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INVERSE COOKING

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Abstract: Certain cooking items still fall under the same classifications. The problem is that the general public has limited access to updated records. The objective of this study is to ascertain the difficulty of automatically identifying a meal in a photograph for cooking and then automatically generating the appropriate recipe. Due to significant overlaps in food dishes and the possibility that meals from various categories may simply resemble one another visually, the chosen job is more challenging than previous supervised classification difficulties (also known as high intra-class similarity). Convolutional Neural Networks (or CNNs for short) are used to distinguish objects or food courts while concurrently looking for adjacent neighbours (Next-Neighbour Classification).

INTRODUCTION

Image identification of food goods would be a practical method for storing food records. A photograph would therefore make a good record. We are however conscious of the significant variations in cuisine. Even within a single dietary category, there are numerous options. Given this, the performance of food item recognition is remains subpar despite efforts. The right recipe can be found after the food has been identified. Food is necessary for survival. It affects our culture and feeling of self in addition to providing us with energy. Food-related activities including cooking, eating, and talking about food take up a significant portion of our everyday life because "we are what we eat," the adage remains true. Food culture is more widespread than ever in the contemporary digital era as people share more food-related photos on social media. Indicating the unquestionable significance of food in our culture, an Instagram search for #food returns at least 300 million photos, while a search for #foodie returns at least 100 million photographs. Eating customs and cooking culture have also evolved over time. Nowadays, we frequently consume food that has been prepared by someone else instead of the majority of meals traditionally being cooked at home (e.g., takeaways, catering and restaurants). The inability to find thorough information about prepared foods makes it impossible to know exactly what we consume. Food and the components it contains vary greatly across classes and undergo major deformations while cooking, making food recognition more challenging than natural visual perception. In a prepared dish, ingredients arrive in a variety of colours, shapes, and textures, and they frequently get lost in the mixture. Additionally, sophisticated reasoning and background knowledge are needed for the detection of visual components (e.g., cake will likely contain sugar and not salt, while croissant will presumably include butter). Food recognition is challenging for even the most advanced computer vision systems because it calls for them to go beyond the obvious and take into account prior knowledge in order to create high-quality structured descriptions of food preparation.

LITERATURE SURVEY

[1] "Using Deep Learning for Food and Beverage Image Recognition", In this paper authors describe their deep learning contributions to the field: NutriNet, a novel deep learning architecture, and a pixel-level classification solution for images of fake food. NutriNet was trained on a food image dataset of a larger size and containing more food classes than previous works, and was the first to recognize beverage images. The work on fake-food image recognition includes the first automatic system for recognizing images of fake food, while the visual similarity of fake and real food makes it useful for fake-food experiments as well as real food recognition.

[2] "Food recognition by combined bags of color features and texture features", propose a discriminated food image representation that can perform effective identification of food images in this paper. The conventional image representation mainly includes color and texture distributions (histogram), which are the statistical information based on uniformly quantized color or texture levels. However, these conventional techniques using uniform quantization of the on-hand color and texture in the image lead much information loss for reliably constructing the image. Therefore, this study proposes to characterize the color and texture information by incorporating the strategy of patch-based bag of features model. This technique can adaptively learn the representative color or texture (prototypes) from the food images for food recognition, and it is possible to recover a more reliable image using the learned prototypes. The experiments using the proposed approaches show that the recognition rate can be greatly improved compared with the conventional method.

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[3] "Auto-recognition of food images using SPIN feature for Food-Log system", propose to extract rotation invariant features using circle-segmentation called SPIN for food recognition, and construct a Food-Log system, which records the contents of food menu, calories and nutritional value for management of the dietary life.

[4] "Sparse model in hierarchic spatial structure for food image recognition", Propose to apply a sparse model for coding a local descriptor extracted from the food images. Sparse coding: an extension of vector quantization for local descriptors, which is popularly used in Bag-of-Features (BoF) for image representation in generic object recognition, can represent the local descriptors more efficient, and then obtain more discriminant feature for food image representation. Moreover, in order to introduce spatial information, a hierarchic spatial structure is explored to extract the feature based sparse model. Experiments validate that the proposed strategy can greatly improve the recognition rates compared with the conventional BOF model on two databases: the constructed RFID and the public PFID. Pittsburgh Fast-Food Image Dataset (PFID) consists of various fast-food images which include 61 categories and 18 images in each category. Due to the better recognition performance, the nonlinear SVM classifier, which has high computational cost, is applied in BoF model. However, the proposed strategy can further improve the recognition performance even with linear SVM

PROBLEM STATEMENT

The lack of methods to identify food recipe automatically using machine learning from images is a concern as it may raise bars for food recognition.

OBJECTIVES

Reprise the recipe of the food whose image is given as input

EXISTING STUDY

A food image is provided to the recipe generation system, which then utilises it to generate a set of cooking instructions. These instructions are generated by an instruction decoder that is fed two embeddings. While the second encodes the image's constituents, the first reproduces the visual components that were retrieved from the image.

Merits: Components that come in a variety of hues, forms, and textures are typically hidden in cooked dishes. To recognise food, modern computer vision systems must go beyond what is immediately visible.

METHODLOGY

The inverse cooking system uses the food photographs to generate the recipe title, ingredients, and cooking directions. We use neural joint embedding, a method that involves placing two data sets in a single embedding space (a recipe and an image). Embedding makes large-input machine learning problems easier, such as those needing sparse vectors to represent words. Cuisine is categorised by food components created via inverted cooking. The meal will be separated into numerous groups depending on kind. There are many various sorts of food available, including Thai, Chinese, French, Italian, Mexican, Indian, and Thai. Using food photos, consumers may identify a cuisine. People who have never eaten before can greatly benefit from it.

Since comprehending the items that go into a dish and the modifications they experienced, such as slicing, blending, or mixing with other ingredients, is necessary to create a recipe from an image, it might be challenging. We argue that rather than merely extracting the recipe from an image, a recipe producing pipeline would benefit from an intermediate phase that forecasted the ingredients list. Following that, the list of ingredients would be used to produce the directions, which could then communicate with the image to add more information about how the various elements were utilised to create the finished dish.

1. Pre-processing phase
2. Building and training models
3. Performance evaluation of the models

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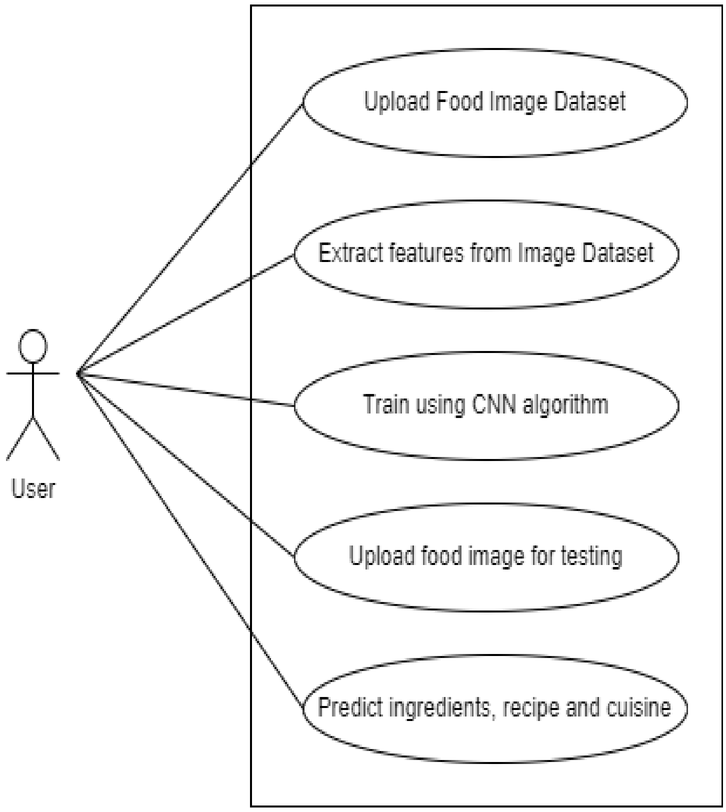

CONCLUSION

We developed a technique that turns food photos into complete recipes complete with titles, ingredient lists, and cooking directions. Before that, we used images of food to forecast sets of components and show the value of dependency modelling. The development of instructional materials with both implicit and explicit components offers a case study for the requirement of simultaneously considering both modalities.

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