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Automated Food Prediction Using Deep Learning with Calorie Estimation Algorithm

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Abstract- Automated food image prediction and classification using deep learning is a popular and powerful approach to categorize and classify food images based on their visual features. Deep learning models, particularly Convolutional Neural Networks (CNNs), have proved effective in multiple visual analysis tasks, including image categorization. This research presents automatic food categorization algorithms based on deep learning methodologies. For food image categorization, SqueezeNet and VGG-19 CNNs were utilised. Automated food image classification in the health and medical field has several potential applications, including dietary analysis, nutritional monitoring, and personalized healthcare. SqueezeNet is a deep neural network architecture specifically designed for efficient model size and computation. VGG-19 known for its deep network architecture and has 19 weight layers, including convolutional and fully connected layers which are able to recognize quite a good accuracy. In Food image classification VGG-19 is get good classification results compare to VGG-16.The classify food item name with images approximately recognition the item. Also introduced food calorie estimation algorithm to predict the calorie content of a food item based on its features or characteristics.

Indexed Terms- Automated Food Classification, Deep Learning, SqueezeNet, VGG-19, Calorie Estimation Algorithm.

I. INTRODUCTION

Food image classification is the task of automatically categorizing or labeling images based on the type of food or dish depicted. It involves using computer vision techniques, particularly deep learning models, to analyze the visual features of food images and classify them into different food categories [1]. The success of the recognition system heavily depends on the quality and diversity of the dataset, as well as the choice of appropriate features and models. Continuous improvement and updates to the model may be necessary to handle new food items, cuisines, or variations [2].

Automated food image classification is a technique that uses deep learning algorithms to identify and classify food items in images [3]. This technology has a wide range of potential applications, including: Diet and nutrition tracking: Automated food classification can be used to track what people are eating, which can help them make healthier choices. Calorie counting: Automated food classification can be used to estimate the calorie content of food, which can help people lose weight or maintain a healthy weight. Food safety: Automated food classification can be used to identify food that is contaminated or spoiled, which can help prevent foodborne illness. Restaurant menu planning: Automated food classification can be used to help restaurants plan their menus, ensuring that they offer a variety of appealing and healthy options [4].

Automated food image classification is still a developing field, it has the ability to change the way people eat and live. CNNs were a sort of deep learning system that excels at image categorization. CNNs work by extracting features from images, such as edges, shapes, and colors. These characteristics are then utilised to categorise the image into a specific group [5]. CNNs are a sort of deep learning system that excels at image categorization. CNNs work by extracting features from images, such as edges, shapes, and colors. These characteristics are then utilised to categorise the image into a certain group.

II. RELATED WORKS

Due to the enormous diversity and sophistication of food appears, automatic food identification is a difficult undertaking. It is critical to maintain a proper nutritional balance, especially in infants. Whenever the body lacks critical nutrients, it may cause major sickness and organ damage, which may result in serious health problems in adulthood [6]. Deep learning has resulted in an assortment of image processing advancements. Specifically, there have been considerable advancements in the use of deep learning approaches to food image categorization [7]. Under terms of the impact of universal poverty, over 65% of Sub-Saharan nations are expected to be malnourished, while some agricultural areas are under drought [8]. The food preparation and processing sector is the most important throughout the numerous industrial in the world, subsidised by the greatest employability [9].

The technology integrates deep learning for fake-food image detection with food matching and standardisation utilising natural language translation [10]. The above compost maturity forecasting method automates reactive composting, saving money on labour [11]. Food quality and safety are crucial issues for the whole society since they are the foundation of human wellness, social progress, and stability [12].

III. PROPOSED MODEL

The classify food item name with images approximately recognition the item. Also introduced food calorie estimation algorithm to predict the calorie content of a food item based on its features or characteristics and block diagram of the proposed system is shown in fig 1.

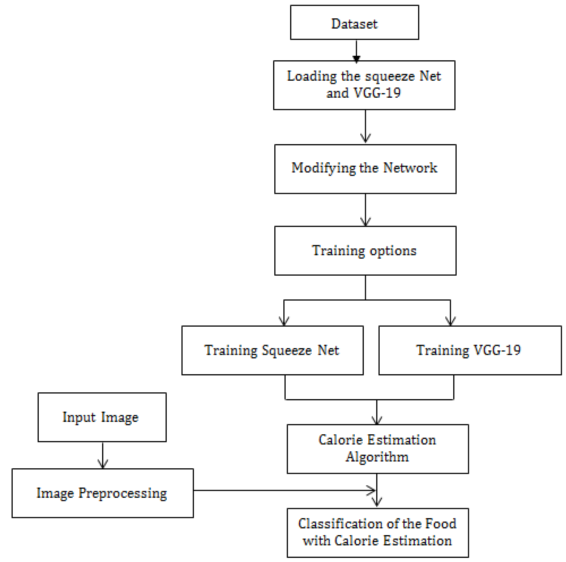

Figure 1: Block diagram illustrating the suggested technique

3.1 Dataset Preparation:
Collect a labeled dataset of food images, where each image is associated with the corresponding food category or class. Split the dataset into training and testing sets, ensuring a balanced distribution of images across classes. Kaggle is a popular platform for hosting and sharing datasets, including those related to food image classification. Here are a few Kaggle datasets that you can explore for food image classification: Food-101: This dataset contains 101 food categories with 1000 images per category, making it a comprehensive dataset for food classification. Each image is labeled with its corresponding food category. Dataset collected from: https://www.kaggle.com/dansbecker/food-101.

3.2 Image Preprocessing:
Preprocess the food images to enhance the quality and facilitate effective feature extraction. Common preprocessing techniques include resizing the images to a fixed size (e.g., 224x224 pixels), normalization of pixel values, and optionally applying data augmentation techniques like rotation, flipping, or cropping to increase the diversity of training samples.

3.3 Feature Extraction:
Use the SqueezeNet architecture to extract features from the preprocessed food images. Pass each image through the SqueezeNet model until a desired intermediate layer (e.g., the layer before the final

classification layer). Extract the feature maps from the selected layer as the representative features of the image.

3.4 Classifier Training:
Train a classifier, such as a support vector machine (SVM) or a neural network with complete connectivity, using the extracted features from the SqueezeNet. Use the training set with the corresponding labels to train the classifier. Fine-tune the classifier to optimize its performance on the food classification task.

3.5 Evaluation and Performance Analysis:
Evaluate the trained classifier using the testing set to measure its performance in classifying food images. To evaluate the classifier's performance, compute metrics that include precision, recall, accuracy, and F1-score. Analyze the confusion matrix to identify any specific challenges or misclassifications.

3.6 Fine-tuning with VGG19:
Take the trained classifier from Step 4 and fine-tune it using the VGG19 architecture. Replace the SqueezeNet feature extraction layer with the VGG19 architecture. Retrain the classifier using the VGG19 features and the training set. Evaluate the fine-tuned classifier using the testing set and analyze the performance improvements.

By combining the SqueezeNet architecture for efficient feature extraction and the VGG19 architecture for more detailed features, this framework aims to leverage the strengths of both models in automated food image classification. Experimentation and tuning may be required to optimize the hyperparameters, such as learning rate, batch size, and regularization techniques, to achieve the best results.

3.7 Calorie Estimation Algorithm:
A calorie estimation algorithm aims to predict the calorie content of a food item based on its features or characteristics. While estimating calorie content accurately from images alone is a challenging task, several approaches can provide rough estimates.
pseudocode for calorie estimation algorithm
Step 1: Preprocessing
PreprocessFoodImage(image): // Apply necessary preprocessing steps (e.g., resizing, noise removal, normalization)
Step 2: Feature Extraction
ExtractImageFeatures(image): // Extract relevant features from the preprocessed image
Step 3: Calorie Prediction
PredictCalorie(features):
// Train or load a SqueezeNet and VGG-19 Model
Step 4: Main Algorithm
EstimateCalorieFromImage(image):
preprocessedImage = PreprocessFoodImage(image)
features = ExtractImageFeatures(preprocessedImage)
caloriePrediction = PredictCalorie(features)
return caloriePrediction
Additionally, training the regression model would require a labeled dataset with food images and their corresponding calorie values.

IV. RESULTS AND DISCUSSIONS

The Deep Learning Toolbox is a MATLAB toolbox that provides functions, algorithms, and tools for deep learning. It includes pre-trained models, layers, and utilities for building, training, and deploying deep neural networks. MATLAB is the core software required to run deep learning algorithms and perform related tasks. It can utilize a CUDA-enabled GPU (Graphics Processing Unit) with MATLAB. MATLAB supports integration with deep learning libraries such as TensorFlow and PyTorch. If you prefer using these libraries in conjunction with MATLAB, you will need to install and configure them separately.

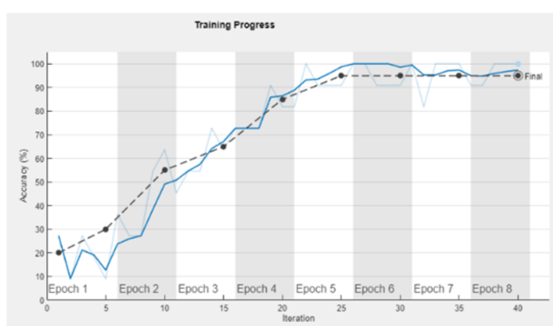

Figure 2: Training Progess

The performance and accuracy of automated food classification is 95.6 % using SqueezeNet or VGG19 will depend on the quality and diversity of the training data, proper preprocessing techniques, appropriate hyperparameter tuning, and the specific requirements of the food classification task at hand as shown in fig 2.

(a) Prediction: Sandwich Calories Estimation: 252

(b) Prediction: French Fries Calories Estimation: 312

(c)

Figure 5: Predicted Food Image with Calories Estimation

Automated food classification using SqueezeNet and VGG19 is experimented with both models and evaluate their performance on the specific food image dataset of interest to determine the most suitable model for the task as shown in fig 3.

CONCLUSION

In conclusion, the automated food classification using SqueezeNet and VGG19, two popular convolutional neural network (CNN) architectures, has shown promising results in accurately categorizing food images. Both approaches have had widespread use in the area of computer vision, particularly in image classification problems. SqueezeNet, known for its compact architecture, achieves a good balance between model size and accuracy. On the other hand, VGG19 is a deeper and more complex CNN architecture with a larger number of layers. Both SqueezeNet and VGG19 can be trained on large food image datasets with labeled categories. By fine-tuning these pre-trained models on food-specific datasets, they can learn to recognize and classify various types of food accurately. In addition, our proposed model provide calories estimation results.

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