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Food Recognition and Calorie Assessment from Images Using Convolutional Neural Networks

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Abstract: In human life there are many things that are required to live but there are three basic needs of every human. These three needs are a must in every human life that are food, clothes and house. Nowadays humans are very much interested in eating different types of foods. Interested to know different kinds of foods from different places. We have developed a food recognition and calorie estimation system that utilises images of food provided by the user to recognize the food item and estimate its calorie content. Food image recognition is a promising application of visual object recognition in computer vision. Our system leverages image processing techniques and computational intelligence to accurately recognize food items. We have trained a large and deep convolutional neural network using a dataset of 1000 high-resolution images for each food category. The trained CNN is capable of classifying the input food images with high accuracy, enabling accurate recognition of the food items. Additionally, our system incorporates calorie estimation algorithms to estimate the calorie content of the recognized food items, providing valuable information for users concerned about their nutritional intake. Overall, our food recognition and calorie estimation system offers an efficient and effective solution for automatically recognizing food items and estimating their calorie content using state-of-the-art deep learning techniques.

Key words: *Food recognition, Deep convolutional neural network, Artificial neural network, Calorie Assessment, Food Segmentation, Food classification, Image processing, Computer vision,Calorie Estimation*

1. Introduction

Nowadays health is the most important thing in human life. After covid-19 disease people are becoming very caring about their health monitoring. People are using smart devices for health monitoring. These devices help people for health improvement. Due to poor nutritions many people are suffering from Obesity. This disease is the base for two types of diabetes and heart related diseases and many more. People also like to taste different kinds of foods and with tasting different delicious foods they also want good health also. To solve this problem we have invented this research. In this research we are combining two different models together. First, it will recognize the different foods based on its shape, colour and area covered by it and after recognizing the model will also assure the calories of that food. In this research we are recognitioning different types of foods by taking pictures of those foods. Recognition of the food from images is the first part of research which is represented in this paper. With curiosity to know different foods humans are worried about health also. Many diseases are closely related to our food intake like diabetes, stroke, and many cardiovascular diseases. Taking food in daily routine directly has an effect on human health. Different kinds of foods have different nutritions and in this scenario calorie intake in food is very essential to know. Before eating the food from that food image humans are able to know calories in that food is the second part of research which is presented in this paper. In previous research researchers showed food recognition different methods and for identification and recognition of different foods from images. In

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this research with recognition how much calorie the food is shown by using artificial intelligence. Using Artificial Intelligence now we can do a lot of research and as we know AI is a very big area and subset of AI is machine Learning and subset of it is Deep learning and Deep learning is having different neural networks for classification, Image Processing, NLP and many predictions based on given database. In this research we have used convolutional neural networks for recognition of different food dishes and the calorie estimation according to that food dishes. Different kinds of food items have calories as per the food and we can know that this much calorie is having by this particular food and is this good for our health or not. Convolutional neural network for recognizing the food and calorie estimation according to the food. Different kinds of food have calories and we can know if this much calorie is good for our body or not. For doing this research we have used the food 101 dataset. Which has a total 101 categories of different foods. First of all we are training the model using images of different kinds of foods. First model will recognize the food using the image of that food. After knowing food . We will show that this food dish which is represented in the image is having how much calorie. Many kinds of diseases are based on food which we are taking as a need of our body. Our Proposed Study is on making an efficient and reliable model for recognizing the food and measuring the calories in that food. In this research methodology we have used the best method suitable for this problem. This research is invented specially for recognizing the different food items based on images using visual object recognition in computer vision and finding estimated calories based on food items. The Model is working based on image processing and Artificial Intelligence for food recognition using its images. We are training a very large deep convolutional neural network to identify and give different classes based on food images. Train the model through images which are high resolutions and the number of images in each category is 1000.

Our contributions are summarised as follows:

1) We propose the AI-based model, Food recognition and estimated calorie of that food from food images.
2) We have built a new model that contains food images with its calorie database that has been collected from kaggle.
3) We have designed and developed an innovative series of AI algorithms that can provide good performance on small quantity training data. The newly developed algorithms include, for instance, the Convolutional Neural Networks (CNNs) for food segmentation, and few-shot learning based classifier for food recognition. Extensive experiments have been conducted to demonstrate the advantages of these proposed methods.

The structure of the paper unfolds as follows: Section II conducts a thorough analysis of existing literature. Section III delves into the proposed methodology for the current research. In Section IV, we elaborate on the obtained results, while Section V encapsulates the conclusion and outlines potential avenues for future work.

2. Literature Survey

Ya Lu et al. (2020) Monitoring the nutritional intake of hospitalized patients is crucial for mitigating the risk of malnutrition associated with diseases. While various methods have been devised to assess nutrient intake, there remains a clear need for a more dependable and fully automated technique to enhance data accuracy, alleviate participant burden, and reduce healthcare costs. This paper introduces an innovative system leveraging artificial intelligence (AI) to precisely estimate nutrient intake. The proposed system processes RGB Depth (RGB-D) image pairs captured both before and after meal consumption.

Key components of the system include a novel multi-task contextual network for food segmentation, a few-shot learning-based classifier for food recognition using limited training samples, and an algorithm for 3D surface construction. This combination enables sequential food segmentation, recognition, and estimation of consumed food volume, enabling fully automated nutrient intake estimation for each meal. To develop and evaluate the system, a dedicated database comprising images and nutrient recipes for 322 meals is created, coupled with innovative data annotation strategies. Experimental results demonstrate a high correlation (> 0.91) between estimated and ground truth nutrient intake, with minimal mean relative errors (< 20%). The proposed system outperforms existing techniques for nutrient intake assessment.

[2] In this paper, the authors propose a novel system based on artificial intelligence (AI) that accurately estimates nutrient intake by processing RGB Depth

(RGB-D) image pairs captured before and after meal consumption. The system leverages the power of deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to analyse changes in the RGB-D images and estimate nutrient intake with high accuracy. This automated approach eliminates the need for manual food diaries or self-reporting by participants, reducing burden and potential inaccuracies. The proposed system offers a promising solution for improving data accuracy, reducing participant burden, and lowering health costs in the field of dietary assessment, with potential benefits for managing and monitoring nutrient intake in a more reliable and convenient manner. In this paper, we present a cutting-edge solution that addresses the need for a more precise and automated method to determine nutrient intake. By leveraging artificial intelligence (AI) technology, our proposed system utilizes RGB Depth (RGB-D) image pairs captured both before and after meal consumption to accurately estimate nutrient intake. This innovative approach aims to improve data accuracy, reduce participant burden, and lower health costs compared to traditional methods.

The proposed system comprises several components, including a novel multi-task contextual network for food segmentation, a few-shot learning-based classifier for food recognition with limited training samples, and an algorithm for 3D surface construction. This allows for sequential food segmentation, recognition, and estimation of consumed food volume, enabling fully automatic estimation of nutrient intake for each meal.

To develop and evaluate the system, we assembled a dedicated new database containing images and nutrient recipes of 322 meals, along with innovative strategies for data annotation. Experimental results demonstrate that the estimated nutrient intake is highly correlated (>0.91) with the ground truth and shows very small mean relative errors (<20%), outperforming existing techniques proposed for nutrient intake assessment.

In summary, the proposed system is a novel approach that leverages AI and RGB-D image processing to accurately estimate nutrient intake in a fully automated manner. The system shows promising results in terms of accuracy and outperforms existing techniques, offering potential for improved nutrient intake monitoring in hospitalised patients and other relevant settings.

[3] Food is a fundamental requirement for human survival and has been a topic of significant interest in healthcare conventions. In today's era, advancements in dietary assessment and nutrition analysis tools have opened up new opportunities to aid individuals in understanding their daily eating habits, exploring nutrition patterns, and maintaining a healthy diet. In this study, we propose a deep model-based food recognition and dietary assessment system that analyses food items from daily meal images, such as those captured by smartphones.

Our system employs a three-step algorithm for recognizing multi-item (food) images, utilising deep convolutional neural networks (CNN) for object classification. The system first generates multiple region proposals on input images by employing the Region Proposal Network (RPN) derived from the Faster R-CNN model. It then identifies each region proposal by mapping them into feature maps and classifying them into different food categories, while also locating them in the original images. Finally, the system analyses the nutritional ingredients based on the recognition results and generates a dietary assessment report by calculating the amount of calories, fat, carbohydrates, and protein.

[4]To evaluate our system, we conducted extensive experiments using two popular food image datasets - UEC-FOOD100 and UEC-FOOD256. Additionally, we generated a new dataset of food items based on FOOD101 with bounding. The model was evaluated using various evaluation metrics. The experimental results demonstrate that our system accurately recognizes food items and efficiently generates dietary assessment reports, providing users with valuable insights into healthy dietary choices and guiding their daily recipe selections to improve overall body health and wellness.

Regular monitoring of nutrient intake in hospitalised patients is crucial in reducing the risk of disease-related malnutrition. While several methods have been developed to estimate nutrient intake, there is a clear need for a more reliable and fully automated technique to improve data accuracy, reduce burden on participants, and lower health costs. In this study, we propose a novel system that utilises artificial intelligence (AI) to accurately estimate nutrient intake by processing RGB Depth (RGB-D) image pairs captured before and after meal consumption.

Our system incorporates several innovative components, including a multi-task contextual network for food segmentation, a few-shot learning-based classifier for food recognition using limited training samples, and an algorithm for 3D surface construction. These components enable sequential food segmentation, recognition, and estimation of the consumed food volume, allowing for fully automatic estimation of nutrient intake for each meal. To develop and evaluate the system, we assembled a dedicated new database comprising images and nutrient recipes of 322 meals, along with innovative data annotation strategies.

Experimental results demonstrate that our system achieves high correlation (>0.91) with ground truth in estimating nutrient intake and exhibits small mean relative errors (<20%), outperforming existing techniques proposed for nutrient intake assessment. The use of AI-based approaches in processing RGB-D image pairs for nutrient intake estimation holds great promise in providing a reliable and automated solution for monitoring nutrient intake in hospitalised patients, with potential applications in clinical settings to improve patient care and outcomes.

[5] The importance of maintaining a healthy diet, along with regular physical activity, has long been recognized by dieticians and healthcare professionals as crucial in preventing obesity and various health-related issues such as diabetes, stroke, and cardiovascular diseases. However, traditional methods of dietary assessment suffer from limitations such as imprecision, underreporting, time consumption, and low adherence.

Recent advancements in machine learning applications and technologies have opened up possibilities for developing automatic or semi-automatic dietary assessment solutions that offer a more convenient approach to monitor daily food intake and control eating habits. Vision-based approaches, utilizing image processing and computer vision techniques, have gained significant attention in this domain.

In this survey, we extensively explore recent vision-based approaches and techniques for automatic dietary assessment. We outline the current methodologies and approaches used in these solutions, along with their performances, feasibility, and unaddressed challenges and issues. These approaches leverage the power of machine learning algorithms, such as convolutional neural networks (CNNs), to automatically recognize and quantify food items from images captured by users. These solutions aim to address the limitations of traditional dietary monitoring systems and provide more accurate and efficient ways of assessing dietary intake.We delve into the performance of these vision-based approaches, including their accuracy in food recognition and estimation of portion sizes. We also discuss the feasibility of these approaches in real-world scenarios, considering factors such as ease of use, user compliance, and potential limitations. Additionally, we highlight the challenges and issues that are yet to be fully addressed in this field, such as dealing with variations in food appearance, overcoming portion size estimation errors, addressing cultural and regional food differences, and ensuring user privacy and data security.In conclusion, recent advancements in machine learning and computer vision technologies have paved the way for automatic dietary assessment solutions based on vision-based approaches. These approaches offer promising opportunities to overcome the limitations of traditional dietary monitoring systems and provide more accurate and convenient ways to assess dietary intake. However, there are still challenges and issues that need to be addressed to fully realise the potential of these solutions in improving dietary assessment and promoting healthy eating habits.

3. Proposed Methodology

In this Model, we developed a food recognition and calorie estimation system that utilises user-provided food images to identify food items and estimate their calorie content. Food image recognition is an exciting application of computer vision, and our system leverages image processing and computational intelligence to achieve accurate food item recognition. We trained a deep convolutional neural network with a large dataset of high-resolution images, consisting of 1000 images for each food category, to enable robust and reliable classification of food items.

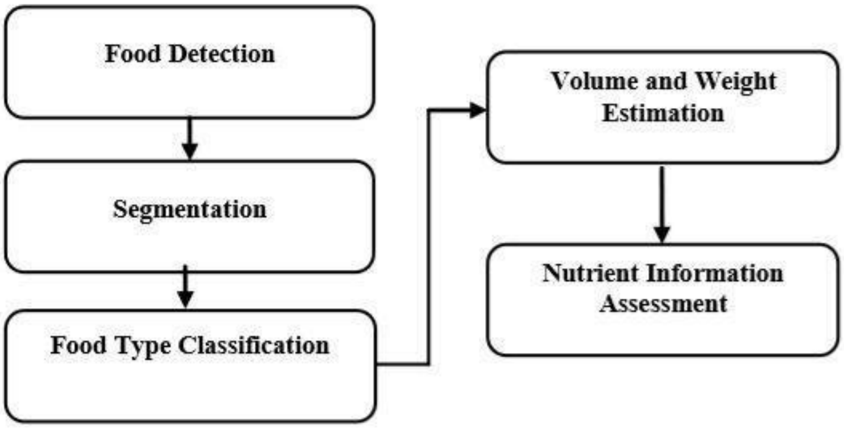

Fig: 1 Flow of Proposed Model

3.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a powerful technique for image classification tasks, including food recognition, with high accuracy. In recent years, advancements in deep learning, particularly in CNNs, have significantly improved the accuracy of image identification and recognition, not only due to larger datasets, but also thanks to new algorithms and improved deep architectures. CNNs are also known as LeNet, named after their inventor. The architecture of a CNN typically includes convolutional layers, pooling layers, and sub-sampling layers, followed by fully-connected layers. The input image goes through convolution and sub-sampling operations in the initial layers. After multiple computations, the data is then fed into a fully connected neural network for classification. One of the main advantages of CNNs is their ability to learn efficient high-level features and their robustness against small rotations and shifts in images.

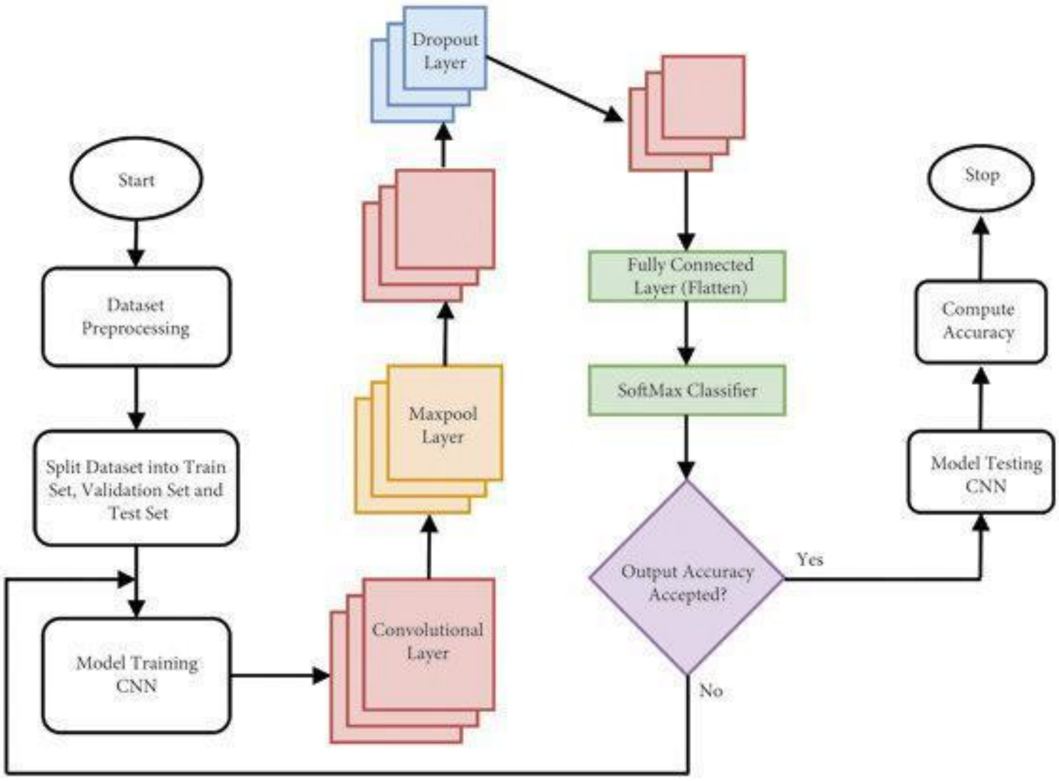

Fig:2 Working of Proposed Model

A CNN consists of several layers, including:

1. Convolutional Layers: These layers perform convolution operations on the input image to extract local patterns or features. Each convolutional layer has multiple filters or kernels that convolve with the input image to produce feature maps.
2. Pooling Layers: These layers down sample the feature maps to reduce their spatial dimensions while retaining important features. Common pooling operations include max pooling and average pooling.
3. Sub-sampling Layers: These layers further down sample the feature maps using operations such as stride or sub sampling, which reduces the size of the feature maps while preserving important information.
4. Fully-Connected Layers: These layers are traditional neural network layers that take the flattened feature maps from the previous layers and perform classification or regression tasks. They connect all neurons in one layer to all neurons in the subsequent layer.

The typical flow of data in a CNN is as follows:
Input Image -> Convolutional Layers -> Pooling Layers -> Sub-sampling Layers -> Flattening -> Fully-Connected Layers -> Output
The architecture of a CNN allows it to learn hierarchical representations of input images, starting from low-level features such as edges and textures in the early layers, and gradually capturing more complex and abstract features in the deeper layers. This makes CNNs highly effective for image classification tasks, such as food recognition, due to their ability to automatically learn relevant features from large datasets and their robustness against image variations.

3.2 Food 101 dataset

The dataset utilised in this project comprises subsets of the full food-101 data, with images downscaled to enable quick testing. The data has been reformatted into HDF5, specifically Keras HDF5Matrix, for easy reading. The dataset contains 101 categories, each with 1000 images, and most of them have a resolution of around 512x512x3 (RGB, uint8).

Name of the dataset	Food-101 dataset.
Total Images in dataset	101,000 Images
Categories in dataset	101 category
Tested Images in dataset :	250 images in one category
Trained Images in dataset	750 images in one category

Table 1: Dataset Details

For this research , only 15 categories were utilised, including Apple Pie, Club Sandwich, Grilled Cheese Sandwich, Tacos, Hamburger, Samosa, French Fries, Pizza, Ravioli, Cake, Spring Rolls, Donuts, Waffles, Sushi, and Nachos.

3.3 Methodology

The first layer in the Convolutional Neural Network (CNN) architecture is a 2D Convolutional layer, which consists of 32 kernels with a size of 3x3. This layer takes an input of size 100x100x3, where 100x100 represents the rescaled size of the images, and 3 denotes the colour aspect of the image (RGB). The next layer is a Max Pooling layer with a pool size of 2x2, which helps in reducing the spatial dimensions and extracting the most relevant features from the convolved images. These two layers are then repeated to obtain better filtered convolved images and improved feature extraction through the Max Pooling layer.
The above layers are repeated one last time, but with an increased number of kernels from 32 to 64. This is done to obtain more filtered images that can be utilised in the subsequent fully connected layers. Two fully connected layers are used next, with 128 and 90 neurons respectively. Dropout layers with a rate of 0.01 are added between the dense layers to prevent overfitting. Dropout randomly sets the weights of some neurons to zero during training, preventing them from dominating the learning process and leading to overfitting on specific neurons.

All the Convolutional 2D layers and fully connected layers in the CNN architecture utilise the Rectified Linear Unit (ReLU) activation function, which introduces non-linearity into the network and helps in capturing complex patterns in the data. The last layer in the architecture is the output layer, consisting of 15 neurons, which is equivalent to the number of categories in the dataset. Each neuron in the output layer produces an output in the form of a probability corresponding to a particular category. The CNN predicts the category with the highest probability as the final predicted class for the input image.

The CNN architecture consists of the following layers:

1. Input Layer: The input images are of size 100x100x3, where 100x100 represents the rescaled size of the images, and 3 denotes the color channels (RGB).
2. Convolutional Layer 1: The first convolutional layer consists of 32 kernels with a size of 3x3, which convolve with the input images to extract local patterns or features.
3. Max Pooling Layer 1: The output of the first convolutional layer is then passed through a max pooling layer with a pool size of 2x2, which reduces the spatial dimensions and extracts the most relevant features from the convolved images.
4. Convolutional Layer 2: The output from the first max pooling layer is then passed through a second convolutional layer with 64 kernels of size 3x3, to obtain more filtered images for improved feature extraction.
5. Max Pooling Layer 2: The output of the second convolutional layer is then passed through another max pooling layer with a pool size of 2x2, further reducing the spatial dimensions.
6. Fully Connected Layer 1: The output from the second max pooling layer is flattened and passed through a fully connected layer with 128 neurons.
7. Fully Connected Layer 2: The output from the first fully connected layer is then passed through another fully connected layer with 90 neurons.
8. Dropout Layers: Dropout layers with a rate of 0.01 are added between the dense layers to prevent overfitting.
9. ReLU Activation Function: All the convolutional and fully connected layers utilize the Rectified Linear Unit (ReLU) activation function, which introduces non-linearity into the network and helps capture complex patterns in the data.
10. Output Layer: The last layer in the architecture is the output layer, consisting of 15 neurons, which is equivalent to the number of categories in the dataset. Each neuron in the output layer produces an output in the form of a probability corresponding to a particular category. The category with the highest probability is predicted as the final class for the input image.

This CNN architecture is designed for image classification tasks, such as food recognition, and aims to capture relevant features from the input images through convolutional and pooling layers, followed by classification using fully connected layers and ReLU activation function, with dropout layers to prevent overfitting.

4. Results

After applying various machine learning algorithms, including Support Vector Machines, K-Nearest Neighbour, Random Forest Classification, and the deep learning algorithm Convolutional Neural Networks (CNN), we have concluded that CNN is the most suitable method for image classification on our dataset, considering both speed and accuracy. CNN has shown superior performance, particularly in cases where the dataset is large.

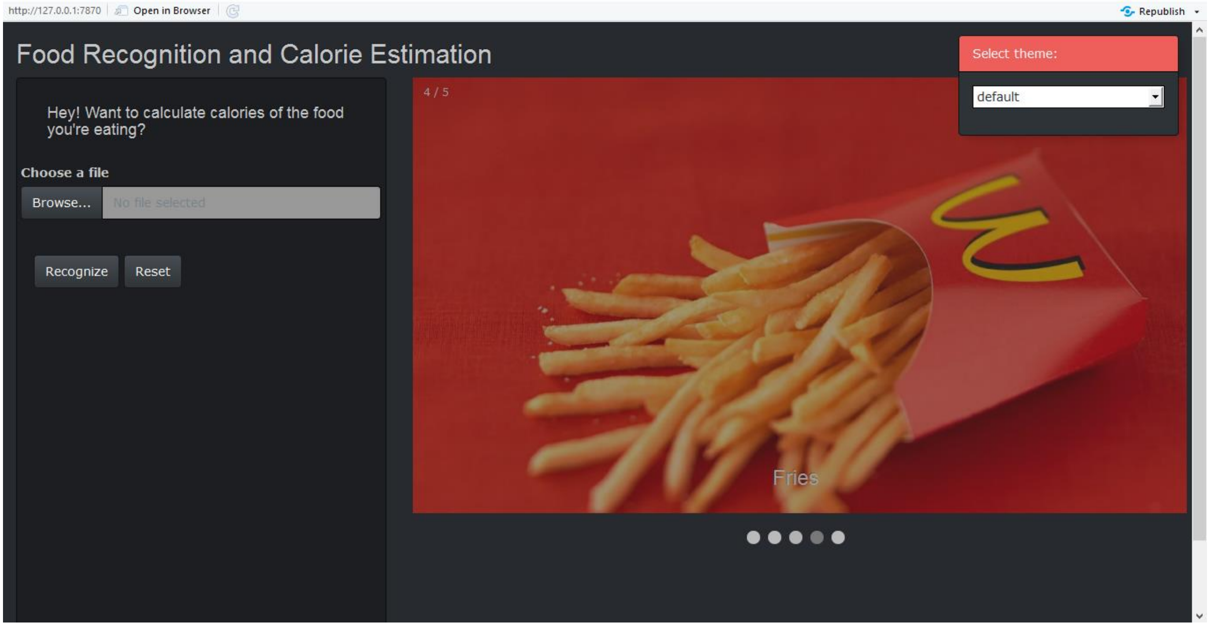

Fig 3: Before Uploading food image into model

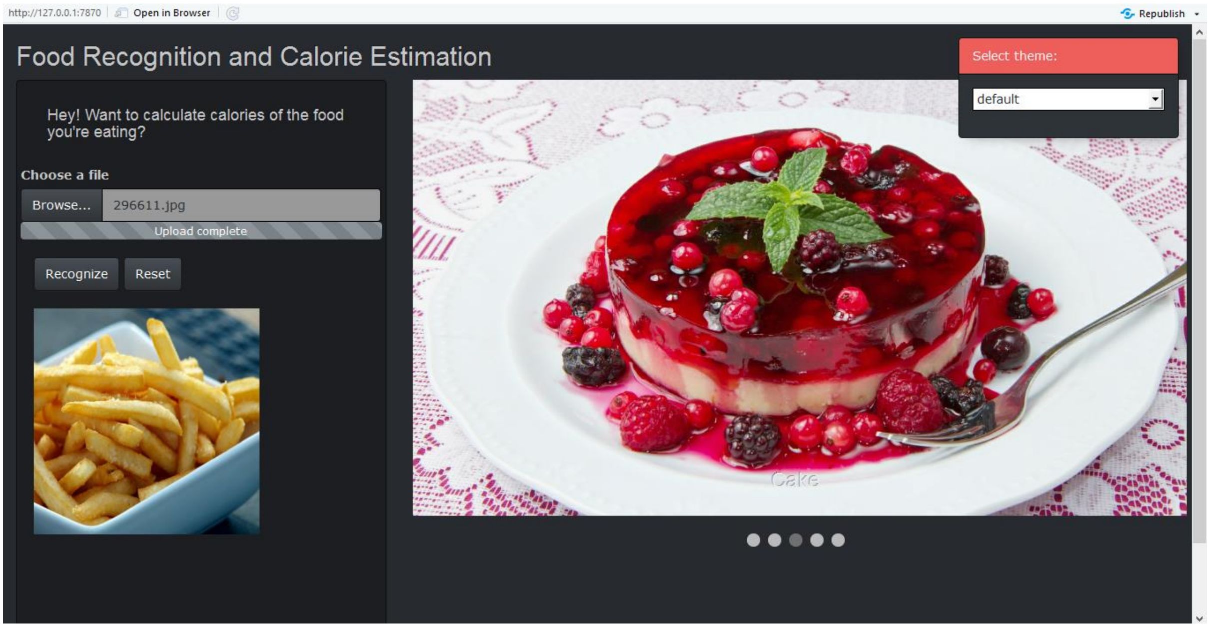

Fig 3: AfterUploading image into model

The accuracy of the trained CNN model on the training set is 86%, indicating that it has learned the patterns and features of the images in the training data with a high level of accuracy. This implies that the CNN has effectively captured the complex relationships between the input images and their corresponding labels during the training process.

Furthermore, the accuracy of the CNN model on the test set is 80%, indicating its ability to generalise well to new, unseen images. This suggests that the CNN model is capable of accurately classifying images from the dataset that it has not seen before, which is a crucial aspect of image classification tasks.

The results obtained from the comparison of different algorithms highlight the superior performance of CNN in terms of both accuracy and speed for our specific image classification problem. The high accuracy achieved on both the training and test sets demonstrates the effectiveness of CNN in accurately classifying images in our dataset, making it the most viable method for our image classification task.

5. Conclusion and Future work

The proposed method in this project aims to create a food recognition and detection and calorie estimation system using multiple algorithms, including Convolutional Neural Networks (CNN), Random Forest, and Support Vector Machines (SVM), with the goal of achieving high accuracy in food image classification. The project utilised a publicly available food image dataset(food 101 dataset) for training and evaluation purposes.

CNN was chosen as the primary algorithm for image recognition due to its ability to automatically learn complex patterns and features from images. CNNs are highly effective in capturing relevant features from images, making them suitable for tasks such as food recognition, where images may contain varying shapes, sizes, and colours of food items.

The models were trained using the food image dataset, which provides a diverse range of food images for the algorithms to learn from. During the training process, the models were optimized and hyperparameters were tuned to further improve their accuracy. This involved selecting the optimal set of hyperparameters, such as learning rate, batch size, and number of layers, to achieve the best performance on the food image dataset.

The Model also utilized other algorithms such as Random Forest and SVM for comparison and evaluation purposes. These algorithms were trained and evaluated using the same food image dataset to compare their performance with the CNN model. By using multiple algorithms, the project aimed to identify the most effective approach for food recognition and detection based on the dataset and specific requirements of the project.

Furthermore, the accuracy of the models was further improved through optimization techniques, such as hyperparameter tuning. Hyperparameter tuning involves systematically searching and selecting the optimal set of hyperparameter values to maximise the performance of the models. This process helps to fine-tune the models and achieve higher accuracy in food image recognition.

In summary, the proposed method in this model involves using multiple algorithms, including CNN, Random Forest, and SVM, for food recognition and detection. The models were trained using a publicly available food image dataset and optimised through hyperparameter tuning to achieve higher accuracy. This comprehensive approach aimed to identify the most effective algorithm for food recognition based on the dataset and specific requirements of the model.

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