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# A Food Recommender Based on Frequent Sets of Food Mining Using Image Recognition

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## Abstract

Food recommendation is an important service in our life. To set a system, we searched a set of food images from social network which were shared or reviewed on the web, including the information that people actually chose in daily life. In the field of representation learning, we proposed a scalable architecture for integrating different deep neural networks (DNNs) with a reliability score of DNN. This allowed the integrated DNN to select a suitable recognition result obtained from the different DNNs that were independently constructed. The frequent set of foods extracted from food images was applied to *Apriori* data mining algorithm for the food recommendation process. In this study, we evaluated the feasibility of our proposed method.

**Keywords:** food recommender, food data mining, image recognition, deep neural network, data mining algorithm

## 1. Introduction

People are now consuming more high energy foods, fats and meat, and most of them do not eat enough fruit, vegetables and other dietary fiber. The make-up of a diversified and combined food will vary depending on individual characteristics such as age, gender, lifestyle and degree of physical activity, cultural context, locally available foods and dietary customs. While the increase of food services plays an important role in food market and business, the food service industry is a vital part of economy [1–3]. The business relies on its management to control costs, keep customers happy, and ensure smooth operations on a daily basis. There are many different types of food service types or procedures, but the major category of the food service is Buffet and Family style services.

Being an industry that serves the human needs, the food service is always the forefront of innovation. Even the food safety practices have been continuously updated along with legislation, the service is still facing a number of issues such as food technologies and consumer trends. For example, a customer wants to know the food information in order to have a set of food on the table. Foreigners who are not familiar with the local foods would like to enjoy having foods in a common style in those countries. In addition, a food designer is seeking a new decoration idea for the beautification of foods on plate. Food recommendation therefore is an important

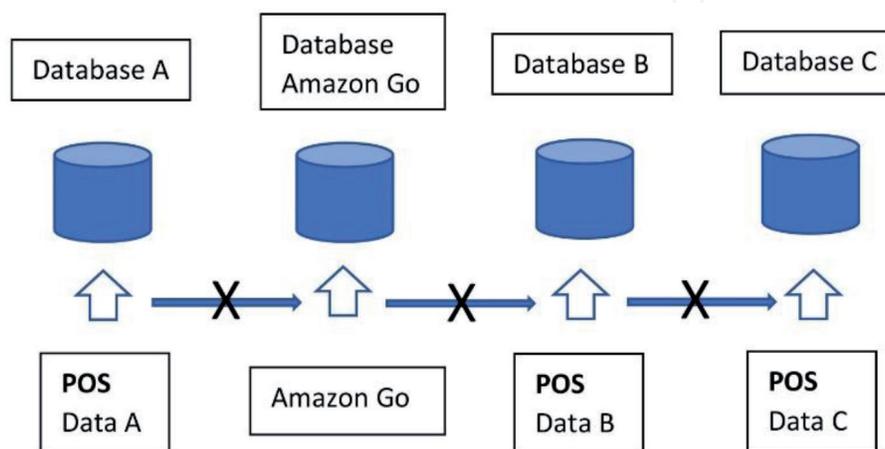
tool to enrich our life. It can be defined as a system that will recommend items to the users/customers within an environment depending on their past activities.

There was demonstration that digital imaging could estimate food information in many environments and it had many advantages over other methods [4, 5]. However, to derive the food information such as food type, food combination and portion size from food images remains uncertainty.

Accordingly, to achieve better food recommendation, it would be useful to analyze foods that people are actually eating in daily life. POS (Point of Sale) is a large-scale transaction data relevant to the customer's purchase tendency [6]. The data is used only by individual store and not open for public. Therefore we cannot analyze the food purchase data among different stores, restaurants, canteens, and so on. *Amazon Go* is a smart store where a purchase transaction can be detected by a camera. Comparing with the POS system, the *Amazon Go* provides an automatic management of information about the foods that people bought, including the items that associated with those products and the appearance of each item with individual preference [7]. In addition, the system can predict the expectation of the market. Note that this kind of *Amazon-Go-like* system has similar constraint for collecting big data. The obtained database from different sources thus is varied. Therefore we can say that there is a limitation of integrating the purchase transaction over different database as shown in **Figure 1**.

From the diagram, it seems to be meaningful to create a system that analyzes the big data of food-images from various communities including companies, restaurants, and groups in social network system for extracting the people's preference of food combination, food design, and food appearance by applying the image recognition technology. In the field of learning representation, there are many established models such as Artificial Neural Network (ANN), Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN).

ANN is a broad term that encompasses any form of deep learning model. It can be either shallow or deep depending on the number of hidden layers. CNNs are designed specifically for computer vision. They are different from standard layers of ANNs as they are constructed to receive and process pixel data. RNNs are the "time series version" of ANNs. They are meant to process the sequences of data. They are at the basis of forecasting models and language models. The most common kind of recurrent layers are called LSTM (Long Short Term Memory) and GRU (Gated Recurrent Units). They contain a series of small, in-scale ANNs that are able



**Figure 1.** Limitation of integrating the purchase transaction over different database.

to choose the existed information they want to let it flow through the model. That is how they establish the “memory”.

However, some problems for food recognition by these models may occur as there are tremendous number of foods. In addition, it remains a challenging issue due to the complexity of emotional expressions, arising from the food variety, gender differentiation, cross culture and age-related differences [8, 9]. Thus, it is hard to find the proper model that can recognize all of them.

## 2. Related work

Food image recognition is one of the promising applications of visual object application, as it will help estimate food characteristics and analyze people’s eating choices for daily life. Many research works represented food recognition more practical by using the convolutional neural network (CNN) model [10–12]. CNN was applied to the tasks of food detection and recognition through parameter optimization. A dataset of the most frequent food items was constructed in a publicly available food-logging system. The CNN showed significantly higher accuracy than a conventional method did. In addition, the color feature is not always helpful for improving the accuracy by comparing the results of two group of controlled trials. It was reported that the achievement of CNN model was at 70–80% on one dataset and 60% on the multi-food dataset. The improvements could be expected by collecting more images and optimizing the network architecture and hyper-parameters.

For example, Deep Convolutional Neural Network (DCNN) was introduced for food recognition based on a combination of CNN-related techniques such as pre-training with the large-scale ImageNet data, fine-tuning and activation features extracted from the pre-trained CNN [13, 14]. Another approach was based on two main steps: firstly, to produce a food activation map on the input image (i.e. heat map of probabilities) for generating bounding boxes proposals and, secondly, to recognize each of the food types or food-related objects presented in each bounding box [15]. Interestingly, the Max-Pooling function was used for the data and the features extracted from this function were used to train the network. An accuracy of 86.97% for the classes of the FOOD-101 data set was recognized [16]. It was found that the image classification could be extended using prominent features that could categorize food images. Note that the feature-based approach and the multi-level classification approach (hierarchical approach) were highly appreciable to avoid mis-classifications when the number of classes was increased. However, these methodologies consumed high computational time.

### 2.1 Concept of convolutional neural network (CNN)

Convolutional neural network is a network that employs a mathematical operation called convolution. There are two main processes in CNN architecture – Learning extraction and Classification [17].

#### **Step-1: Learning extraction**

This process executes feature extraction from images through the following three layers -

- a. Convolution layer: this is the first layer to extract features from an input image. There are matrix filters (feature map) that multiplies with image in order to extract some features such as edge, blur, and color.

- b. Activation layer: this layer is used to increase non-linearity of the network without affecting receptive fields of convolution layer. The output is  $f(x) = \max(0, x)$ .
- c. Pooling layer: this layer reduces the number of parameters when the images are too large. This operation means that the layer reduces the dimensionality of each map but keeps the important information.

### Step-2: Classification

This process executes image classification. There are two main layers as follows:

- a. Fully connected layer (FC layer): to connect every neuron in one layer to every neuron in another layer. We flattened our matrix into vector and feed it into a fully connected layer like neural network.
- b. Softmax layer: A special kind of activation layer, usually at the end of FC layer outputs. It produces a discrete probability distribution vector.

At this stage, the pretrained models such as *AlexNet*, *VGGNet*, *GoogLeNet*, and *ResNet* will be applied in order to integrate the CNNs. The procedure is to merge the multiple CNNs with fixed number of CNNs and trained them after merging.

## 2.2 Association rule

Association rule is utilized in data mining phase as it is a machine learning method which finds the relationship between the items based on the frequency of item sets [18, 19]. To do this, a mathematical algorithm is needed to arrange the frequent item sets, for extracting association rule of food sets.

There are three measures in association rule task as shown in **Figure 2**:

- a. Support: It indicates how often the items appear in the data-set.
- b. Confidence: It indicates how often a rule is found to be true.
- c. Lift: It indicates how the *antecedent* and the *consequent* are related to one another. If the Lift value is 1, it means that the *antecedent* and the *consequent* are independent. If the Lift value is less than 1, it means that the *antecedent* has negative effect on occurrence on the *consequent*. In addition, if the Lift value is more than 1, it means that the *antecedent* and the *consequent* are dependent.

$$\begin{array}{l}
 \text{Rule: } X \Rightarrow Y \begin{cases} \nearrow \text{Support} = \frac{frq(X,Y)}{N} \\ \longrightarrow \text{Confidence} = \frac{frq(X,Y)}{frq(X)} \\ \searrow \text{Lift} = \frac{\text{Support}}{\text{Supp}(X) \times \text{Supp}(Y)} \end{cases}
 \end{array}$$

**Figure 2.**  
Basic terminologies of association rule measure.

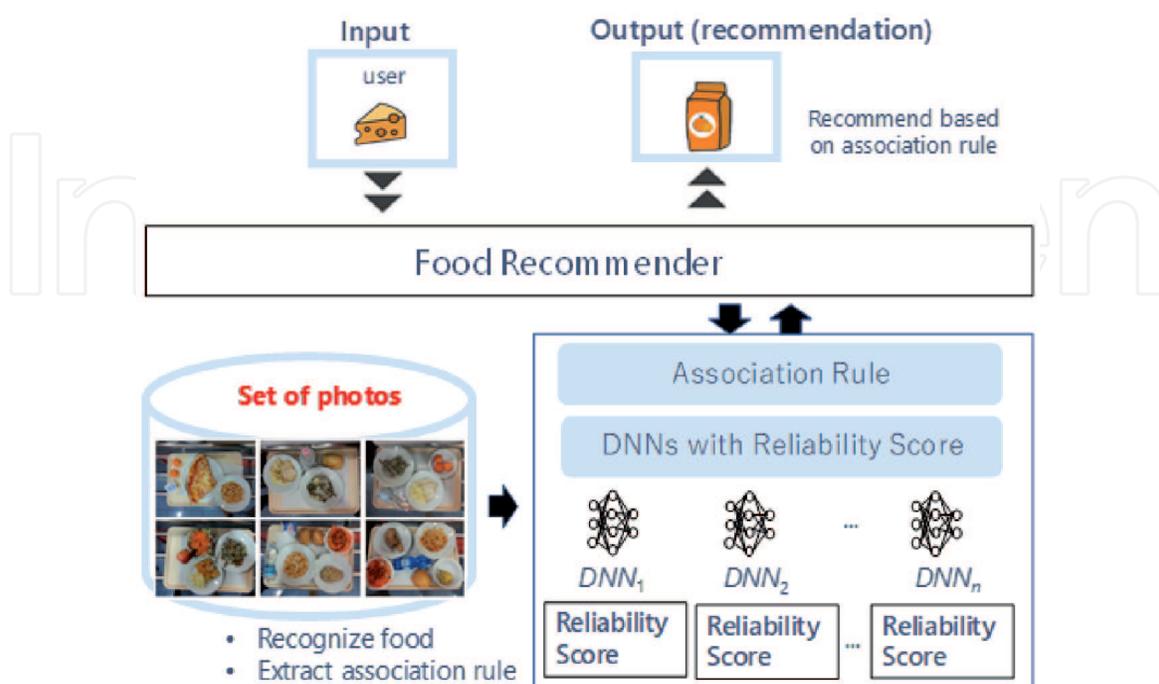
### 3. Proposed method

As the uncertainty of convolutional architecture due to the fix number of CNNs and the interpretability after merging of CNNs [20]. Simpler and more highly scalable method to integrate the multiple networks is necessary and therefore there are three features in consideration - liability score for the system, no further training after integration, and high scalability. Deep neural network (DNN) may be an alternative choice to solve this problem [21]. It provides the neural basis for efficient visual object recognition in humans. Its architecture comprises more than three layers. Each of layers contains a combination of convolution, max-pooling and normalization stages, whereas these layers are fully connected. It inherently fuses the process of feature extraction with classification into learning using Fuzzy Support Vector Machine (FSVM) and enables the decision making [22, 23]. Many efforts were made to speed up both the training time as well as inference time of DNNs. Since the flexibility and the performance scalability to deal with various types of networks are crucial requirement of the DNN accelerator design [24], we therefore proposed a scalable architecture for integrating different deep neural networks with a reliability score to increase the probability to return correct class as the result of food recognition. The reliability score allowed the integrated DNN to select a suitable recognition result obtained from the different DNNs that were independently constructed. In this study, we evaluated the feasibility of our proposed method.

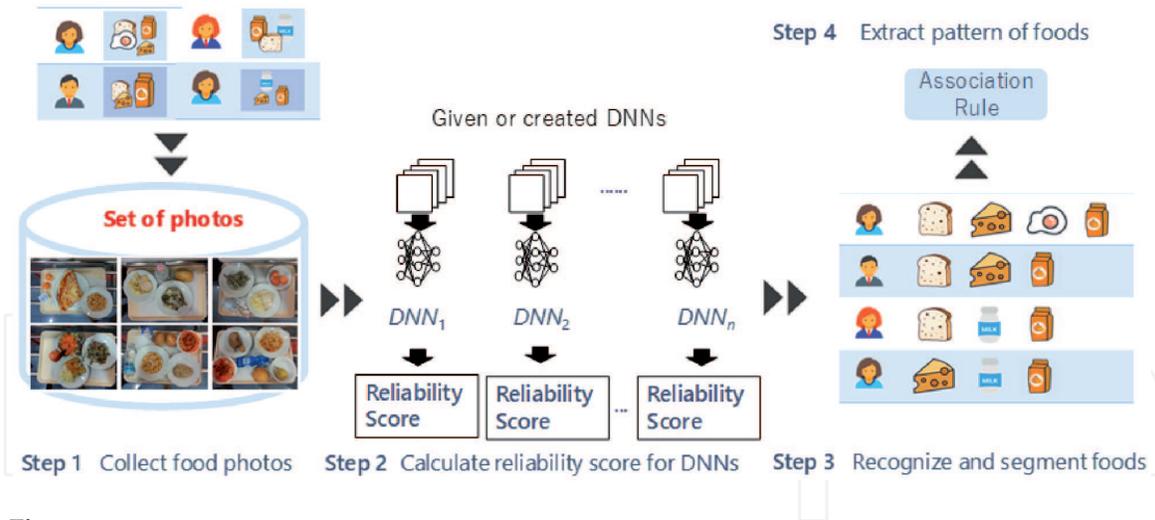
The frequent set of foods extracted from food images was applied to a data mining algorithm such as the *Apriori* algorithm for the food recommendation process.

**Figure 3** shows the schematic diagram of food recommender. This system would recommend a set of foods suitable for users based on association rule, which were extracted by food set mining from food images.

The process of food recognition and extraction of association rule is given in **Figure 4**. Firstly, the food set images from database were collected. Secondly, the reliability score was calculated by Eq. (1). Then the food recognition and



**Figure 3.**  
 Schematic diagram of food recommender.



**Figure 4.**  
 Process of recognition of food set images and extraction of association rule.

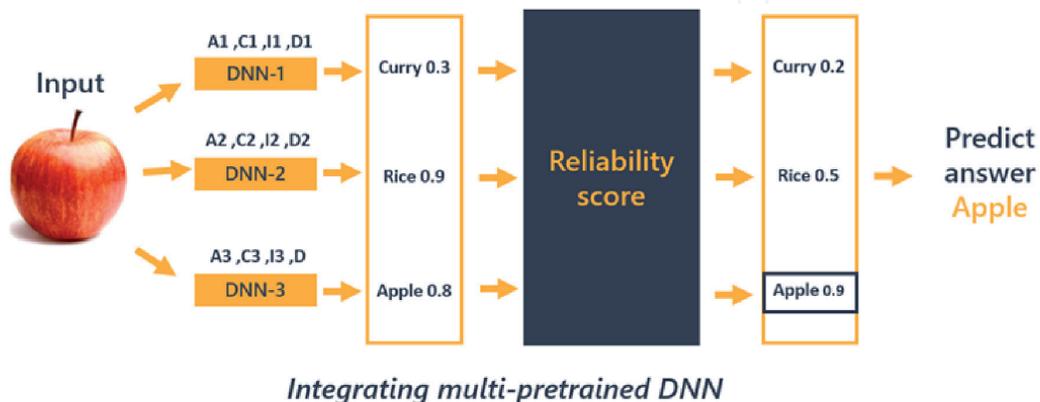
segmentation from the images were operated using DNNs. Finally, the extraction of association rule was obtained as the frequent food sets.

$$\text{Reliability score} = A \times C \times I \times D \quad (1)$$

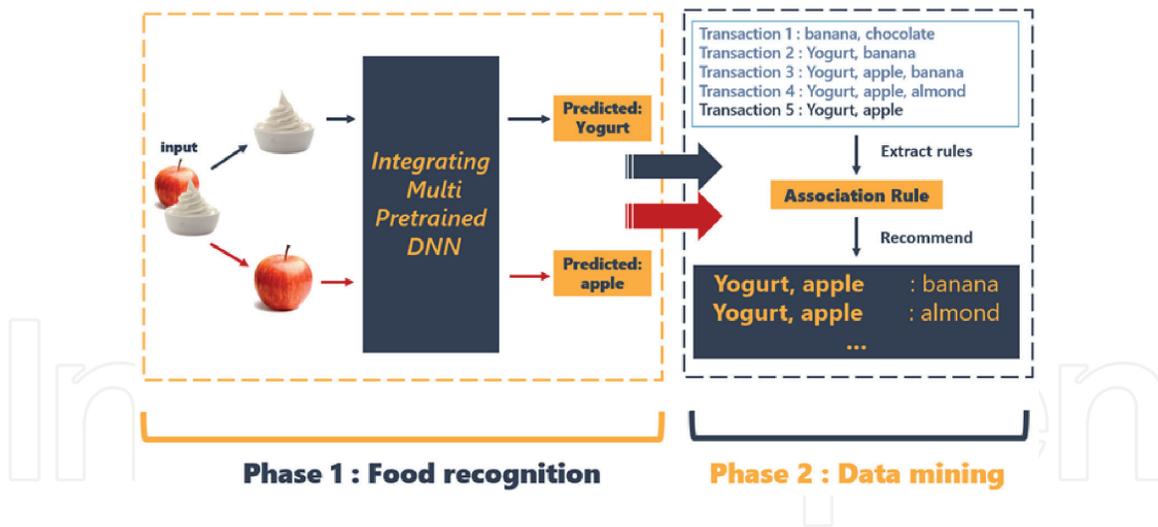
where A, C, I, and D represented the accuracy of the learning process, number of classes, number of learning images, and difference between learning data and test data, respectively.

We combined several DNNs and calculated new probability with reliability scores as shown in **Figure 5**. Each DNN has different reliability score depending on following factors:

- accuracy of the learning process
- number of classes
- number of learning images
- difference between learning data and test data



**Figure 5.**  
 The feature of proposed method.



**Figure 6.**  
 Workflow of proposed food recommender.

If the learning data and the test data are similar, the accuracy will be high but it may be not reliable. As we test with the unseen data, the DNN may predict wrong answer. Therefore, the difference between the learning data and the test data is necessary.

We calculated the reliability score and the weight output ( $W$ ) of fully connected layer as the new probability using Eq. (2). The label of the new probability as the predicted result was provided.

$$\text{New probability} = W \times \text{Reliability score} \quad (2)$$

Accordingly, the food set could be recognized from food images using different DNNs with the reliability scores as shown in **Figure 6**. Based on the recognition results, transactions of food were formed and applied to conventional association in the phase of data mining.

#### 4. Experimental and evaluation

We implemented our prototype of merging the results from different DNNs using MATLAB. The performance of recognition accuracy and the relationship between the recognition accuracy and the number of classes were evaluated. We used the dataset of food images for creating the DNNs and evaluated them as shown in **Table 1**. Three DNNs with different number of recognition classes for each data-set were created as given in **Table 2**. In addition, we made each DNN from *Scratch* by applying the transfer learning using *GoogLeNet*. Accordingly, we totally had 18 DNNs in this experiment.

Recognition accuracy was calculated using the following equation:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (3)$$

where TP, TN, FP, and FN were True Positive, True Negative, False Positive, and False Negative respectively.

Type of dataset	Dataset	Number of classes	Number of images
Pretrained	Food-101	101	101,000
Pretrained	UEC-256	256	31,395
Pretrained	Fruit-360	81	77,917
Test	UNIMIB2016	33	1,047

**Table 1.**  
Dataset of food images.

Dataset	Number of classes	Scratch	GoogLeNet
food-101	34	$DNN_1^{\text{food}}$	$DNN_1^{\text{food}^*}$
	50	$DNN_2^{\text{food}}$	$DNN_2^{\text{food}^*}$
	101	$DNN_3^{\text{food}}$	$DNN_3^{\text{food}^*}$
uec-256	85	$DNN_1^{\text{uec}}$	$DNN_1^{\text{uec}^*}$
	128	$DNN_2^{\text{uec}}$	$DNN_2^{\text{uec}^*}$
	256	$DNN_3^{\text{uec}}$	$DNN_3^{\text{uec}^*}$
fruit-360	27	$DNN_1^{\text{fruit}}$	$DNN_1^{\text{fruit}^*}$
	40	$DNN_2^{\text{fruit}}$	$DNN_2^{\text{fruit}^*}$
	81	$DNN_3^{\text{fruit}}$	$DNN_3^{\text{fruit}^*}$

**Table 2.**  
Deep neural network with different number of classes.

No.	Number of DNNs	Type of DNN	Dataset
1	1	GoogLeNet	Food-101
2	2	GoogLeNet	Food-101 + UEC-256
3	3	GoogLeNet	Food-101 + UEC-256 + Fruit-360
4	1	Scratch	Food-101
5	2	Scratch	Food-101 + UEC-256
6	3	Scratch	Food-101 + UEC-256 + Fruit-360

**Table 3.**  
Integrated deep neural network.

Types of food label	
1	Predicted label by integrated DNN using <i>GoogLeNet</i>
2	Predicted label by integrated DNN made from <i>Scratch</i>
3	Corrected label (no prediction)

**Table 4.**  
Food labels used for association rule.

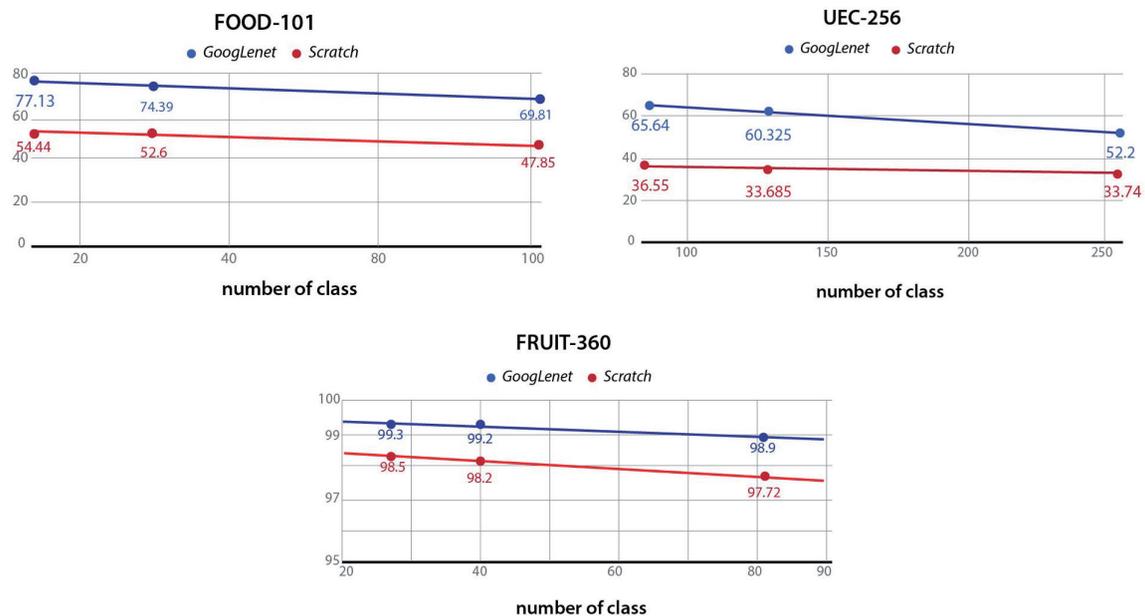
To evaluate the performance of integrated deep neural network, we created two single DNNs and four integrated DNNs as shown in **Table 3**. The *UNIMIB2016* dataset for the test was employed. Recognition accuracy then was calculated using Eq. (3).

To evaluate the accuracy of extracted frequent food set, we employed three food labels as shown in **Table 4** for extracting the association rule.

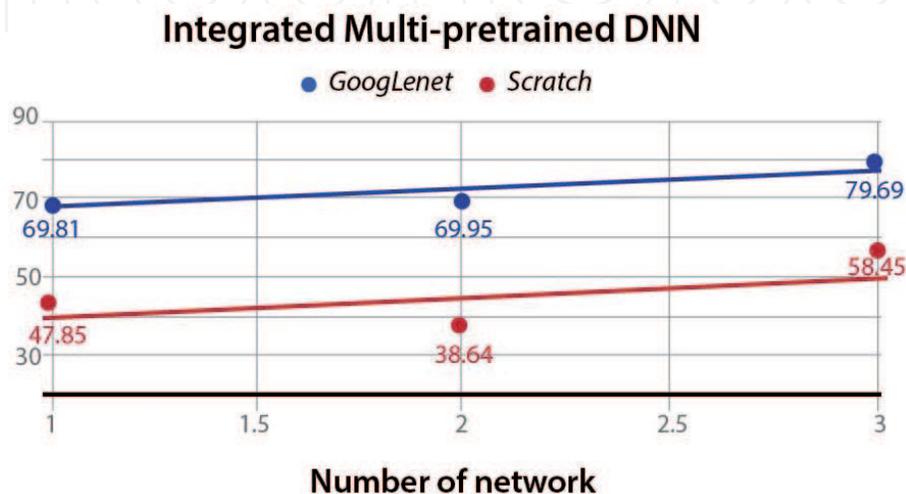
## 5. Results and discussion

**Figure 7** shows the recognition accuracy of DNN by food-101 dataset, uec-256 dataset, and fruit-360 dataset respectively. There was a relationship between the recognition accuracy of DNN and the increase of the number of class for each database. It was found that the recognition accuracy of DNN slightly decreased according to the increase of the number of recognition classes. In addition, the performance of DNNs where *GoogLeNet* applied was higher than the DNNs made from *Scratch*.

**Figure 8** shows the result of integrated deep neural network. It implied that if the number of networks was increased, the recognition accuracy of the integrated



**Figure 7.**  
 Recognition results of food-101, uec-256 and fruit-360.



**Figure 8.**  
 Result of integrated deep neural network.

DNNs would be enhanced. In addition, it was found that the performance of DNNs where *GoogLeNet* applied was higher than the DNNs made from *Scratch*. It is because the proposed reliability score allowed the integrated DNNs to select a suitable recognition result obtained from the three different networks, which were constructed from the food-101, the uec-256 and the fruit-360 dataset. Note that although the DNN constructed from the fruit-360 dataset showed the high accuracy of 97.72% for 10 classes recognition, it could not return a suitable result for an image of general food other than a fruit. This is the disadvantage of a DNN constructed from a specific image dataset.

**Tables 5–7** show the results of food labels where the association rules were sampled from the whole results. It was found that the number of bad and good results for “Kiwi, Doughnut” was almost equal. While “Pineapple mini and Ice-cream” in **Table 6** gave better results. It was confirmed that the number of good results in the integrated networks using *GoogleNet* was preferable. In **Table 7**, “Steak and French fries” showed good result relevant to the test data.

Antecedents	Consequents	Result
Kiwi, Doughnut	Pineapple, Orange	Good
Kiwi, Doughnut	Orange, Miso soup	Bad
Kiwi, Doughnut	Spaghetti Bolognese, Orange	Good
Kiwi, Doughnut	Orange, Spam musubi	Bad
Kiwi, Doughnut	Pineapple, Miso soup	Bad
Kiwi, Doughnut	Pineapple, Spaghetti Bolognese	Good
Kiwi, Doughnut	Pineapple, Spam musubi	Bad
Kiwi, Doughnut	Spaghetti Bolognese, Miso soup	Bad
Kiwi, Doughnut	Spam musubi, Miso soup	Good
Kiwi, Doughnut	Spaghetti Bolognese, Spam musubi	Bad

**Table 5.**  
*Results of integrated DNNs made from Scratch.*

Antecedents	Consequents	Result
Pineapple mini, Ice-cream	Apple red/yellow	Good
Pineapple mini, Ice-cream	Cantaloupe	Good
Pineapple mini, Ice-cream	Cocos	Good
Pineapple mini, Ice-cream	French loaf	Good
Pineapple mini, Ice-cream	Granadilla	Bad
Pineapple mini, Ice-cream	Grapefruit pink	Good
Pineapple mini, Ice-cream	Kiwi	Good
Pineapple mini, Ice-cream	Peach flat	Good
Pineapple mini, Ice-cream	Peach abate	Good
Pineapple mini, Ice-cream	Pitahaya Red	Good

**Table 6.**  
*Results of integrated DNN using GoogLeNet.*

<b>Antecedents</b>	<b>Consequents</b>	<b>Result</b>
Steak, French fries	Banana, Roll bread	Good
Steak, French fries	Baklava, Orange	Good
Steak, French fries	Roll bread, Orange	Good
Steak, French fries	Spaghetti, Orange	Good
Steak, French fries	Baklava, Roll bread	Bad
Steak, French fries	Spaghetti, Baklava	Good
Steak, French fries	Spaghetti, Roll bread	Good
Steak, French fries	Yogurt, Roll bread	Good
Steak, French fries	Spaghetti, Yogurt	Good
Steak, French fries	Spaghetti	Good

**Table 7.**  
*Results of corrected labels.*

## 6. Conclusion

In food recognition phase, integrated networks (DNNs) showed higher recognition accuracy (80%) than a single network. Since the proposed reliability score allowed the integrated networks to select a suitable recognition result obtained from the different network with different domains. The performance of networks where *GoogLeNet* applied gave higher recognition accuracy. In addition, it was found that when we used the test dataset different from the trained dataset, we could not get the suitable results.

In Data mining phase, we could extract some meaningful rules by applying the *Apriori* algorithm to recognize the results of canteen image dataset. In our future work, we will modify this system in recognition phase and will increase the performance of the networks. We will evaluate the effectiveness of modified system using bigger size of food data. In addition, we are developing visual food mining using mixed model of DNN and RNN (recurrent neural networks) for continuing our research.

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## Conflict of interest

The authors declare no potential conflict of interest.

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