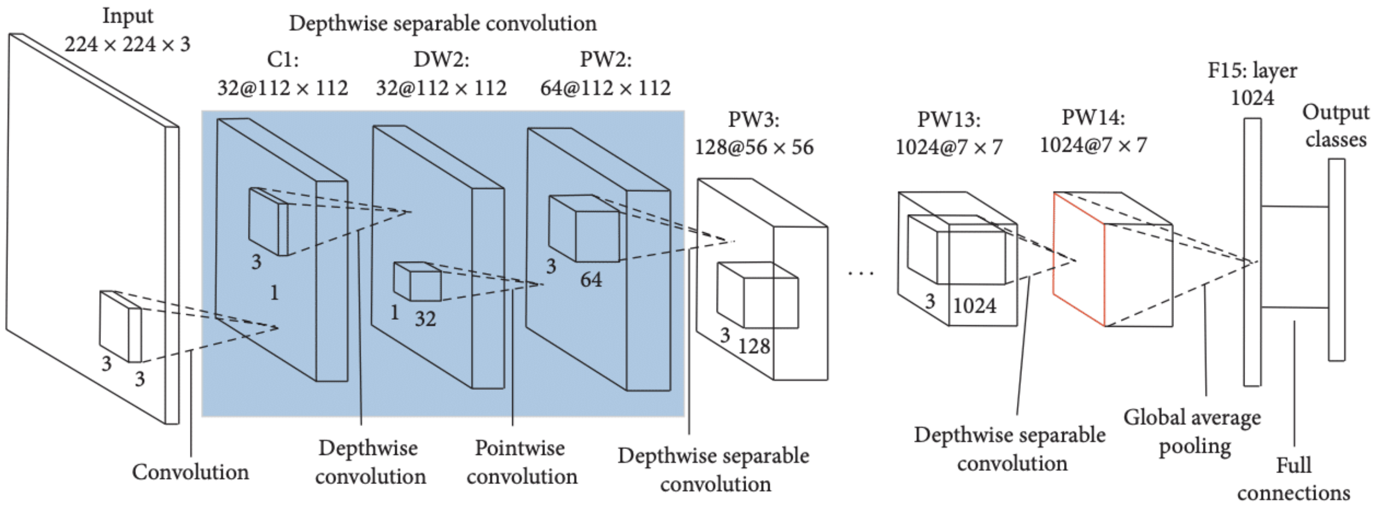

Fig: Design on MobileNet architecture

Description of the MobileNet algorithm:

1. InputLayer:

- Receives an input image with standard dimensions of 224x224 pixels and three color channels (RGB).

2. ConvolutionalBlocks:

- Initial convolutional layer with 3x3 filters.

- DepthwiseSeparable Convolution:

- Depthwise Convolution (3x3): Applies a separate convolutional filter for each input channel independently.

- Pointwise Convolution (1x1): Utilizes 1x1 convolutions to merge information across channels.

3. Bottleneck Design:

- Bottleneck structures are employed to decrease the number of parameters and computations.

- 1x1 Convolution (pointwise) is used to reduce the number of channels before the more computationally intensive 3x3 depthwise convolution.

- Another 1x1 Convolution (pointwise) is used to expand the number of channels.

4. WidthMultiplier:

- Introduces a hyperparameter known as the "width multiplier," represented by the symbol α. This parameter allows users to adjust the number of channels in each layer, enabling a trade-off between model size and accuracy.

5. Global Average Pooling:

- Spatial dimensions are condensed to 1x1 through global average pooling, aggregating information across the entire feature map.

6. Fully Connected Layer:

- The final layer typically consists of a fully connected layer with a softmax activation function.

7. Activation Function and Batch Normalization:

- Rectified Linear Unit (ReLU) activation.

VI. RESULTS AND DISCUSSION

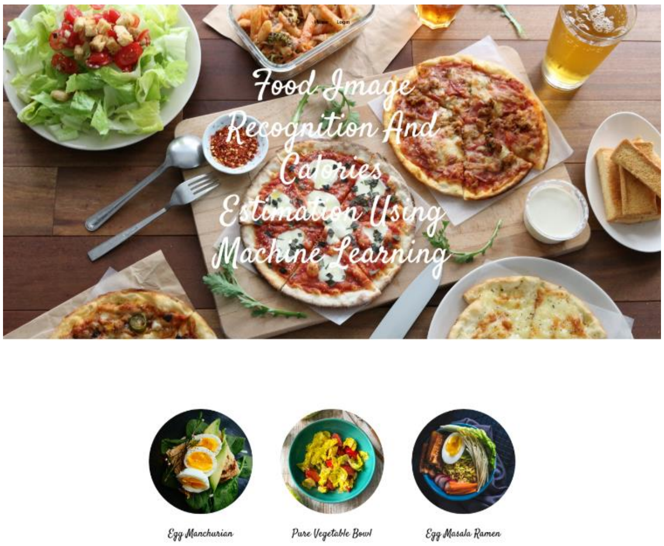

Fig: Home Page

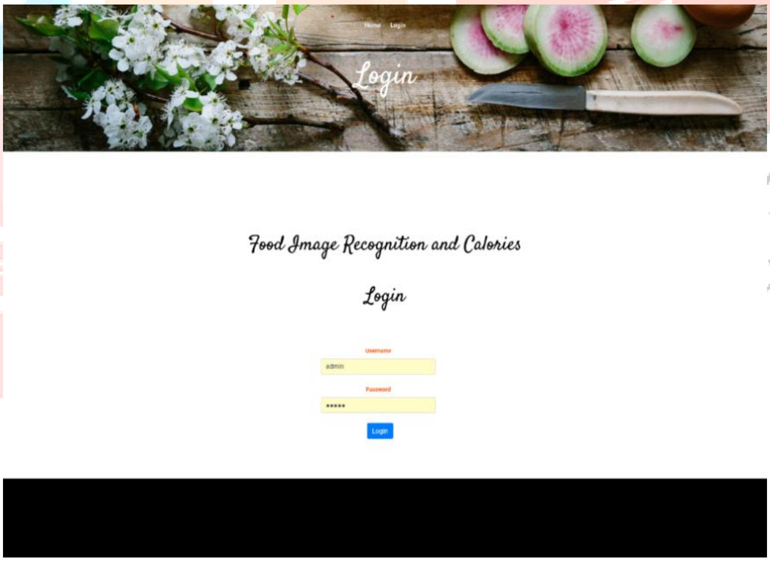

Fig: Login Page

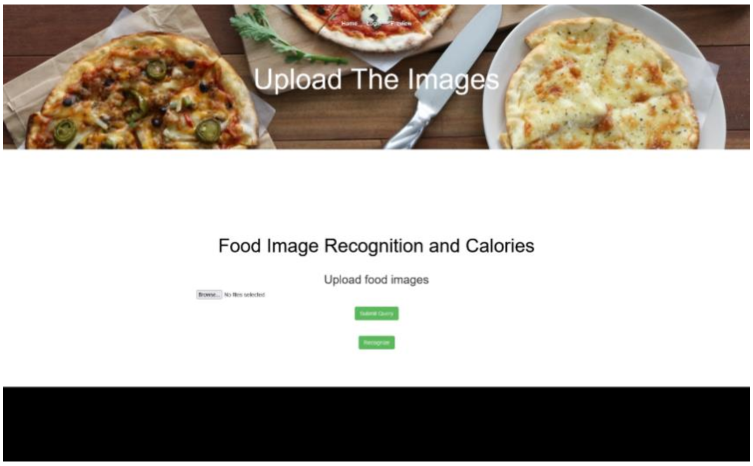

Fig: Uploading And Choosing Image

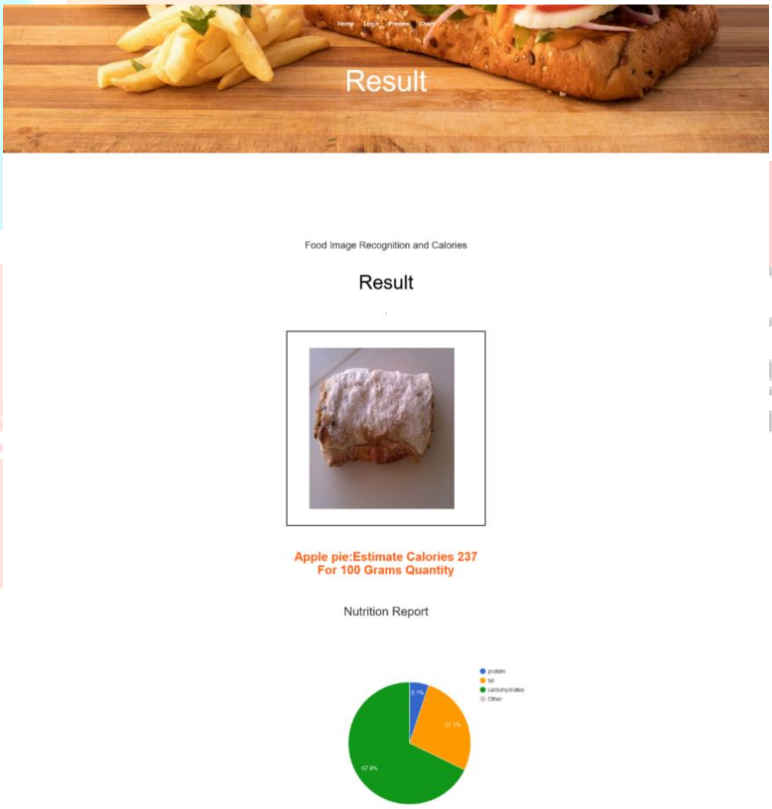

Fig: Final Output

VII. CONCLUSION

With the help of a large food dataset and deep learning algorithms, the "SmartBite" project has successfully developed an advanced system for precise food recognition and calorie estimate. Through the use of the Food 101 dataset and an advanced MobileNet architecture, the system is able to detect a wide variety of food products with greater accuracy, accommodating a wide range of dietary preferences. Instantaneous nutritional insights are provided via real-time calorie estimating capabilities, enabling users to properly monitor their caloric intake and make well-informed judgments. "SmartBite" establishes the groundwork for transforming intelligent diet monitoring, encouraging healthy eating habits, and improving general well-being with its user-friendly interface and scalability for future improvements.

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