

Real-time Calorie Extraction and Cuisine Classification through Food-Image Recognition

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Abstract

The self-monitoring of user-activity tracking is the most common method of both individuals and most health-care systems. A growing demand for services that can easily monitor food and calorie information through the use of food photographs has also emerged. In this paper, an existing food-recognition and calorie-extraction system is combined with a context-recognition system that recognizes the meal type. To recognize the food images, a preceding Tensorflow-based machine-learning process was performed, and an Expert.js-based semantic network was constructed for the meal-type recognition. The food-recognition accuracy rate is 55.3 %, and Korean, Chinese, and Italian food were recognized. As a result, the objective is the combining of the context awareness with the existing self-monitoring systems to enable the user to implement dietary adjustments.

Keywords: Vision system, Cuisine classification, Calorie extraction, Image recognition, Machine learning

1. Introduction

Health care is one of the most important social issues, and to improve personal health, people engage in exercise or dieting. The tracking of user activities through self-monitoring is the most common practice and is included in most health-care systems [1]. A system that can be easily self-monitored through the use of a vision system also exists [2, 3]. In this paper, a food-classification procedure is combined with an existing self-monitoring system using the vision system. By analyzing the food in real time through photos of the food that the user eats, the calories are extracted and the type of food (Korean, Chinese, *etc.*) that the user has consumed is classified according to a maximum of three extracted food names. Accordingly, the service can recommend food depending on the context, thereby helping the dietary control of the user.

2. Design of the System

In this paper, the functions of the food-type extraction in the existing calorie-extraction system are combined through the food-recognition process. Claus (a classifier that uses real-time images) recognizes the photos in the vision system in real time, extracts the food names and the calorie data in real time, classifies the food types in the classification system using the extracted food-name data, and the user interface (UI) makes its structure directly visible to the user. As shown in Figure 1, the system consists of a vision system, a classification system, and the UI. The overall system is made up of a Web platform that is easy to access. To construct the whole system, HTML and

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Javascript are used, while real-time client-server data transmissions allow Ajax to materialize the asynchronous UI, as shown in Figure 2.

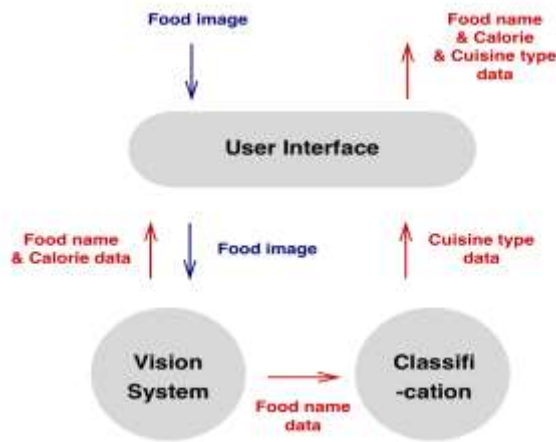


Figure 1. Structure of the System



Figure 2. Data Transfer Between the Client and the Server

A MySQL database is used to store the user data. The database consists of the following two tables: a user table for the storage of the user ID and password, and an ItemTbl table for the recording of the user food name, ID, date, and calories.

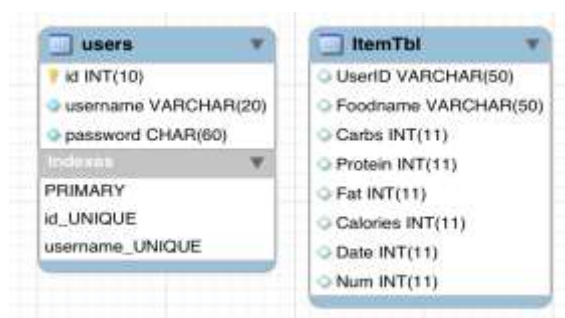


Figure 3. Components of the Tables

The vision system aims to recognize the names of foods and the corresponding calorie information through its attainment of the user food images. For this information, it is necessary to construct a classification model using machine

learning. To construct the classification model, the training data are needed, and the food data corresponding to the list of Figure 4 are collected and used.

- | | |
|--|-----------------------------|
| Tofu Stew | reuben sandwich |
| Radish kimchi | Ma Po Tofu |
| Fried tofu | steak |
| Yukgaejang (Spicy beef soup with vegetables) | cornbread |
| Kimchi | jambalaya |
| Chow Mein | new mexican flat anshiladas |
| po-boy | fajitas |
| Carbonara | roasted turkey |
| Chicken Cacciatore | curry |
| Gelato | avocado roll |
| Dweenjang Chigas | Peking Roasted Duck |
| Spring Rolls | - |
| Sweet and Sour Pork | - |
| Gong Bao Chicken | - |

Figure 4. Trained Food List

The goal of machine learning is the programming of computers so that example data or past experience can be used to solve a given problem [4], as shown in Figure 5.

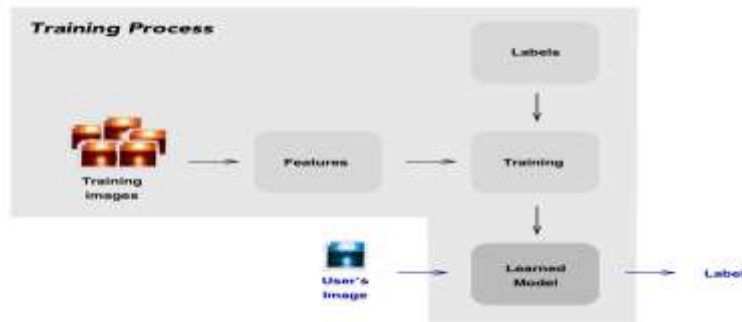


Figure 5. Process of Machine Learning

Tensorflow, a system that allows machine-learning practitioners and researchers to experiment with new techniques, was used for the machine learning [5]. By using Tensorflow, it was possible to develop a machine-learning system that can be processed in a simpler and faster way, and thus, it is possible and easy to develop the real-time interactions into a website.

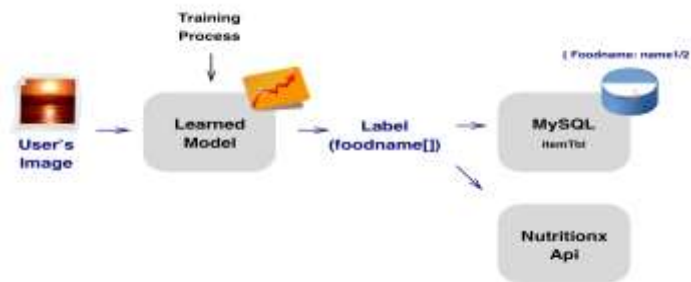


Figure 6. Structure of the Vision System

As shown in Figure 6, the food is recognized through photographs that are sent to the Nutritionx API with the recognized names in an array. The Nutritionx API returns the nutrient data that consist of the total calories and the essential nutrients according to the name of the food. The nutrient data is sent directly to the UI, and the name of the food is also sent to the UI and stored in the user-specific database that is mainly used in the classification system. An example of the data that are

stored in the database is shown in Figure 7. The food names are stored in one of the variables that are separated by slashes (/), which are again separated later by the JavaScript split function. The unit of all of the nutrients except for the calories is grams (g).

UserId	"id"
Foodname	"Food1/Food2/Food3"
Carbs	30
Protein	5
Fat	10
Calories	150
Date	20170201
Num	3

Figure 7. Illustrative Data of the Database

The classification process uses the names of the foods that are recognized by the vision system to derive the food types, and it stores the combinations and the types in the database. To do this, a miniature semantic-network framework called Expert.js is used [6]. Expert.js is a framework that provides digital-subscriber-line (DSL)-like constructs for the construction of semantic networks [6]. By using Javascript as the scripting language, it is easy to develop this framework. In Expert.js, the following two concepts are used to specify the rules: isa and example, where the isa is the parent label of the label, and the example is the inverse of the isa. For example, the isa of "cat" and "dog" is "mammal," and the examples of "mammal" are "cat" and "dog." By using the label name that is learned in the vision system, the upper labels that are included in the label are designated using the isa relationship and the example, as shown in Figure 8. When the user uses the vision system, it invokes a top label (isa) with the food name that is received in real time as a parameter. The process is shown in Figure 9.

```

148 korean
149   .example(TofuStew)
150   .example(Redishkimchi)
151   .example(Friedtofu)
152   .example(Yukgaejang)
153   .example(Kimchi)
154   .example(Dryseaweed)
155   .example(Dakgangjeong)
156   .example(Bulgoggi)
157   .example(BudaeChigae)
158   .example(DwenjangChigae)
159   .example(SpicyChicken);
    
```

Figure 8. Definition of Classify.js using the isa and example Relationships



Figure 9. Structure of the Classification System using Expert.js

For a maximum of three food labels per photograph, each food type is derived through the isa, and the label to which a large number of foods belong is estimated as a meal type.

This experiment classifies the following three types of meals: Korean food, Chinese food, and Italian food.

The UI allows the user to view the data on the nutritional facts and the meal classification without the need to refresh. Figure 10 is a list of the information that is displayed on the UI.

Foodname	List of foodnames
Carbs	(g)
Protein	(g)
Fat	(g)
Calories	(Kcal)
Cuisine Type	National cuisine type

Figure 10. Data that is Displayed on the User Interface (UI)

3. Implementation

HTML, CSS, Javascript, and Node.js were used to implement the website, MySQL was used to store the database, and Ajax was used for the asynchronous transmission that facilitates the communication between the client and the server. The file structure that constitutes the whole system is shown in Figure 11.

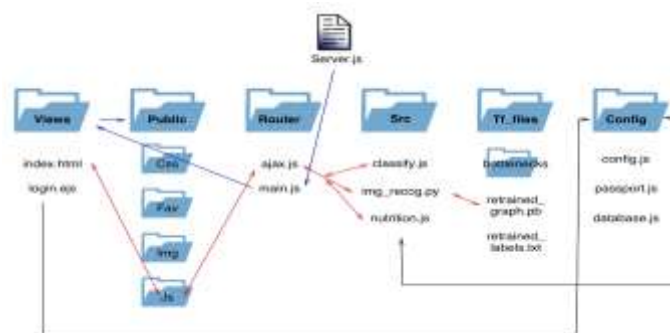


Figure 11. File Structure of the System

For the implementation of the system, a database construction must be implemented beforehand. The two tables in the MySQL database were created using the components that are shown in Figure 3 of Chapter 2, while Figure 12 shows the generated tables.

```

+-----+-----+-----+-----+-----+-----+
| Field | Type | Null | Key | Default | Extra |
+-----+-----+-----+-----+-----+-----+
| id | int(10) unsigned | NO | PRI | NULL | auto_increment |
| username | varchar(20) | NO | UNI | NULL | |
| password | char(60) | NO | | NULL | |
+-----+-----+-----+-----+-----+-----+
3 rows in set (0.88 sec)

+-----+-----+-----+-----+-----+-----+
| Field | Type | Null | Key | Default | Extra |
+-----+-----+-----+-----+-----+-----+
| UserID | varchar(50) | YES | | NULL | |
| Foodname | varchar(50) | YES | | NULL | |
| Carbs | int(11) | YES | | NULL | |
| Protein | int(11) | YES | | NULL | |
| Fat | int(11) | YES | | NULL | |
| Calories | int(11) | YES | | NULL | |
| Date | int(11) | YES | | NULL | |
| Num | int(11) | YES | | NULL | |
+-----+-----+-----+-----+-----+-----+
8 rows in set (0.00 sec)

```

Figure 12. Generated Tables using MySQL

Tensorflow was used to train the vision system. Tensorflow machine learning consists of the following three steps, which are shown in Figure 13: training-image exploration, bottleneck generation, and step-by-step training. As a result of the machine learning, an accuracy of 55.3 % was generated, as shown in Figure 14.

```
8000 bottleneck files created.  
8100 bottleneck files created.  
8200 bottleneck files created.  
8300 bottleneck files created.  
8400 bottleneck files created.  
8500 bottleneck files created.  
8600 bottleneck files created.  
8700 bottleneck files created.  
8800 bottleneck files created.  
8900 bottleneck files created.  
9000 bottleneck files created.  
9100 bottleneck files created.  
9200 bottleneck files created.  
9300 bottleneck files created.  
9400 bottleneck files created.  
9500 bottleneck files created.  
9600 bottleneck files created.  
9700 bottleneck files created.  
9800 bottleneck files created.  
9900 bottleneck files created.  
10000 bottleneck files created.  
10100 bottleneck files created.  
10200 bottleneck files created.  
10300 bottleneck files created.  
10400 bottleneck files created.  
10500 bottleneck files created.  
10600 bottleneck files created.  
10700 bottleneck files created.  
10800 bottleneck files created.  
10900 bottleneck files created.  
11000 bottleneck files created.  
11100 bottleneck files created.  
11200 bottleneck files created.  
11300 bottleneck files created.  
11400 bottleneck files created.  
11500 bottleneck files created.  
11600 bottleneck files created.  
11700 bottleneck files created.  
11800 bottleneck files created.  
11900 bottleneck files created.  
12000 bottleneck files created.
```

```
2017-05-25 16:17:44.529748 Step 10. Cross entropy = 4.981174  
2017-05-25 16:17:44.735799 Step 10. Validation accuracy = 0.0% (N=100)  
2017-05-25 16:17:44.941851 Step 20. Train accuracy = 10.0%  
2017-05-25 16:17:44.216122 Step 30. Cross entropy = 4.44602  
2017-05-25 16:17:44.236747 Step 30. Validation accuracy = 11.0% (N=100)  
2017-05-25 16:17:47.539782 Step 40. Train accuracy = 10.0%  
2017-05-25 16:17:47.539836 Step 40. Cross entropy = 4.422101  
2017-05-25 16:17:47.559454 Step 40. Validation accuracy = 15.0% (N=100)  
2017-05-25 16:17:45.927439 Step 50. Train accuracy = 10.0%  
2017-05-25 16:17:45.927487 Step 50. Cross entropy = 4.303227  
2017-05-25 16:17:45.935658 Step 50. Validation accuracy = 17.0% (N=100)  
2017-05-25 16:17:46.388922 Step 60. Train accuracy = 15.0%  
2017-05-25 16:17:46.388977 Step 60. Cross entropy = 4.332712  
2017-05-25 16:17:46.388932 Step 60. Validation accuracy = 18.0% (N=100)  
2017-05-25 16:17:47.922481 Step 70. Train accuracy = 24.0%  
2017-05-25 16:17:47.922536 Step 70. Cross entropy = 4.288804  
2017-05-25 16:17:47.922591 Step 70. Validation accuracy = 21.0% (N=100)  
2017-05-25 16:17:47.922546 Step 80. Train accuracy = 22.0%  
2017-05-25 16:17:47.922601 Step 80. Cross entropy = 4.248184  
2017-05-25 16:17:47.922656 Step 80. Validation accuracy = 21.0% (N=100)  
2017-05-25 16:17:47.922611 Step 80. Train accuracy = 24.0%  
2017-05-25 16:17:47.922666 Step 80. Cross entropy = 4.169822  
2017-05-25 16:17:47.922721 Step 80. Validation accuracy = 22.0% (N=100)
```

Figure 13. Process of the Tensorflow Supervised Learning

```
2017-05-25 16:24:08.649750 Step 1030. Validation accuracy = 50.0% (N=100)  
2017-05-25 16:24:09.461375 Step 1040. Train accuracy = 57.0%  
2017-05-25 16:24:09.482929 Step 1040. Cross entropy = 1.918889  
2017-05-25 16:24:09.329849 Step 1040. Validation accuracy = 51.0% (N=100)  
2017-05-25 16:24:10.187941 Step 1050. Train accuracy = 54.0%  
2017-05-25 16:24:10.187997 Step 1050. Cross entropy = 2.092013  
2017-05-25 16:24:10.479022 Step 1050. Validation accuracy = 61.0% (N=100)  
2017-05-25 16:24:11.208126 Step 1060. Train accuracy = 56.0%  
2017-05-25 16:24:11.208179 Step 1060. Cross entropy = 1.668888  
2017-05-25 16:24:11.384355 Step 1060. Validation accuracy = 49.0% (N=100)  
2017-05-25 16:24:12.183692 Step 1070. Train accuracy = 56.0%  
2017-05-25 16:24:12.183747 Step 1070. Cross entropy = 1.862618  
2017-05-25 16:24:12.272382 Step 1070. Validation accuracy = 52.0% (N=100)  
2017-05-25 16:24:13.070754 Step 1080. Train accuracy = 54.0%  
2017-05-25 16:24:13.070812 Step 1080. Cross entropy = 1.861220  
2017-05-25 16:24:13.195889 Step 1080. Validation accuracy = 54.0% (N=100)  
2017-05-25 16:24:13.958546 Step 1090. Train accuracy = 60.0%  
2017-05-25 16:24:13.958603 Step 1090. Cross entropy = 1.535029  
2017-05-25 16:24:14.054368 Step 1090. Validation accuracy = 54.0% (N=100)  
2017-05-25 16:24:14.772642 Step 1095. Train accuracy = 60.0%  
2017-05-25 16:24:14.772744 Step 1095. Cross entropy = 1.728473  
2017-05-25 16:24:14.854443 Step 1095. Validation accuracy = 57.0% (N=100)  
Final test accuracy = 55.3% (N=1052)
```

Figure 14. Accuracy of the Tensorflow Supervised Learning

The vision system is the first part of the user website access. The photos that are taken by the webcam are transmitted to the server in real time through Ajax, as shown in Figure 15. The server classifies the transmitted images using the learned classifier and stores the results in the database. The Nutritionx Api is contacted simultaneously, and the data that are stored in the database via the Nutritionx Api are shown in Figure 16. The vision system recognizes the foods, as shown in Figure 17.



Figure 15. Execution Screen of the Vision System

```
{  
  UserID: "hi",  
  Foodname: "jerky/chocolate bar/fortune cookies",  
  Carbs: 35,  
  Protein: 10,  
  Fat: 18,  
  Calories: 348,  
  Date: 20170523,  
  Num: 2  
}
```

Figure 16. Food and Calorie Data that are Stored in the Database



Figure 17. Recognition Results of Various Foods

In the classification process, the food names that are recognized by the vision system are classified and sent to the UI. The classification rules are declared via Expert.js. In the ItemTbl table of the database, the Foodname element is stored into a JavaScript array as “FoodNameArray,” and it is divided into “/” using the split function, as shown in Figure 18. Subsequently, the isa element of each food name with the data of each room in the FoodNameArray is stored in Classify.js as the parameter, as shown in Figure 19. Figure 20 shows the food-classification results.

```
42 var sqlQuery = "INSERT INTO itemtbl SET ?";
43 var post = {userid : req.user.username, Foodname : foodname[0] + "/" + foodname[1] + "/" + foodname[2]};
44 var query = connection.query(sqlQuery, post, function (err, result) {
45     if (err) throw err;
46     console.log("1 record inserted");
47 });

318 function classify(req) {
319     connection.query('SELECT Foodname from itemtbl where userid=?',{req.user.username}, function(err, rows) {
320         if(err) throw err;
321         num = rows.length-3;
322         console.log("rows.length-3: "+num);
323
324         FoodNameArray[0] = rows[(rows.length-1)];
325
326         for (var i = 0; i < 3; i++) {
327             isaArray[i] = FoodNameArray[0].Foodname.split('/')[i].replace(/s/g, "");
328             console.log(isaArray[i]);
329         }
330     })
331 }
```

Figure 18. Codes for Storing the Foodnames

```
322     for (var i = 0; i < 3; i++) {
323         isaArray[i] = FoodNameArray[0].Foodname.split('/')[i].replace(/s/g, "");
324         console.log(isaArray[i]);
325     }
326
327     for (var i = 0; i < 3; i++) {
328         res[i] = isa( eval(isaArray[i]));
329         res[i] = _map( res[i], function(c){ return c.id; });
330         res[i] = JSON.stringify(res[i]).replace(/s/g, '').replace(/ /g, '').replace(/"/g, '');
331     }
332 }
```

Figure 19. Codes to Find the isa Element of the FoodNameArrays

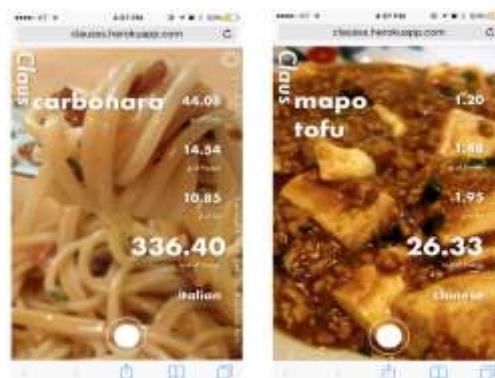


Figure 20. Results of the Cuisine Classification

The UI displays the name, calorie, and type of food in real time without the need to refresh. To receive this data, the user is encouraged not to refresh through the Spinner. Figure 21 shows the UI including the Spinner. The user can take food pictures using the website webcam screen. The food images that are taken by the user are recognized, classified, and calorie-extracted, and the food names, nutritional facts, and meal type are displayed on the UI.



Figure 21. User Interface

4. Conclusion

In this paper, the function of a food-type classification is combined with a calorie-extraction monitoring system using food photographs. The system was trained to recognize food images using machine learning, and the food type was classified with a semantic-network framework using the “isa-example rule.” This framework allows a simple photograph-based recognition of the context of the user food type. In the future, an improvement of the user-diet control for which the context recognition is combined with the existing self-monitoring systems will be explored so that, for example, the food context can be recognized and the context-appropriate foods can be recommended.

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