Food Recognition System Using Classification Methods on UEC

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ABSTRACT

The development of an autonomous food recognition system has a number of intriguing applications, including food waste management, marketing, calorie estimation, and daily nutrition tracking. Despite the importance of this topic, there aren't many papers on it. Furthermore, the literature comparison only considered best-shot performance, rather than the most popular approach of averaging across multiple trials. This experiment achieves the most recent accuracy of 90.02% on the UEC Food-100 database, outperforming the current best-shot performance experiment. This paper surveys the most popular deep learning methods used for food classification, presents publicly accessible food databases, publishes benchmark results for the food classification experiment averaged over 5-trials, and surveys publicly accessible food databases. The best results were obtained using the ensemble technique, which averaged the predictions of the ResNeXt and Dense Net models. The UEC Food-100 database and other food databases are used for all tests because it is one of the most popular datasets and because it presents a challenge due to the presence of multi-food photographs that must be clipped before processing.

Index Terms—Artificial Neural Networks, Image Classification, Machine Learning

Keywords: Abstract, Maximum

I INTRODUCTION

A widely researched issue, automatic food classification has a variety of intriguing uses, including automated waste detection, calorie estimation, understanding dietary patterns, and advertising. For instance, a computerized waste tracking system that logs the quantity and type of food wasted throughout the day in a restaurant or food facility is crucial for both reducing food waste and raising social awareness. These systems rely heavily on image classification, which is a difficult job due to numerous technical and environmental factors like lighting, image quality, noise, orientation, scale, etc. With various cooking techniques that result in the same food having different shapes, such as raw and cooked food combined with sauces, the food classification issue becomes even more complicated; in other words, the food item is inherently deformable with high intra-class variation. With multi-food images, or when a dish includes a variety of various foods that may overlap, the food recognition task becomes even more difficult. A candidate area detection algorithm is usually used in this situation, followed by a classification phase. Candidate region detection, a crucial pre-processing phase, is used to extract all the regions in an image that only contain food, or regions of interest, and it enables the following steps of feature extraction, classification, and learning higher level representation. The food regions that were extracted from multi-food images are obviously of lower grade. The databases with multiple food pictures are therefore more difficult and useful for both detection and recognition tasks.

II OBJECTIVES OF THE PROJECT

The deep learning algorithms, which fundamentally altered the traditional machine learning strategy consisting of feature extraction and classification, are responsible for the best classification results reported in the literature. Data with labels are used as the input for supervised deep learning techniques; during training, the network learns the weights, and during testing, the pipeline of layers forecasts the class of the input data. Deep learning models, in other words, are all-purpose algorithms that can extract higher level representations of the data, such as food items, and categories them.

III STUDY ON EXISTING SYSTEM

- Only 12,000 pictures from a small dataset were used.
- Only used data from the UEC Food-100 database, which results in a lower accuracy rate.
- The primary drawback is the absence of large, global databases, which are required to train the algorithms.

IV STUDY ON PROPOSED SYSTEM

This system provides an overview of the key classification algorithms for foods, describes the current food item databases, and displays the outcomes of several deep learning algorithms, taking into account both the best-shot performance and the average over five attempts. This paper surpasses the previous mark by 0.44 percentage points in the best shot performance experiment, achieving 90.02% on the UEC Food-100 database, the state-of-the-art accuracy. However, we think that comparing methods based on average performance over five trials is more suitable because all methods are highly sensitive to the selection of the training and test sets. We believe that this is the first method to report the accuracy averaged over five trials on the UEC Food100, UNIMIB, and PFID databases.

Advantage:

• Despite the fact that food categorization systems are extremely important, there are currently not enough studies or advancements in this area.

• New techniques can aid in enhancing the functionality of accessible datasets.

•The method targets the detection problem on the UEC Food-100 database by using more databases and addresses the classification challenge of other food item databases.

V MODULE DESIGN

- The Databases Of Food
- Deep Convolutional Neural Network Models
- Residual Networks (ResNet)

The Databases of Food:

There aren't many food image databases, but those that do vary in their number of food categories, total number of images, type of cuisine (e.g., Western (French, Italian, Turkish,...), Asian (Japanese, Chinese, Thai,...), or fast food (since it may be regarded as a global type of food), quality and type of images (e.g., single versus multi-food images), and context (e.g., the same dish may contain The diversity in the databases that are available makes comparison a challenging job. This project concentrates on openly accessible databases that contain more than 1,000 images and 60 classes.

Deep Convolutional Neural Network Models:

Convolutional neural networks (CNN) offer completely connected layers for classification and convolution and pooling layers for feature extraction. The convolution layer extracts hierarchical features from the pictures using sliding boxes, also known as filters. Critical hyperparameters for deep learning systems include the number of convolutional layers, pooling and fully connected layers, coefficients, and the size and number of filters. There is one more layer, known as the categorization or SoftMax layer.

Residual Networks (ResNet) :

This module introduced the residual block, which augments the output feature produced by processing the input with one or more convolutional layers by including the initial input. That is, by skipping connection blocks and using residual blocks, a layer can supply both the layer after it and levels that are several layers ahead of it in the architecture. The term of this block refers to the mathematical function that is being used, which learns the residual (or difference) between the input and output signals. ResNet employs a global averaging pooling layer prior to the categorization layer, just like Inception.

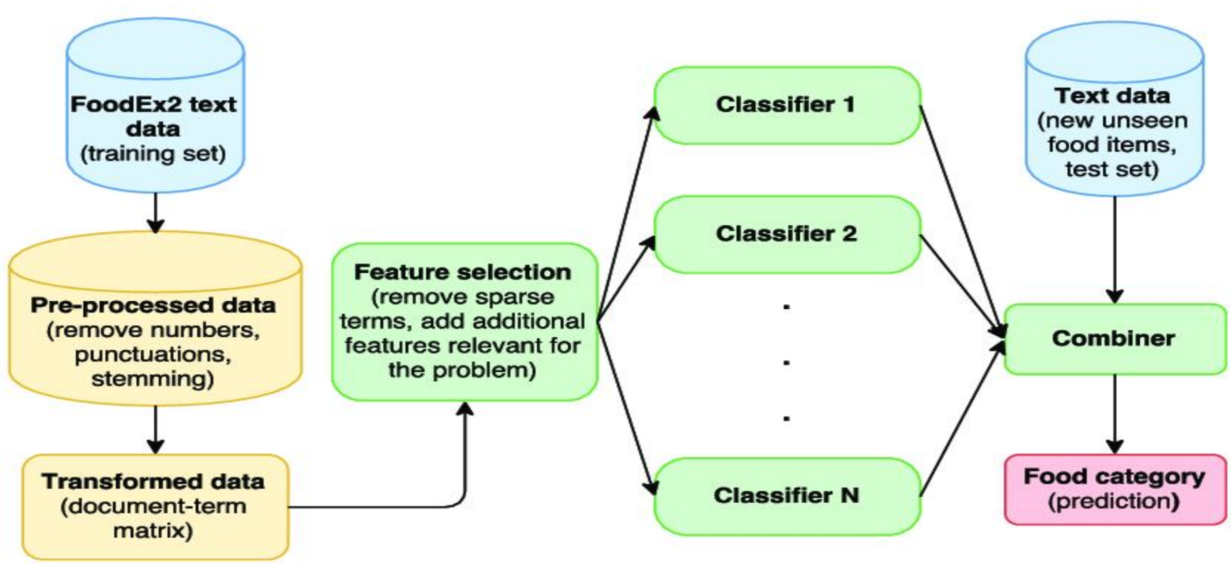
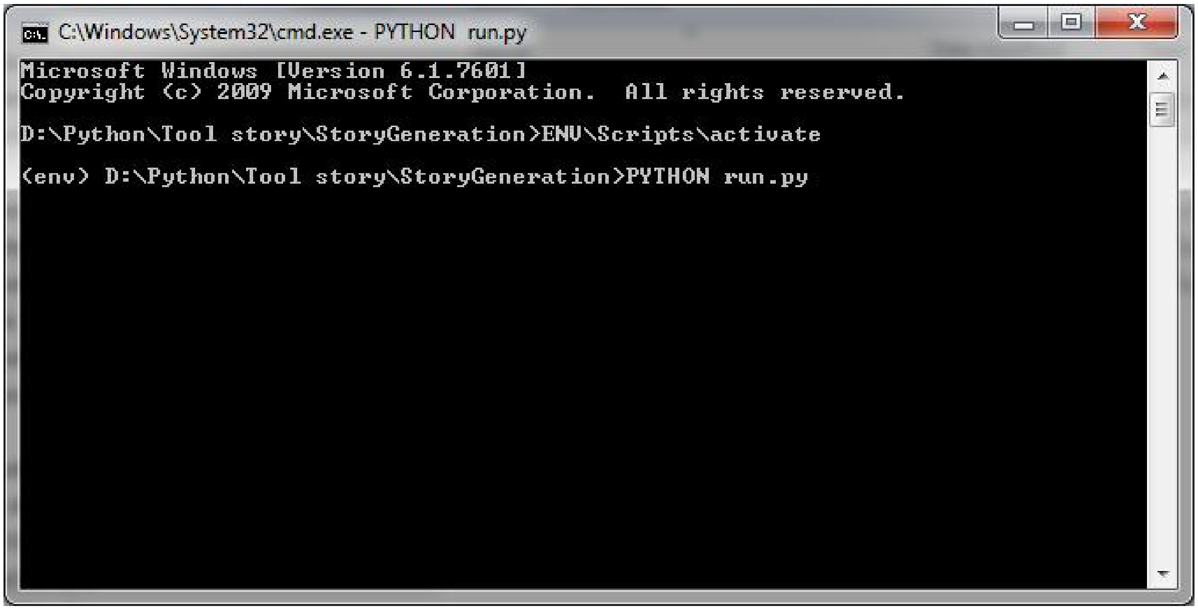


Figure 1: Flowchart of the Project

RESULTS:

Executing in terminal



Welcome page

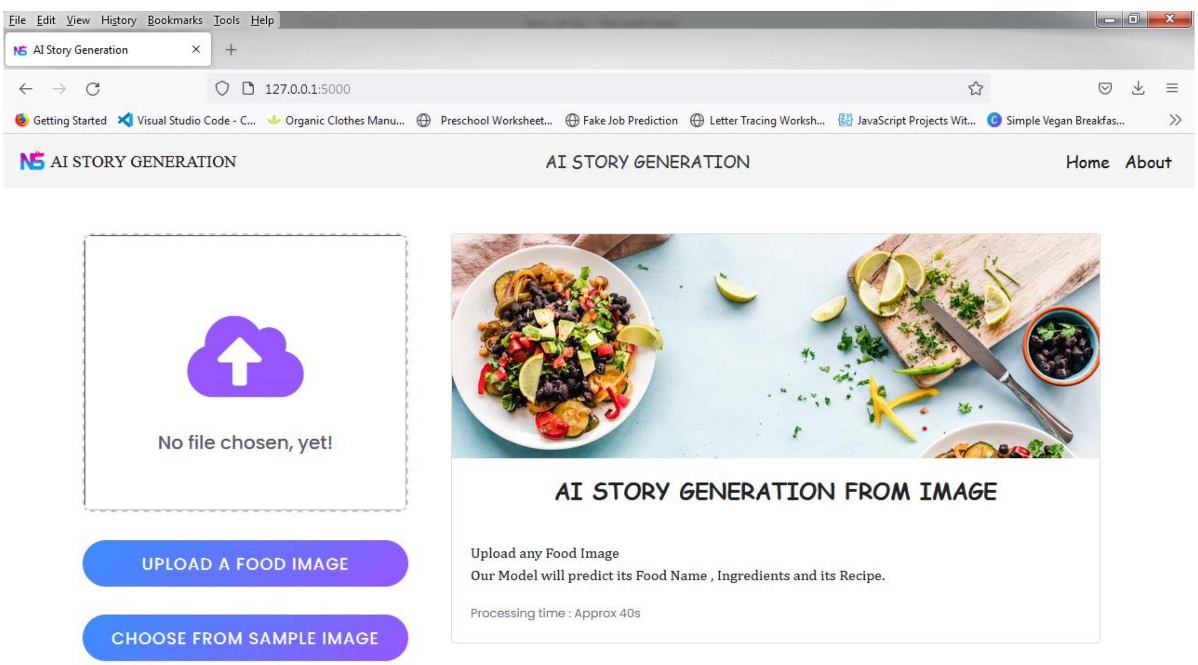
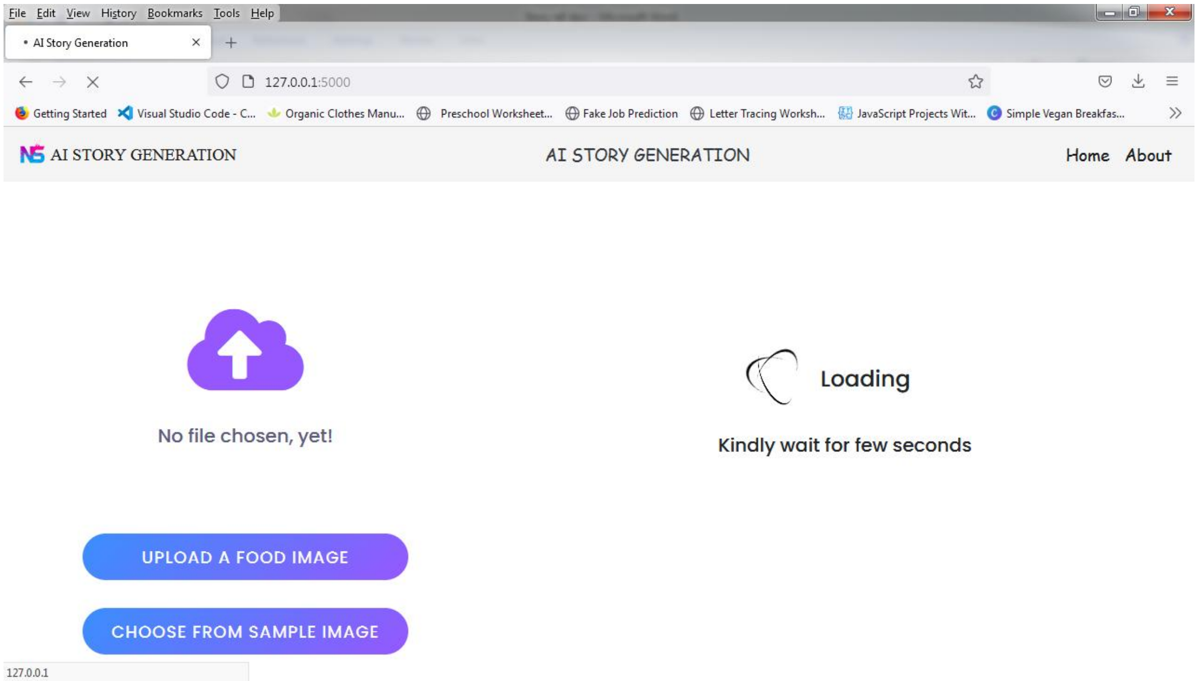
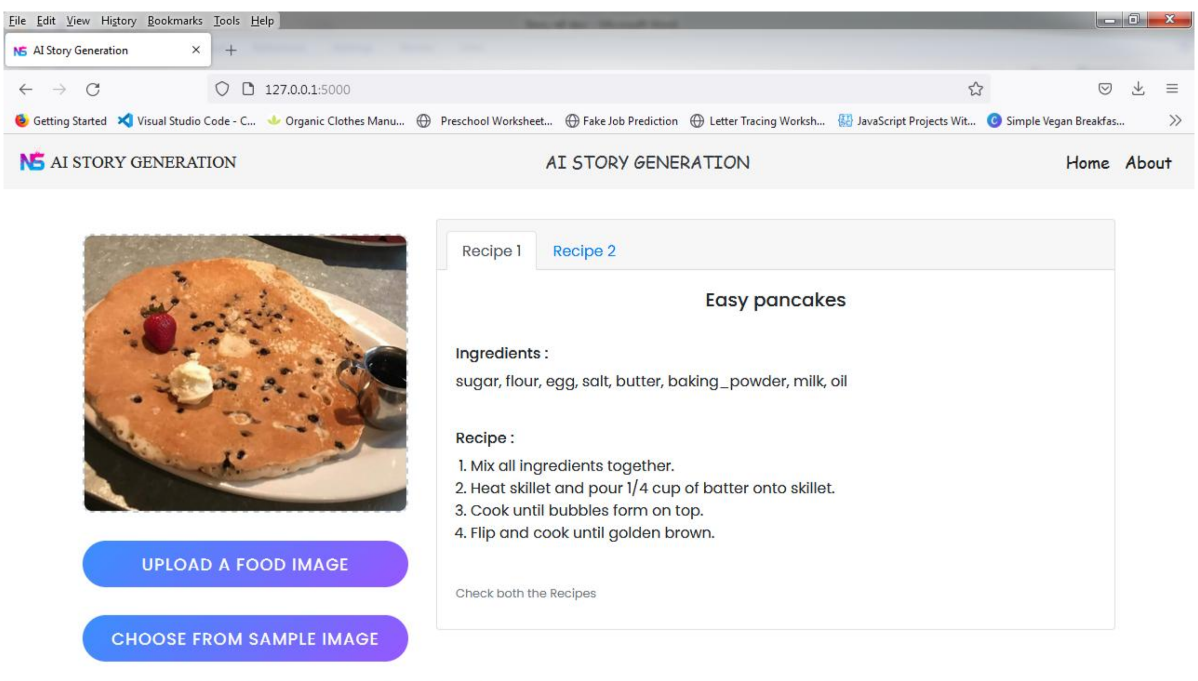
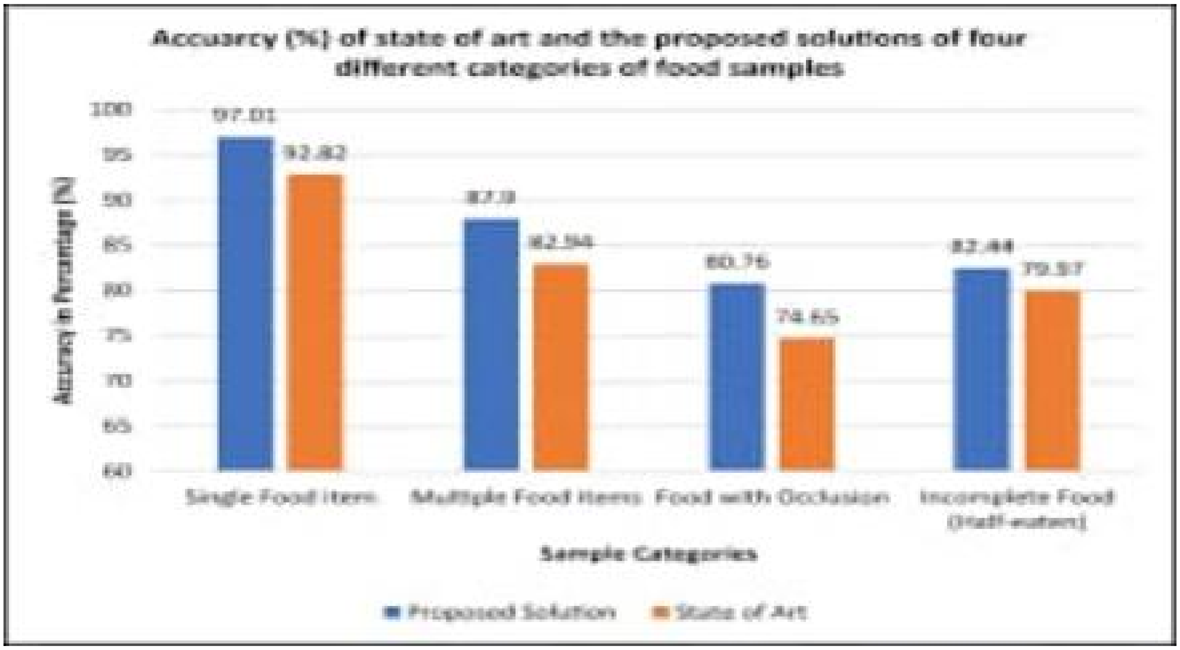


Image upload:



Generated food:





VI CONCLUSION

Despite the fact that food categorization systems are extremely important, there are currently not enough studies or advancements in this area. Lack of large, global databases, which are required to train the algorithms, is the primary drawback. New techniques can also help to boost the efficiency of the accessible databases. This work provides an overview of the key classification algorithms for foods, describes the current food item databases, and shows the outcomes of several deep learning algorithms, taking into account both the best-shot performance and the average over five trials.

VII SCOPE FOR FURTHER ENHANCEMENT

Modern accuracy on the UEC Food-100 database of 90.02% is an improvement of 0.44 percentage points over the prior record. However, we think that comparing methods based on average performance over five trials is more suitable because all methods are highly sensitive to the selection of the training and test sets. To the best of our knowledge, this is the first piece of work that gives the accuracy on the UEC Food100 averaged over five trials and can be used as a benchmark. Future study will target the detection problem on the UEC Food-100 database as well as the classification problem of other food item databases.

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V. CONCLUSION

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All references have to be in APA format.