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Multi-source data fusion using deep learning for smart refrigerators

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ABSTRACT

Food recognition is one of the core functions for a smart refrigerator. But there are many challenges for accurate food recognition due to reasons of too many kinds of food inside the refrigerator which tends to obscure each other, and they may look very similar. This paper proposes a fruit recognition approach that fuses weight information and multi deep learning models. The proposed approach can remarkably improve recognition accuracy. We have extensively evaluated the proposed approach for its performance and accuracy, which demonstrate the effectiveness of the proposed approach.

1. Introduction

Smart refrigerator is an essential appliance in a smart home. As one of the core functions of a smart refrigerator, recognizing food in a refrigerator is very important for, e.g. knowing whether the food is fresh and the amount of storage left in the refrigerator. However, recognizing food (e.g. fruits as demonstration approach in our paper) efficiently in a refrigerator is challenging due to the fact that food may be piled together, food may look very similar, and different food may obscure each other.

There exists quite some work on fruit recognition. Bolle et al. [1] proposed Veggie vision, which can identify fruits by extracting the characteristics of color, texture and density. However this work is sensitive to illumination changes. Zawbaa et al. [2] explored fruit shape and color to identify fruits. Naskar et al. [3] extract color, sharp and texture features, using artificial neural network to identify the fruit. Patel et al. [4] proposed an algorithm for fruit detection based on multi-feature. Shebiah et al. [5] proposed an efficient fusion of color and texture features for fruit recognition.

Deep learning provides new possibilities for effective recognition of objects, as illustrated by the classification results for the ImageNet problem with deep convolution neural network (deep CNN, or DCNN) [6]. It performs better in object recognition than most of traditional approaches [7]. But as fruits may have the same color, shape, and texture, like orange and tangerine, these existing methods are hardly effective to recognize food.

Therefore in this paper, we propose an integrated data fusion approach where multi convolution neural models together with weight information are combined to conduct fruit recognition. Through this multi-source data fusion approach, the accuracy of fruit recognition is improved significantly when handling similar fruits with the same color, shape and texture, where three SSD [8] models are introduced to identify the fruit.

Besides the data fusion approach, two different architectures, running remotely or locally, are proposed for realizing this multi-source data fusion approach. The first one is using RPi (raspberry pi)[1] which carries camera and weighing sensors to collect data. RPi will send the data to the server. The server will use HBase[2] to store data. Then the result of recognition will feedback to RPi. This method is called the cloud mode. Another architecture uses TX1[3] which collects data and identify the fruits by itself, this method is called local mode. The performance of the cloud mode is compared with the local mode.

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1 RPi is a micro-computer based on ARM which the size is as small as a credit card. https://www.raspberrypi.org/.
2 http://hbase.apache.org/.
3 NVIDIA Jetson TX1 can provide good computing performance which up to 1 T-Flops, and support the NVIDIA CUDA technology. http://www.nvidia.com/object/jetson-tk1-embedded-dev-kit.html.

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0166-3615/

The contributions of this paper are:

- A novel fruit recognition approach is proposed, where we design the recognition algorithm using neural network with multi-model fusion, combining with weight information. Through multi-source based data fusion, the accuracy of fruit recognition is improved significantly, when handling fruits with the same color, shape and texture.
- A data set for fruits is built for the refrigerator environment, which contains ten kinds of fruits with different shooting angels and different lighting environments.
- Two architectures of the smart refrigerator are proposed, running locally or remotely, using RPi plus HBase, and using TX1 respectively.

The remainder of the paper is organized as followed: Section 2 presents the smart refrigerator framework; based on this platform, Section 3 presents the approach of multi-source based data fusion for fruit recognition. Section 4 discusses the evaluations of the fruit recognition. Section 5 shows some related work. Conclusion and future work end the paper.

2. Algorithm of fruit recognition using multi-source data fusion

Intuitively, different deep neural network models may extract different features for recognition, and the combination of these models can lead to a higher recognition accuracy than a single model. There, our first attempt is using neural network (BP in our case) with multi-model fusion, based on three SDD models, namely ResNet [9], VGG16 and VGG19 [7]. Although there are many CNN based recognition approaches can be used for fruit recognition, such as Faster R-CNN [10], YOLO [11]. Due to its performance, and accuracy, we choose SSD models instead as the basis for our approach.

2.1. Multi-model fusion

The multi-model fusion method for fruit recognition is shown in Fig. 1. The same data set is used to train SSD models, three outputs of these three models are used as the input of BP neural network.

The outputs of these three models serve as the input for the BP neural network, where we show the structure of it in Fig. 2. The node number of the input layer is 3, and the node number of hidden layer is 10, while the output layer only has one node. The neuron between the node of hidden layer and output layer uses a linear transfer function. The relationship between the state of neuron X_i and output Y_i is a linear transformation,

$$Y_i = f(X_i) = X_i. \tag{1}$$

We assume D_1, D_2, D_3 is the input of the neural network, the output is

$$E_i = D_I, \quad i = 1, 2, 3. \tag{2}$$

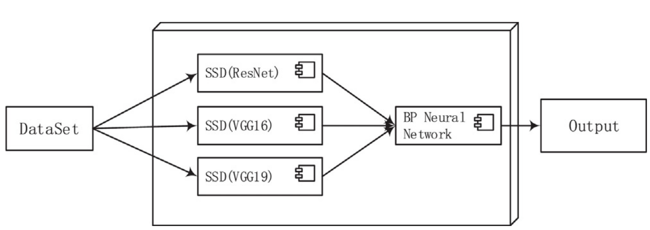

Fig. 1. The structure of multi-model fusion.

For the hidden layer, the input of node j is

$$F_j = L_{j1} \cdot E_1 + L_{j2} \cdot E_2 + L_{j3} \cdot E_3 + M_j; \tag{3}$$

the output is

$$H_i = f(X_j), \quad j = 1, 2, 3 \cdots, 10. \tag{4}$$

For the output layer, the input is

$$k = L_{1j}^2 H_j + M^2; \tag{5}$$

the output is

$$Y = f(k) = k. \tag{6}$$

L_{ji} and L_{1j}^2 are the linked weights, M_j and M^2 are the constant bias.

2.2. Multi-source data fusion

The usage of multi-model fusion can improve the recognition accuracy to some degree, but it is still hard to differentiate similar fruits. In our approach, we use the weight information of a fruit to help the recognition process. We build a priori knowledge data set for each kind of fruit including name of the fruit, weight range and a list of similar fruits. After obtaining the name of the fruit using multi-model of deep learning, and its weight range from the knowledge base, the decision on fruit type will be made based on the combination of these information.

Fruits that cannot be measured by weight are also taken into consideration, such as a bunch of grapes, bananas and a box of strawberries, etc. For such kind of fruit, it usually has unique features, which makes weight information useless. The fusion method is given in Algorithm 1.

Algorithm 1. Multi-source data fusion

```
Type Fruit
  Dim names As STRING
  Dim weights As STRING
  Dim SimilarList As LIST
HashMap ⟨string, Fruit⟩ weightMap ← new HashMap ⟨string, Fruit⟩
For every fruits
  fruit.names ← db.names
  fruit.weightranges ← db.weights
  fruit.similiar ← db.similarlist
  WeightMap.put ⟨fruit. name, Fruit⟩
done
objects ← detect(pretrain model)
addFruit ← Objects-LastObjects
lastObject ← Objects
weight ← addfruit.weight
name ← addfruit.name
fruit ← WeightMap.get(name)
weightRange ← fruit.weightranges
similar ← furit.similar
Dim maxName As STRING
Dim maxProb As INTEGER ← 0
For similarFruit: similar
  If (similarFruit.Prob > maxProb) and (similarFruit.weight in range)
    maxName = similarFruit.name
    maxProb = similarFruit.Prob
  done
done
return maxName
```

3. Multi-source based data fusion for smart refrigerators using deep learning

Considering the requirement of running fruit recognition locally or remotely, we have designed two architectures. The first one uses RPi (raspberry pi) to send sensed data to a remote