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The Design and Implementation of an Ingredient-Based Food Calorie Estimation System Using Nutrition Knowledge and Fusion of Brightness and Heat Information

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ABSTRACT To measure the calorie of food, which are varied depending on its ingredients and volume in each cooking time, it is required to calculate calories of food before consuming. Based on nutrition knowledge, ingredients that are components of food naturally have different calories. This paper proposes a method of ingredient-based food calorie estimation using nutrition knowledge and thermal information. In this method, an image of the food is first recognized as a type of food, and ingredients of the recognized food are retrieved from the database with their nutrition knowledge and pattern of brightness and thermal images. Simultaneously, the image is segmented into boundaries of ingredient candidates, and all boundaries are then classified into ingredients using fuzzy logic based on their heat pattern and intensities. The classified ingredients from all boundaries are finally calculated for total calories based on area ratio and nutrition knowledge. The performance of our proposed method shows acceptable results comparing with the calories set up by the conventional destructive method.

INDEX TERMS Food calorie, ingredient-based, nutrition knowledge, fuzzy model, food-calorie estimation, classification, hardware implementation, fusion of heat and brightness information.

I. INTRODUCTION

Originally, food is input into the human body for the objective of energy, growth, organ tuning and maintenance, immunity, etc. While the human society has developed in civilization, human food tends to become worse due to favorite tastes, delivery convenience, long-term preservation, and so on. Health as the original purpose of food seems to be gradually ignored, and thus, people in civilized societies increasingly become obese and die at a young age [1], [2]. One of the important factors in human food is calories, which a man/woman should strictly consume in daily consumption. To measure food calories in order to calculate daily consumption of calories, food is baked, and burnt as the destructive way in five-hours and eight-minutes time, respectively, and the calories are subsequently measured by the decreased weight [3]. Currently, the calories of food evaluated by the aforementioned destructive way are popularly used as a reliable standard for consumers to count and accumulate their daily-consumed calories. The calorie standard is statistically averaged data, which is exactly not guaranteed to match to all meals, even the same food types. To obtain accurate estimation, it is necessary to develop an automatic system that practically measures calories in each meal in real time.

Some researchers have worked toward this research problem for the final goal of food calorie measurement and estimation in each meal as follows. Sun *et al.* [4] and Pouladzadeh *et al.* [5] proposed a method of determination of food portion size by image processing. This method mainly measures the area of food and calculates total calories by referring to statistical calorie data. Nakayama *et al.* [6] proposed thermal imaging of pancakes (raw materials of the pancake) that are produced for the application in quality control. Thermal images of pancakes in the course of the baking process and thermal signal reconstruction of flour with various water content are introduced using an image processing technique. Pouladzadeh *et al.* [5], [7]–[10] presented a method of measuring calories and nutrition from food images. This uses a food image captured by the built-in camera of mobile devices, segments a dish into food components, and calculates total calories using nutritional fact tables. Kiran and Dawande [11] presented a method of measuring calories and nutrition from food images. This is to identify food items in an image using image processing and segmentation. The K-nearest neighbor (KNN) method is used to recognize the food, and the calorie values are measured with the help of a nutrition table. Pouladzadeh *et al.* [10] and Kuhad *et al.* [12] proposed a method using distance estimation and deep learning to simplify calibration in food calorie measurement and food calorie measurement using a deep learning network. This method assumes the application on a mobile device, which measures food area and converts into food weight as calibration for calorie measurements. Lee *et al.* [13] proposed the MT-Diet: automated smartphone based diet assessment with infrared images. This assumes the application on a smartphone and utilizes infrared to sense food components inside the dish. McAllister *et al.* [14] proposed a semi-automated system for predicting calories in photographs of meals. The system uses a semi-automated approach to allow users to manually draw around the food portion using a polygonal tool. The performance is acceptable. Myers *et al.* [15] presented a system called Im2Calories: towards an automated mobile vision for food diary. The system recognizes the contents of the meal from a single image and predicts its nutritional contents such as calories using CNN, which is trained by many images in advance. The system works well with many types of foods. Hymavathi and Deepthi [16] proposed a method of a food calorie measurement system for obesity management. This system uses a smartphone equipped with a camera and allows the user to capture the food image. The image processing approach for the measurement technique is conducted by MATLAB programming. Chokr and Elbassuoni [17] presented calorie prediction from food images and machine-based-learning. This method recognizes food type, predicts food size, and calculates total calories.

All of the aforementioned methods deal with food that is possibly segmented into components, but some types of foods, such as soup, curry, and cake, are cooked by mixing many ingredients, and their appearances are absolutely changed. It is hard to find and recognize ingredients in those types of foods. Moreover, each meal is not exactly cooked in the same manner, and ingredient amounts are varied, even when cooked by the same chef. The authors therefore set up a research problem for dealing with food, such as soup and curry, whose ingredients are mixed, and their appearances are already changed, to measure calories in each meal in real time. To exactly measure calories in each meal, we approached the solution by sensing ingredients in the curry by using thermal patterns and measuring the meal calories based upon total ingredient calories. First, types of curries and soups are recognized by a brightness image of the meal, which was already studied [18]–[20], and the brightness image is then segmented into boundaries as candidates of ingredients. In a segmented boundary, brightness and thermal images are considered using fuzzy logic to recognize as an ingredient, and these ingredients are finally used to calculate calories of the meal.

This paper is organized as follows. The problem analysis and the basic concept are introduced in Section II. Overview of the system and proposed method of food calorie estimation are described in Section III and IV, respectively. The experiments and discussion are reported in Section V and VI, respectively. Finally, this paper is concluded in Section VII.

II. PROBLEM ANALYSIS AND BASIC CONCEPT

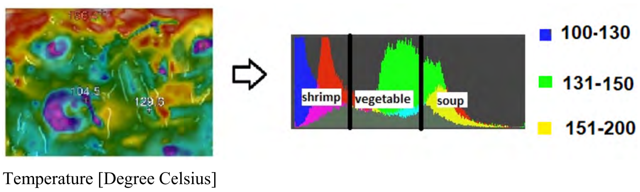
To measure calories of a bowl of curry or soup, since it is cooked and mixed with many ingredients, it might be a good idea to consider volumes of all ingredients and calculate total calories by summarizing calories of all ingredients. Traditionally, curries and soups have been designed in a recipe, and the main ingredients are fixed, even though some changes occur depending on chefs, area, countries, and so on. That is, when we know the curry type, people may roughly be reminded of the needed ingredients. According to this thought, our paper sets up a fundamental goal to recognize curry type at the first step to know the required ingredients. If a reliable standard recipe is provided further in a database, ingredients included in the food could be estimated.

In general, humans recognize curry and soup types by an image of their surface, as shown by image samples of several types of Thai curries in Fig. 1. Each image comprises many features such as boundary shapes, colors, textures, etc. If these are trained in a classifier in advance, it may be possible to automatically classify the curry types. Currently, machine learning tools such as deep learning, SVM, Fuzzy C Mean, and so on, are conveniently used to learn and train for classification so that it goes without saying, currently curry-type classification is able to be performed by many existing machine-learning tools.

FIGURE 1. Types of Thai foods.1. Green chicken curry, 2. Sour soup with shrimp and water mimosa, 3. Hot and spicy pork rib hot pot with tamarind and Thai herbs, 4. Minced pork and soya bean curd soup, 5. Mimosa Tom Yum Kung, 6. Chicken coconut soup, 7. Eggs and pork in brown sauce, 8. Red curry with roasted duck, 9. Pork with panaeng curry, and 10. Massaman curry with chicken.

Based on nutrition knowledge [21], ingredients, which are key components of cooking food, naturally have different calories per volume. This knowledge of ingredient-calories per volume can be considered for use as a database for calculating total calories of a meal in case we can measure all volumes of all ingredients. The problem points for measurement of ingredient volumes are segmentation and recognition of all ingredients in a bowl of curry and soup, and calculation of the total volume of all ingredients. On the other hand, curries and soups are normally cooked by heat, and people prefer to consume the meal while warm with an appropriate temperature.

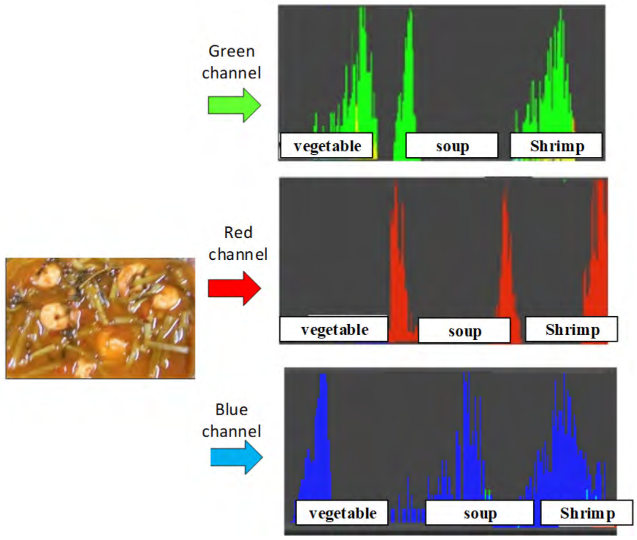
Theoretically, different ingredients have different melting points [22], and this causes temperatures of ingredients in a bowl of curry and soup to become different. Although the ingredients in the curry and soup after being cooked are always cooled down due to the surrounding air environment, the order of temperatures of ingredients should always be maintained. Therefore, the order of ingredient temperature in a curry type can be used as a pattern to recognize ingredient types by classification of temperature ranges when the curry type is recognized. This is exactly one of our basic concepts. For an example of Thai curry as shown in Fig. 2, a bowl of sour soup with shrimp and water mimosa is classified into three ranges from low to high temperature ranges, which represent shrimp, vegetables, and soup, respectively.



(a) (b)

FIGURE 2. Histogram of food thermal image. (a) Original thermal image (b) Histogram of food thermal image.

In a brightness image of the same sour soup with shrimp and water mimosa, as a sample shown in Fig. 3, the green channel is obviously segmented into boundaries of main ingredients, compared with other blue and red channels; thus, the green channel is selected to use in boundary detection for this curry. However, each curry image naturally holds different characteristics so that the appropriate channel for a curry image should be trained and stored in the database in advance. When boundaries are segmented as ingredient candidates in the brightness image, all boundaries are considered as the brightness image, and all boundaries are later considered as ingredients. As an image sample of analysis shown in Fig. 4, boundaries segmented in the brightness image have features in both temperature and gray levels, which sometimes cannot be concluded to be recognized as an ingredient. This method may not always be able to simply determine the ingredient in a boundary from brightness and thermal images. Meanwhile, fuzzy logic is popularly regarded as a good solution for this type of two-factor problem, thus, we apply fuzzy logic and create fuzzy rules between brightness and thermal information for ingredient recognition in all boundaries.



(a) (b)

FIGURE 3. Histogram of food brightness image of a sample of sour soup with shrimp and water mimosa. (a) Original brightness image of a sample of sour soup with shrimp and water mimosa. (b) Green red and blue channel histogram.

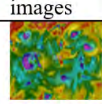
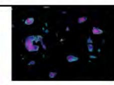
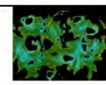
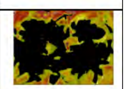
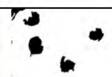
Type of images	Original images	Shrimp	Vegetables	Soup
Thermal image				
Brightness image				

FIGURE 4. Boundaries of ingredients of sour soup with shrimp and water mimosa.

III. OVERVIEW OF SYSTEM

To measure calories of food in each bowl, the authors assume to target some applications, such as food-calorie-estimation devices for consumers at the kitchen, canteen, restaurant, mobile-calorie estimation, and so on, so that the device in terms of hardware can be designed in a box, as shown in Fig. 5. A plate or a bowl of food is laid in the center of the box as a work piece. A CCD (charge coupled device) camera and a thermal camera for capturing brightness and

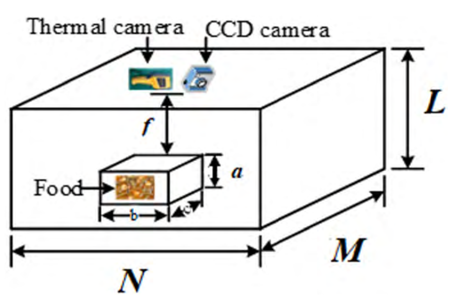


FIGURE 5. Hardware system.

thermal images, respectively, are installed on the top of the box. A LED (light-emitting diode)-array light source is constructed and set up on the box ceiling in a location that may not generate any shadows. In practice, views of CCD and thermal cameras are required to cover the whole surface of the curry and soup so that the relation between focal length and surface area of the container of curry and soup is designed as follows:

$$b \times c < f \times K \tag{1}$$

where f is equal to the focal length, $b$and c represent workpiece size, and K stands for image memory size.

Based on the aforementioned hardware set-up, the software is designed as shown in the flowchart in Fig. 6. First, CCD and thermal cameras installed on the box ceiling capture brightness and thermal images of a bowl of curry. The input-brightness image is classified into a type of curry at the food-type classification process, and the number of ingredients and the list of ingredients are retrieved from database I, according to food type. The number of ingredients is then used at the process of ingredient-temperature-range classification to classify temperature ranges of the ingredients in the curry. Simultaneously, boundaries that are assumed as ingredient candidates on the brightness image are detected at the boundary-detection process so that boundaries obtained from the brightness image and temperature ranges of ingredients obtained from the thermal image at ingredient-temperature-range classification process are considered, and decision making is performed by using fuzzy logic and rules in database II, at the ingredient consideration process.

All boundaries are then determined as ingredients, the number of pixels in the ingredient boundaries are then counted as ingredient area, and the area ratio compared with the whole area of the bowl is finally calculated for the calories of ingredients, based on nutrition knowledge stored in database III. As a final step, total calories of the curry are finally determined by the summation of all ingredient calories.

IV. PROPOSED METHOD OF INGREDIENT-BASED FOOD CALORIE ESTIMATION

The proposed method of ingredient-based food calorie estimation in this paper is demonstrated and discussed in terms of software and hardware as follows.

A. SOFTWARE

The software system, as shown by the flowchart in Fig. 6, consists of databases and several processes. Details of all databases and processes in the software system are explained as follows.

1) DATABASE PREPARATION

There are three databases required for the system: database I, II, and III for food type and ingredients, fuzzy rules of brightness and heat for ingredient determination, and ingredients and calories, respectively.

a: DATABASE I

Database I lists ingredients of the curry when the curry type image is recognized as food type. Initially, users have to train a classifier by selected samples representing food types by the processes, as shown by the flowchart in Fig. 7. In the training, some selected images of food types are extracted

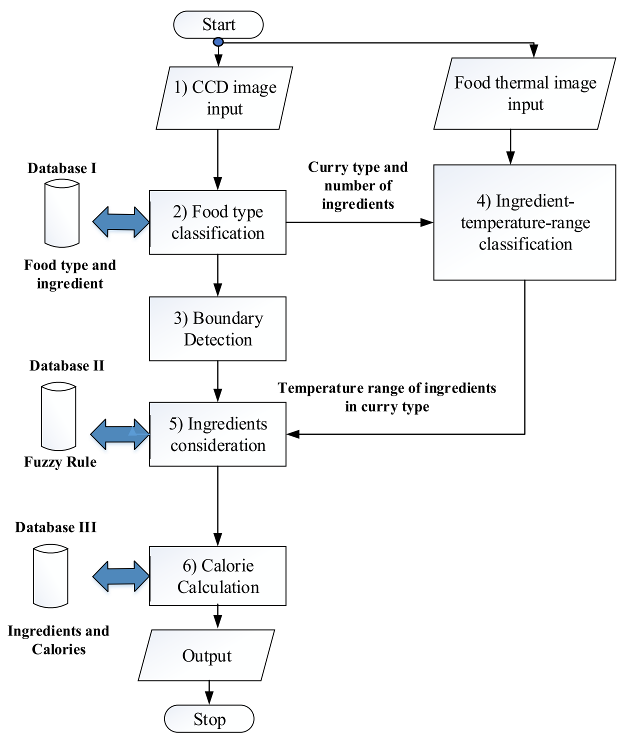


FIGURE 6. Flowchart of software system.

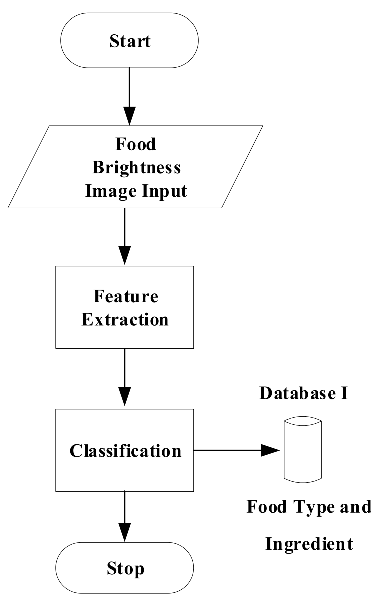


FIGURE 7. Flowchart of food type training.

features and classified by a classifier to obtain important trained weights, which are stored in database I and later used in food classification during the testing process. In addition, a list of all classifying ingredients of each food is also listed in the order of melting points from low to high temperatures in Database I, as shown by the sample in Table 1.

TABLE 1. Temperature order, curry food type and ingredients.

Type of Food	Temperature order of Ingredients	Weight (g)	Channel
Chicken green curry	1) Chicken 2) Vegetables 3) Soup	181	Red
Tom Yum Kung	1) Shrimp 2) Vegetables 3) Soup	137	Green
Hot and spicy pork rib hot pot with tamarind and Thai herbs	1) Pork 2) Vegetables 3) Soup	258	Green
Minced pork and soya bean curd soup	1) Pork 2) Vegetables 3) Soup	175	Red
Sour soup with shrimp and water mimosa	1) Shrimp 2) Vegetables 3) Soup	184	Green

b: Database II

Fuzzy rules of brightness and thermal levels for ingredients in all curry types are created in advance and stored in Database II. Fuzzy rules originally should be created for each food as shown by the sample in Table 2.

1. IF Intensity = shrimp AND Thermal = shrimp THEN Decision = shrimp
2. IF Intensity = shrimp AND Thermal = vegetables THEN Decision = shrimp
3. IF Intensity = shrimp AND Thermal = soup THEN Decision = shrimp
4. IF Intensity = vegetables AND Thermal = vegetables THEN Decision = vegetables
5. IF Intensity = vegetables AND Thermal = soup THEN Decision = vegetables
6. IF Intensity = vegetables AND Thermal =shrimp THEN Decision = vegetables
7. IF Intensity = soup AND Thermal = vegetables THEN Decision = soup
8. IF Intensity = soup AND Thermal = shrimp THEN Decision = soup
9. IF Intensity = soup AND Thermal = soup THEN Decision = soup

c: DATABASE III

Database III lists ingredients with their calories per volume unit based on nutritionist's knowledge. These ingredient lists are created for all food types, as shown by samples in Table 3.

TABLE 2. Fuzzy rules.

Intensity	Thermal		
	shrimp	vegetables	soup
shrimp	shrimp	vegetables	soup
vegetables	shrimp	vegetables	soup
soup	shrimp	vegetables	soup

1. IF Intensity = shrimp AND Thermal =shrimp THEN Decision = shrimp
2. IF Intensity = shrimp AND Thermal = vegetables THEN Decision = shrimp
3. IF Intensity = shrimp AND Thermal = soup THEN Decision = shrimp
4. IF Intensity = vegetables AND Thermal = vegetables THEN Decision = vegetables
5. IF Intensity = vegetables AND Thermal = soup THEN Decision = vegetables
6. IF Intensity = vegetables AND Thermal =shrimp THEN Decision = vegetables
7. IF Intensity = soup AND Thermal = vegetables THEN Decision = soup
8. IF Intensity = soup AND Thermal = shrimp THEN Decision = soup
9. IF Intensity = soup AND Thermal = soup THEN Decision = soup

TABLE 3. Ingredients and calories.

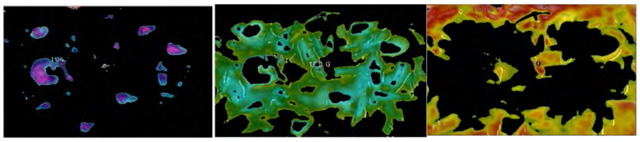
Type of Food	Ingredients	Calories/Weight (1000 g)
Green chicken curry		957.50
	Chicken	373.36
	Vegetables	160.08
	Soup	423.90
Tom Yum Kung		473
	Shrimp	124.94
	Vegetables	133.89
	Soup	214.45
Hot and spicy pork rib hot pot with tamarind and Thai herbs		1,004.37
	Pork	384.66
	Vegetables	205.72
	Soup	413.99
Minced pork and soya bean curd soup		763.77
	Pork	42.7
	Vegetables	462.42
	Soup	258.65
Sour soup with shrimp and water mimosa	Shrimp	1,030.58
	Vegetables	130.24
	Soup	402.54
		497.8

2) FOOD TYPE CLASSIFICATION

Initially, the system has to be trained for the food-type classifier to learn the weights. The flowchart of classifier training is depicted in Fig. 7. It starts with the process of input of food-sample images, feature extraction, and classification. The classifier may be trained for weight for food-type recognition. Currently, there are many convenient machine-learning tools such as Fuzzy C-mean [18], Weighted FCM [18], SVM [19], [20], deep learning [10], [12], and so on, which users may consider utilizing according to their problem conditions.

(a) (b) (c)

FIGURE 8. Original thermal and brightness images of sour soup with shrimp and water mimosa. (a) Thermal image (b) Brightness image (c) Side-view of heat image.



(a) (b) (c)

FIGURE 9. K-means clustering for thermal imaging of sour soup with shrimp and water mimosa. (a) Shrimp (b) Vegetables (c) Soup.

3) INGREDIENT BOUNDARY DETECTION

When a type of curry is recognized at the process of food-type classification, the brightness image of the curry detects boundaries by a boundary detector. Currently, there are many existing boundary detection tools [23]–[28] that users can easily use. Users are recommended to select the one that is suitably matched for their applications.

4) INGREDIENT TEMPERATURE-RANGE CLASSIFICATION

In ingredient classification, since the heat of most of the ingredients in a bowl of food can be completely separated as shown by a histogram in Fig. 3, due to melting-point difference, simple tools such as K-mean can be utilized as an ingredient classifier. Users may select an appropriate classifier by observing the data in advance. According to the concept of K-mean [29], as shown by the following equation, sample heat level (x_i) and heat average (μ_j) are first input for the K-means classifier, and the class (C) is obtained by the following equation:

$$C = \sum\nolimits_{j=1}^{n} \sum\nolimits_{i=1}^{m} \left\| x_i^{(j)} - \mu_j \right\|^2 \tag{2}$$

where j and i stand for number of ingredients (classes) and pixels, respectively.

5) INGREDIENT CONSIDERATION

The boundaries detected in the curry brightness image at the boundary detection process and the temperature ranges of ingredients on boundaries at the ingredient-consideration process are considered to decide food ingredients. In each detected boundary, a couple features of brightness and heat, which sometimes are confused, are considered by fuzzy rules stored in database II for ingredient recognition. As shown by a fuzzy model shown in Fig. 10, temperature and intensity factors are plotted in the graph according to different ingredients. As shown in Fig. 10 (a) and (b), respectively, mean values and borders of all ingredients plotted in the upper graphs in Fig. 10 (a) and (b) are converted to vertex

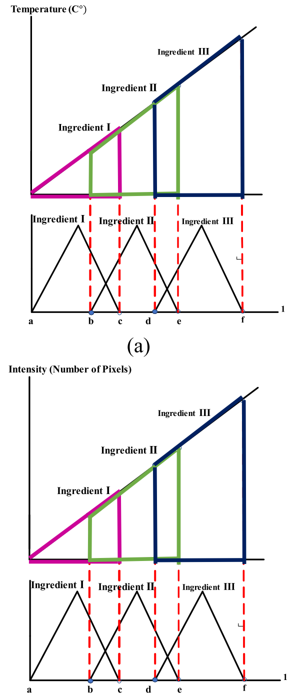


FIGURE 10. Membership function of sour soup with shrimp and water mimosa. (a) Ingredients of Temperature of Fuzzy logic system. (b) Ingredients of Intensity of Fuzzy logic system.

and borders of all ingredients plotted into vertex and the bottom of the triangle model shown in the lower graphs. Both lower graphs in Fig. 10 (a) and (b) representing the probability of all ingredients in factors are then normalized in the same range as shown in Fig. 11 and 12. These are fuzzy models, which are used in testing to find probabilities of ingredients for applying in fuzzy logics determined in advance. Dashed lines in Fig. 11 and 12 indicate input values of factors as a sample. The related fuzzy rules are then raised up, as shown in the upper row of Fig. 13, and their minimum values obtained from fuzzy logic, as shown in the lower row of Fig. 13, are applied to find the centroid of gravity as shown in Equation (3), which is the decided ingredient.

$$COG = \frac{\sum_{x=m}^{n} \mu A\left(x\right) x}{\sum_{x=m}^{n} \mu A\left(x\right)} \tag{3}$$

where x, μ, and a stand for ingredient, membership function, and area, respectively.

1.IF intensity = Ingredient I AND thermal = Ingredient I THEN Decision = Ingredient I (B1, C1)

2.IF intensity = Ingredient I AND thermal = Ingredient II THEN Decision = Ingredient I (B1, C2)

4. IF intensity = Ingredient II AND thermal = Ingredient II THEN Decision = Ingredient II (B2, C2)

6. IF intensity = Ingredient II AND thermal = Ingredient I THEN Decision = Ingredient II (B2, C1)

Output maximization rule

Shrimp : B1

Vegetables : C2

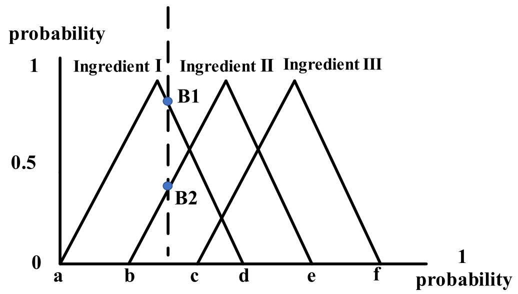


FIGURE 11. Input features of brightness of Fuzzy logic system.

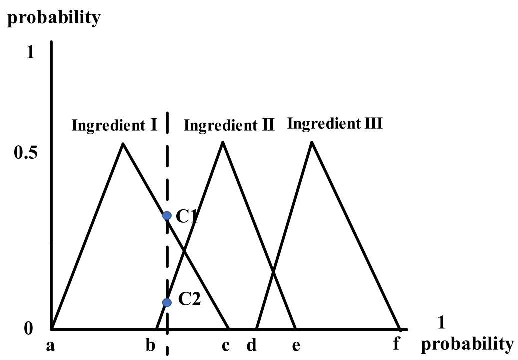


FIGURE 12. Input features of heat of Fuzzy logic system.

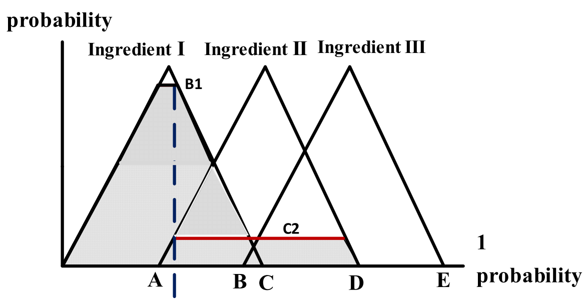


FIGURE 13. Output of Fuzzy logic system of sour soup with shrimp and water mimosa.

6) CALORIE CALCULATION

Based on our concept, the calories of a bowl of curry or food, is assumed as a summation of calories of all ingredients. The ingredient boundaries recognized by thermal and brightness images in the ingredient-consideration process measure the area by counting the number of pixels, total area in each recognized ingredient is summarized, and its ratio (R_{x_i}) against the whole area of the food is consequently obtained. This is assumed as the ratio similar to the ratio of weight so that the whole weight of ingredients can be calculated by multiplying with the whole food weight (W). Suppose calories of ingredients are represented by x_i, and its specific gravity is shown by SG_i. The whole calories of the food (C_{all}) are obtained by using nutritionist-knowledge-based data of calories per weight of ingredients (C_{x_i}) stored in Table 3.

$$C_{all} = \sum\nolimits_{i=0}^{n} WR_{x_i} SG_i C_{x_i} \quad (4)$$

where i stands for the number of ingredients.

B. HARDWARE

In design and implementation of the hardware system, as shown in Fig. 14, the system is divided into two main groups, the processor and memory units. The memory group surrounded by a dash-line box located in the middle of the figure divides the hardware system into two parts, which are processors for images captured by the CCD camera (left side of Fig. 14) and processors for image processing from the thermal camera (right side of Fig. 14). As shown in the top of the figure, CCD and thermal cameras are installed on the ceiling of the box for capturing brightness and thermal images, respectively, and the brightness image stored in the brightness image memory is then fed to a food-type classifier, which is trained by food samples; the trained results are stored in Database I in advance. The classifier in the food-type-classification module utilizes the trained data from database I for classifying the food brightness image into a food type in the testing process, and the classified food type is temporarily stored in a buffer memory (A). Then, the channel selector selects an appropriate channel out of three channels (RGB) by using food type stored in A as a reference, and the selected-

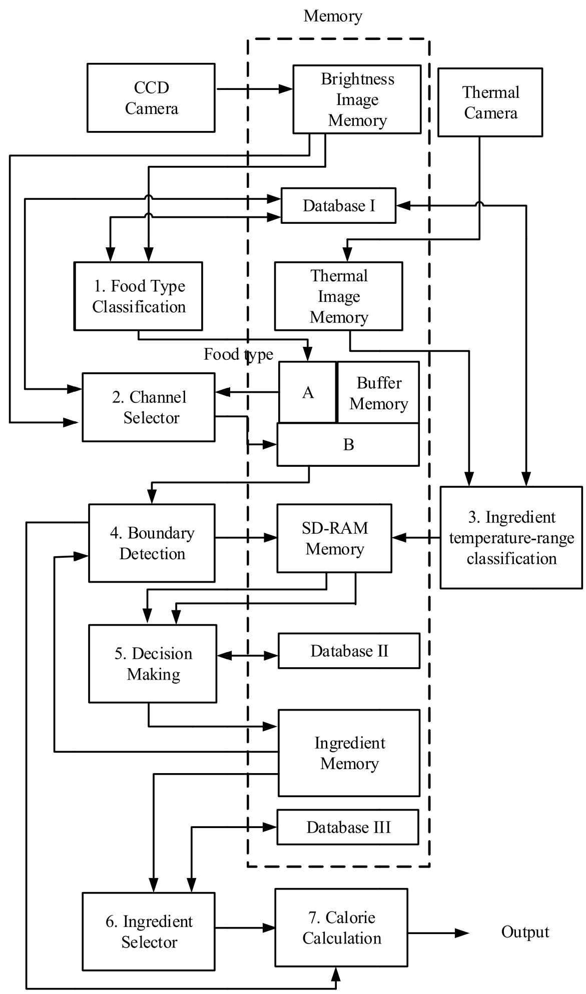


FIGURE 14. Overall Hardware System Design.

channel image is then stored in a buffer memory (B). The boundary detection processor subsequently detects boundaries in the selected-channel image and stores the boundary information in SD-RAM memory. Meanwhile, an image of food, which is captured by the thermal camera located in the top right of Fig. 14 is stored in the thermal image memory, and it is classified by the ingredient-temperature-range-classification processor into ingredient boundaries by using temperature order among ingredient regions and stored in the SD-RAM memory. The ambiguous ingredient regions classified by both thermal and CCD cameras and stored in the SD-RAM are consequently used as input of fuzzy rules in the decision-making processor for determining ingredients in all regions and the results are stored in ingredient memory. Finally, the ingredient selector processor selects ingredient regions for calculating the calories at the calorie calculation processor, and the calorie calculation processor summarizes total calories by using calorie information of ingredients stored in Database III. The hardware detail of mentioned processors are described as follows.

1) FOOD TYPE CLASSIFICATION

In the food-type classification module, the existing neural network, which is applied as a classifier in this paper inputs a line of image data $(x_1, x_2, x_3, \ldots x_n)$ stored in a line buffer, feeds the data to the activation function in hidden layer, and outputs food type in the output layer as shown in Fig. 15.

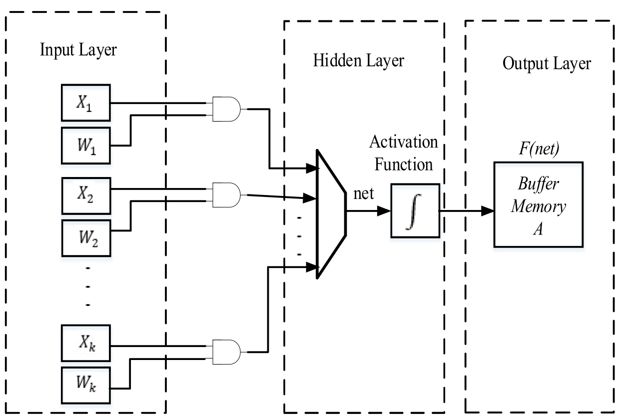


FIGURE 15. Food-type classification using a neural network.

The activation function of a hidden layer based on the following equation is designed as shown in Fig. 16.

$$F_{net} = \frac{1}{2}\left[\frac{net}{1 + \lfloor net \rfloor} + 1\right] \tag{5}$$

2) CHANNEL SELECTOR

While food type is recognized at the neuron classifier, the most appropriate brightness channel is selected by searching the channel selector shown in Fig. 17 (a) by using Database I, where the structure of the channel selector is shown in Fig. 17 (b). The selected-channel image (R or G or B channel) stored at buffer (B) is then used to detect the boundary in the next processor.

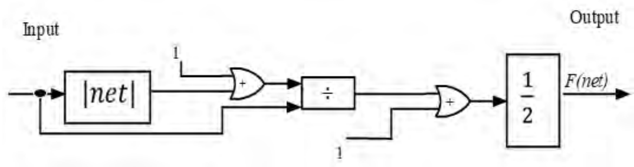


FIGURE 16. Activation function of neural network.

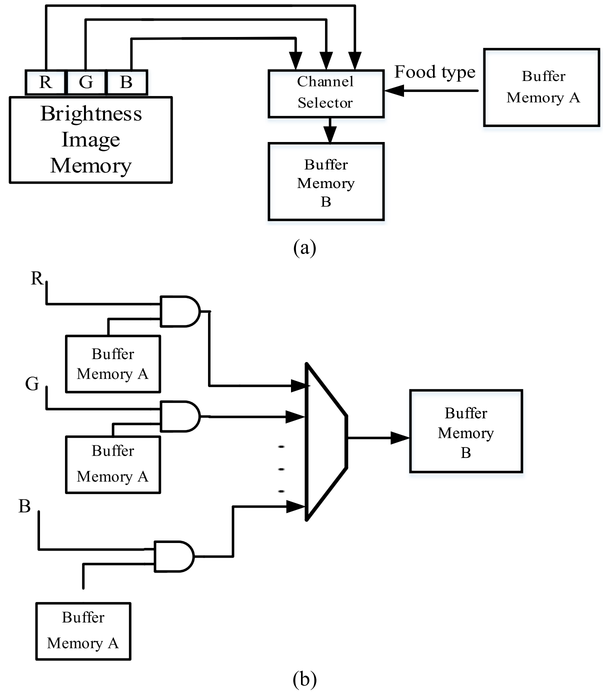


FIGURE 17. Channel Selector module and channel-selector structure. (a) Channel selector module. (b) Channel-selector structure.

3) INGREDIENT TEMPERATURE-RANGE CLASSIFICATION

the processor of ingredient classification is functionally designed based on the mentioned equation (2) of K-mean, as shown in Fig. 18. Input data consists of temperature in pixels of the thermal image (x) and the mean temperature value of each cluster (μ), and the circuit consisting of modules of the nearest center and update means produces output of cluster in terms of class label, and cluster centroids. The design of the module of nearest center and update means is depicted in Fig. 19 and Fig. 20.

The nearest-centroid module, which inputs samples in the cluster and centroid candidates, functionally calculates accumulated distance and produces the nearest centroid in the cluster, as shown in Fig. 19.

The update means module, as shown in Fig. 20, inputs a sample and classes, and functionally calculates means.

4) BOUNDARY DETECTION

The boundary detection module consists of edge detection and boundary determination. In the first part of

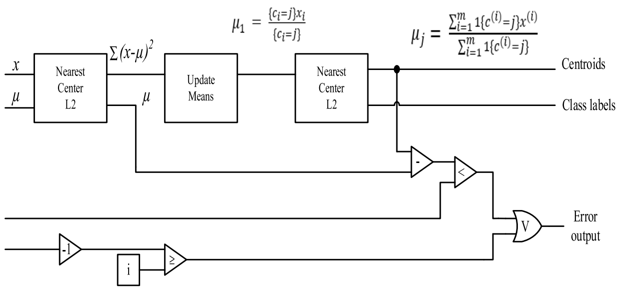


FIGURE 18. Processor of ingredient temperature-range classification.

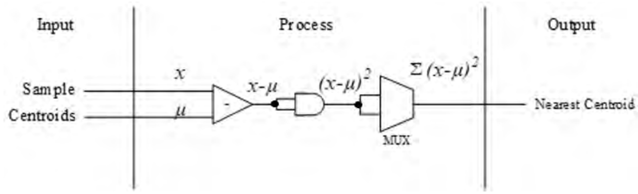


FIGURE 19. Nearest-centroid module.

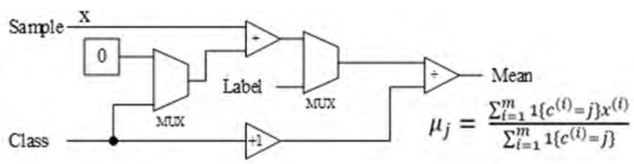


FIGURE 20. Update-mean module.

edge detection, the selected channel food image stored in register B is fed as input data, and all pixels in the food image are scanned, and calculated for detecting the edge. In the process, as shown in Fig. 21, surrounding pixels of the observing pixel are calculated according to the edge detector; Sobel [30]–[32] was selected as the edge detector in this paper, and the detected edge pixels are finally outputted.

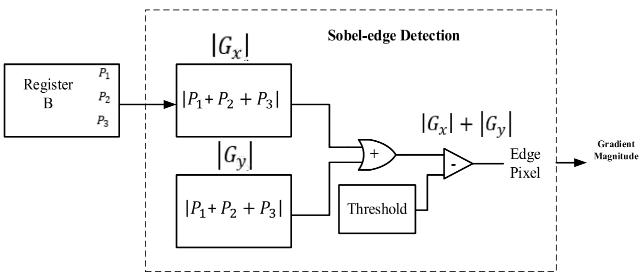


FIGURE 21. Sobel edge detection module.

A brightness image of food stored in the brightness-image memory and information of food type with the appropriate channel selected by the channel selector and stored at the buffer A is input for the Sobel-edge detection process [31]–[33], as shown in Fig. 21. Sobel-edge detection is recommended in this paper due to its simplicity and performance, especially for diagonal edge. Based on the following equation of Sobel, the hardware module was designed, as shown in Fig. 21.

In the second part of boundary determination, which watershed [33]–[35] was applied in this paper, the hardware structure was designed in two sub-parts, gradient magnitude and Watershed, as shown in Fig. 22 (a) and (b), where the structure of Watershed is shown in Fig. 22 (c). In the gradient magnitude, as shown in Fig. 22 (a), the edges obtained by the aforementioned edge detector are fed as

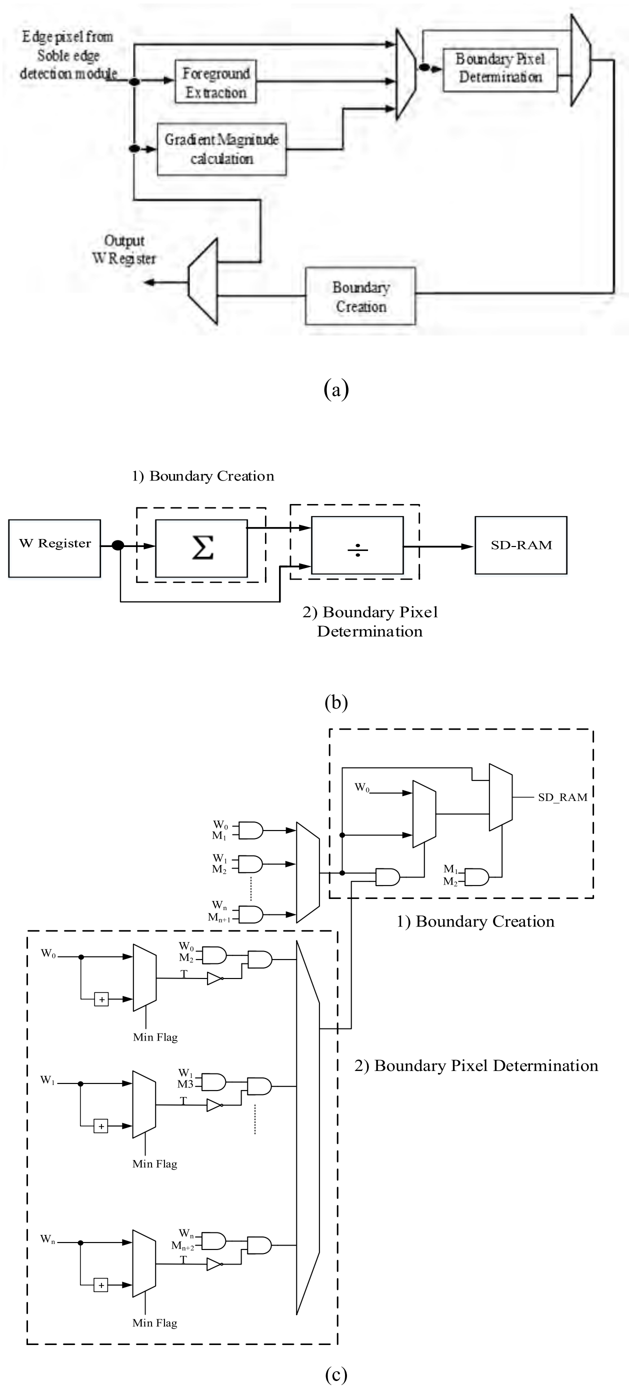


FIGURE 22. Watershed boundary determination. (a) Gradient Magnitude. (b) Overview Boundary determination using Watershed. (c) Structure of boundary determination using Watershed.

input data and the foreground of the image is then extracted; simultaneously, the gradient magnitude is calculated, and both of them are considered as the boundary and finally stored in the W register. The boundary data stored in the W register are subsequently used in the Watershed boundary determination process, as shown by the overview block diagram in Fig. 22 (b), and its structure is designed as shown in Fig. 22 (c).

5) DECISION MAKING

The decision-making module circularly processes at each detected boundary. As shown in Fig. 23, both average data of brightness and thermal images in the detected boundary are fed to registers (SD-ROM) in the fuzzy part as factors for applying fuzzy rules in Database II in the Inference part, and the decision is made in the Defuzzy part based on Mandani [36]–[42].

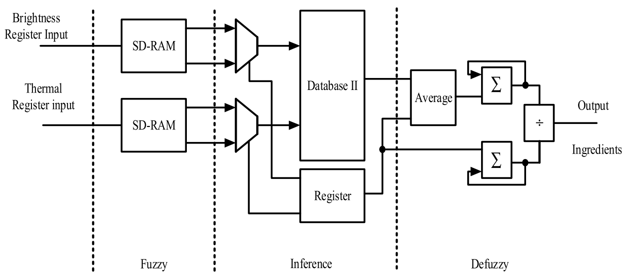


FIGURE 23. Fuzzy rules in the rule memory.

6) INGREDIENT SELECTOR

The ingredient selector processor uses ingredients of a boundary decided by the decision-making processor to retrieve calories per weight I, specific gravity (SG), and the depth (D) of the ingredients from Database III, as shown by a dashline in Fig. 24. The logic circuit in the box of the ingredient selector is shown in Fig. 25. These data are then stored at registers and accessed by the calorie calculation processor for finding calories of the boundary.

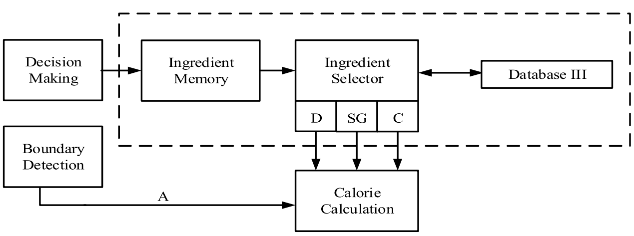


FIGURE 24. Ingredient Selector Diagram.

7) SUMMATION OF CALORIES

All boundaries decided as ingredients are counted for the number of pixels as the area of ingredients, and the ingredient area is geometrically converted into square mm by

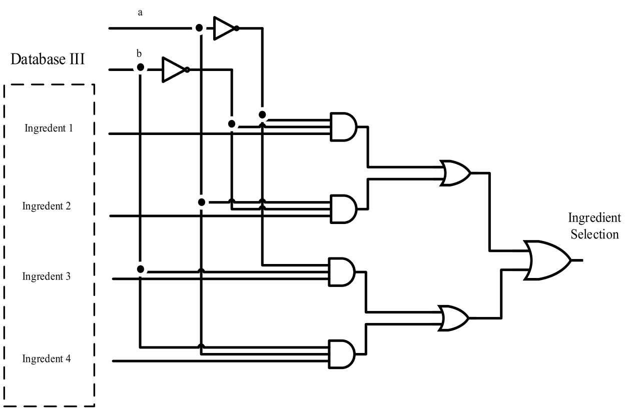


FIGURE 25. Ingredient Selector Circuit.

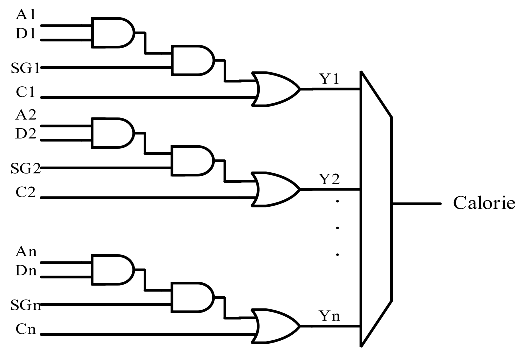
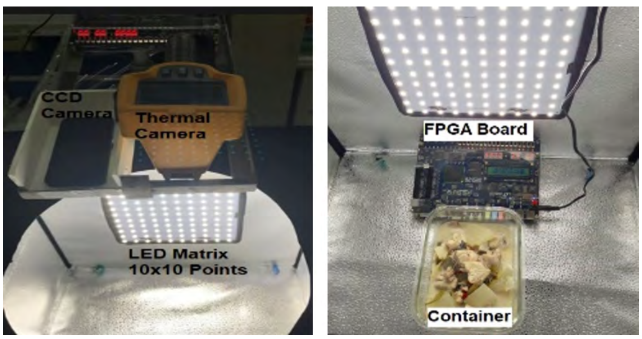


FIGURE 26. Summation of calories.



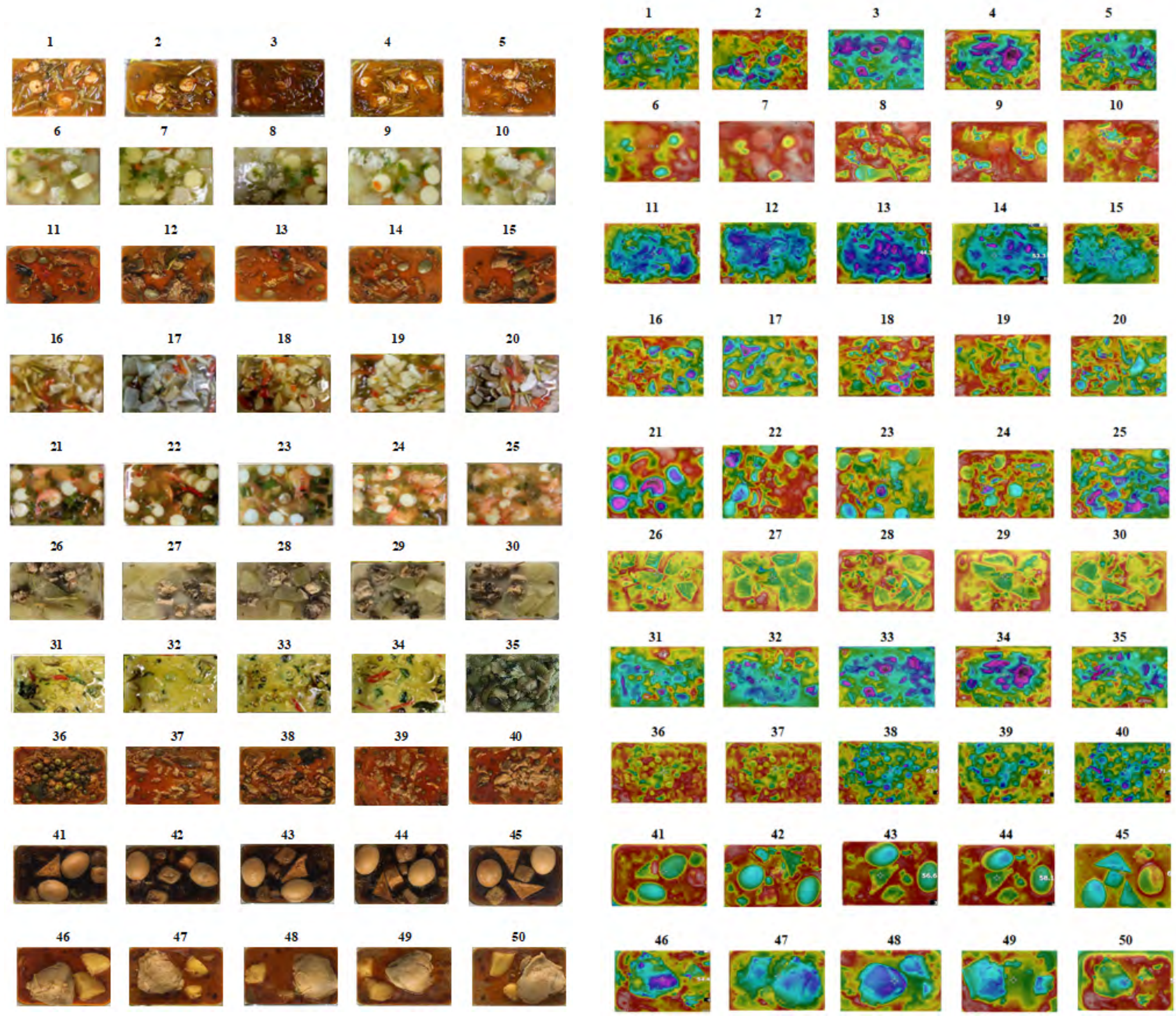
(a) (b)

FIGURE 27. Lab prototype. (a) CCD and Thermal cameras (b) FPGA board and container.

the perspective transform. The ingredient area (A) is calculated for ingredient volume with the height of the food container, the ingredient volume is then converted into ingredient weight by its SG, and the ingredient calories are obtained by the parameter of calories per gram (C), as shown by the following equation. The circuit is designed as shown in Fig. 26.

$$\text{CalorieTotal} = \sum\nolimits_{i=1}^{n} [A_i \times D \times (SG_i)]C_i \qquad (6)$$

where A, D, SG and C represent area of ingredients, height of food container, specific gravity, and calories per weight (gram), respectively.



(a) (b)

FIGURE 28. Samples of curry for experiments. (a) Samples shown as Thai curry brightness image. (b) Samples shown as Thai curry thermal image.

V. EXPERIMENTAL RESULTS

To verify our proposed method and evaluate the performance, we set up an experimental system by the specification, as shown in Table 4, and constructed the lab prototype, as shown by photographs in Fig. 27. In the lab prototype, CCD and thermal cameras are installed on the top as shown in Fig. 27 (a), LED and FPGA board are on the side wall, and curry container is located in the middle of the box as shown in Fig. (b). The evaluating the performance of the proposed method, Thai curry, which is considered as a complicated image in terms of separating into parts, was selected as a food sample for experiments. Since there are as many as approximately 75 types of Thai curry, we selected only 10 types, which were selected as the best 10 Thai curries for experiments [43]. The photographs of those curry samples are shown in Fig. 28.

In experiments, a container whose volume was the same as the standard [44]–[46] was used to store curry as the workpiece, and images of curry samples were taken by CCD and thermal cameras. The results of curry-type recognition by deep learning and neural network in software and hardware, respectively, are depicted in Table 5. Subsequently, those curry samples were formally burnt and baked, according to the calorie standard (issued by the American Society for Testing and Materials in 1997) [3] at the Pilot Plant Development and Training Institute, King Mongkut's University of Technology Thonburi, Bangkuntien campus, and the results are revealed in the second column of Table 6. Compared

TABLE 4. specification of experimental setup.

Item	Configuration	
CCD camera	focal length resolution	2.87 mm 7 M pixels
Thermal camera with super resolution (Ti480)	focal length 320×240, pixel resolution 1280×960 pixels	
Food container	Size 11.17 × 6.70 (cm^2)	
Test samples	training 50 samples testing 200 samples	
Software design Hardware design	MATLAB Version 2017 LABVIEW Version 2017	
Computer	Intel Core i7, 8GB RAM, 8GB, 1TB HDD+128GB SSD, GEFORCE 940, Windows 10, 64bits	

TABLE 5. Curry type classification results in the first step.

Type of food	Proposed method using Deep Learning in software	Proposed method using Neural Network in hardware
1) Chicken green curry	100%	100%
2) Tom Yum Kung	99%	98.5%
3) Hot and spicy	98.5%	98.5%
4) Minced pork and soya bean curd soup herbs	99%	98.5%
5) Sour soup with shrimp and water mimosa	99%	99%
6) Massaman curry with chicken	100%	100%
7) Pork with Panaeng curry	98%	98%
8) Chicken coconut soup	99%	98.5%
9) Red curry with roasted duck	98%	98%
10) Eggs and pork in brown sauce	100%	100%

with the conventional method (third column), our proposed method in software and hardware approaches are shown in the fourth and fifth columns of Table 6. Errors compared with the calorie standard (second column) are shown as a percentage in the parentheses beside calorie results.

Thai curry samples captured by CCD and thermal cameras as shown in Fig. 28 (a), and (b), respectively are fed to the our lab prototype, and those signals are then processed as shown via the serial peripheral interface bus (SPI) by some signal samples in Fig. 29.

VI. DISCUSSION

In this paper, a method of design and implementation of a food calorie estimation system using nutrition knowledge and fusion of brightness and heat information was proposed to measure food calories in each meal. In the method, food type is classified in the first step, ingredients in the classified food are then recognized, and ingredient calories are finally calculated and integrated for entire food calories. The lab prototypes in software and hardware are constructed according to the proposed concept and method, and 50 samples of ten representative types of Thai curry, which are accepted as the most popular curries, were tested with the lab prototypes. The testing results were compared with the destructive test results based on the standard of the American Society for Testing and Materials issued in 1997, and the average statistical data of destructive evaluation published in the public websites. The results show our non-destructive method measures in more precise calories than the average statistical data of destructive evaluation appearing on the public websites. This is certainly acceptable, because the curry samples for our experiments and destructive tests at the lab were the same, but the destructive-evaluation results published in the public webs are average data of some other samples. This means that our proposed approach effectively measures food calories in each meal. The performance of our proposed method evaluated by comparing obtained calories with the calories set up by the conventional destructive method shows in absolute error as 14.49% for software and as 11.54% for hardware. On the other hand, as another reference for users to choose, comparison between hardware and software in computational time is evaluated in our case study that hardware takes more advantage around 24 times than software.

TABLE 6. Calorie calculation results.

Type of food	Destructive (1000 grams)		Non-destructive (1000 grams)	
	Testing on real materials (kCal) [3]	Conventional Method (kCal) [44], [45], [46]	Proposed Method (kCal) software	Proposed Method (kCal) hardware
1) Chicken green curry	957.50	1,280 (33.68%)	939.80 (-1.85%)	978.56 (2.2%)
2) Tom Yum Kung	473	344 (27.27%)	482.24 (1.95)	504.45 (6.65%)
3) Hot and spicy	1,004.37	1,150 (14.5%)	881.68 (-12.22%)	986.78 (-1.8%)
4) Minced pork and soya bean curd soup herbs	763.77	510 (33.23%)	821.56 (7.57%)	823.42 (7.8%)
5) Sour soup with shrimp and water mimosa	1,030.58	1,330 (29.05%)	1,115.78 (8.27%)	1,128 (9.5%)
6) Massaman curry with chicken	1,035.40	1,620 (56.46%)	1,336.58 (29.1%)	1,238.9 (19.7%)
7) Pork with Panaeng curry	905.66	1,531 (69.1%)	1,228.55 (35.65%)	1,023.4 (12.3%)
8) Chicken coconut soup	829.71	1,180 (42.22%)	1,018.40 (22.74%)	1,025.9 (23.6%)
9) Red curry with roasted duck	1,322.09	2,400 (81.53%)	1,274.30 (-3.61%)	1,212.34 (-9%)
10) Eggs and pork in brown sauce	2,026.57	3,300 (62.84%)	1,579.36 (-22.07%)	1,564.5(-22.8%)

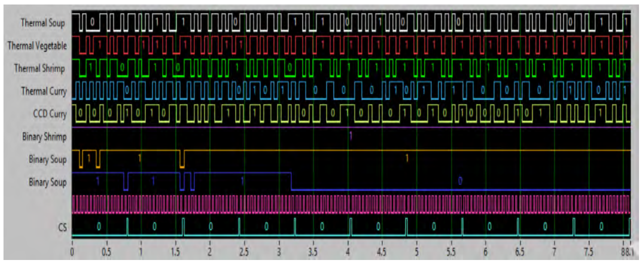


FIGURE 29. Waveform of data transitions in food calorie estimation.

In curry type classification, which is located at the first process of our proposed method, it is radically considered as an important key factor for the latter processes so that the results should be highly reliable. As shown in Table 5, although the classification results are not completely 100%, they are quite close to 100% in all curry types. However, few samples that unfortunately missed the classification were accepted to produce errors in calorie calculation, but they were confirmed by the experimental results to be subjectively acceptable in practice as guidelines for consumers to determine the food calories.

To apply our proposed method in reality, users should first consider selecting software and hardware approaches that are already proved by our experiments, by trading off between accuracy and computational speed.

In this paper, we implemented a lab prototype of food calorie estimation that fuses brightness and heat information. This should be applicable as a food calorie estimation tool in the kitchen, canteen, restaurant, and so on. It is not suitable yet for mobile devices due to the expensive cost of a thermal camera and the bulkiness of the system scale. In application for mobile devices, the technology of thermal cameras and algorithms, which are robust against light change, should be developed. The component cost and system scale are considered as a disadvantage of the proposed method and should be examined in future work.

VII. CONCLUSION

This paper proposed a method of design and implementation of an ingredient-based food calorie estimation system using nutrition knowledge and the fusion of brightness and heat information. This proposed design and implementation method aims to construct a system that measures food calories in each dish, which should calculate calories with more accurate results than the average statistical data of food calories. In the method, ingredients that are components of food are recognized by the fusion of brightness and heat information processing, whose features are boundaries and temperature-range order. The calories of the food are obtained by the sum of all ingredient calories using calories per weight of all ingredients, based upon nutrition knowledge. In performance evaluation of the proposed method, the experiments were performed on our original lab prototypes in software and hardware with 10 types of popular Thai curries, which are difficult to segment into ingredients. The results from each dish significantly showed more accurate calories than the average statistical data of food calories in comparison with the standard destructive-evaluation method of food calories.

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