Knowledge Management of Vegetarian Food for the Elderly Using DCNN: An Empirical Study in Thailand

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ABSTRACT

According to the literature reviews on knowledge management, no evidence has been found on the knowledge management of vegetarian food among elderly people with chronic diseases. The objective of this research is to apply knowledge management in identifying appropriate vegetarian food for the elderly with chronic disease by using the deep convolutional neural network (DCNN). The contribution of this research is to enable people to use knowledge management and collect knowledge to create a machine learning algorithm system so that the elderly can access knowledge of vegetarian food in relation to chronic disease. The benefits of this research are that the elderly can learn to consume appropriate food based upon their chronic disease, and the food producers can provide food menus accordingly.

KEYWORDS

Aging Society, Deep Convolutional Neural Network, Knowledge Management, Machine Learning, Neural Network, Vegetarian Food

INTRODUCTION

The elderly population in Thailand has tended to increase at a high rate, and the National Statistical Office of Thailand has indicated that Thailand has been classified as an aging society since 2005 (National Statistical Office, 2017). For Thailand, the Elderly Act 2003 stipulates that the elderly refers to “persons over sixty years of age and over and that have a Thai nationality.” Thailand has entered the aging society because 17.1 percent of the population is aged 60 years and over (Office of the Civil Service Commission (OCSC), 2017).

The trend of the aging group, which is steadily increasing, has led to risks and health problems, especially chronic diseases. The elderly that receives the proper food and an adequate diet can result in good health or delays in the development of chronic aseptic diseases. Ninety-five percent of the elderly have chronic disease problems, consisting for example of high blood pressure, osteoarthritis, cataracts, high cholesterol, diabetes, dementia, cardiovascular disease, depression, stroke, and emphysema. The main factor in these diseases is dietary behavior. If the elderly consume healthy foods, this can help reduce the risk of chronic disease (Ministry of Public Health, 2017).

As the World Health Organization (WHO) has indicated, many diseases that occur in the elderly are a result of dietary factors (World Health Organization, 2010). Vegetarian food, which consists mainly of fruits and vegetables, can help reduce the risk of chronic disease (Mehta, 2017). Vegetarian
dietary patterns are known to reduce cardiovascular disease (CVD) mortality and the risk of coronary heart disease (CHD) by 40% (Kahleova et al., 2018). Therefore, daily food intake is imperative for the elderly to meet the nutritional needs of the increasingly elderly population. Knowledge management (KM) is a popular concept in the organizational realm. The KM system is one tool that can help to manage an organization’s knowledge through a systematically defined process in order to acquire knowledge and understanding. KM can be applied to the elderly in terms of self-care as well as to the consumption of food that is suitable for them (Haque & Kohda 2018).

Machine learning (ML) is currently used extensively in food research, including food classification, food recognition, and food assessment. ML architecture is used to recognize food images in order to inform and to evaluate food for Parkinson’s disease patients (Mezgec & Seljak, 2017). A web-based decision support system can suggest diet plans based upon daily calorie needs and activity levels by using ML (Mohemad et al., 2018). ML is used to assess the food energy from the eating images captured on a mobile phone (Fang et al., 2019). Sak and Suchodolska (2020) discusses artificial intelligence in nutrient science research and suggests that AI systems used to assess food may provide personalized nutrition, which is essential in certain diseases and can affect consumer health. Lu (2020) has studied an artificial intelligence-based technique for assessing the nutritional quality of hospitalized patients instead nutritionists. An artificial intelligence system can also be applied for evaluating patient food. Machine learning allows computers to mimic and adapt human-like behavior by combining statistics, data analysis, and machine learning, as well as related methods in order to understand and analyze the actual data (Alzubi et al., 2018).

As previously stated, most health-conscious seniors choose vegetarian food. However, some elderly people are unaware of the properties or benefits of vegetarian food. If the elderly are given knowledge this kind of food or information about vegetarian food menus or dietary choices, they may be more satisfied and consume more vegetarian food. There has been no previous research on the knowledge management of vegetarian food among elderly people with chronic diseases. The contribution of this research is to use knowledge management and to collect knowledge in order to create a machine learning system so that the elderly can access knowledge regarding vegetarian food and chronic disease. The objective of this research is to apply knowledge management for identifying food from the images of vegetarian food according to the given chronic disease by using the deep convolutional neural network (DCNN). The appropriate vegetarian food for chronic diseases means that the vegetarian dish has preventive, mitigating, and harmless properties for that disease. The most popular vegetarian food in Thailand, as well as the most common chronic diseases among the elderly in Thailand, can be discussed in this study.

This paper is organized as follows. In the background section, a brief description of the advanced knowledge of the management of vegetarian food and DCNNs is offered. The methodology section, describes the process of the operation of KM for vegetarian food by using the DCNN. The experiment and results section illustrates the process of the experiment and results, including a comparison with each network of the model in this study. Finally, a conclusion and future work are discussed in conclusion section.

**Background**

As mentioned in the introduction section, the objective of this research is to apply knowledge management for identifying food from the images of vegetarian food according to the chronic disease that the individuals have by using the deep convolutional neural network. Therefore, the research related to this study is as follows.

**Knowledge Management**

Knowledge management is the management of organizational knowledge through a systematic and organizational process for acquisition, sustainability, advocacy, knowledge sharing. Knowledge management is about facilitating the processes that create, share, and use knowledge. The stages of
knowledge management are knowledge creation, knowledge storing, knowledge sharing, and the use of knowledge as shown in Figure 1 (Kumar, 2015). However, unmanaged knowledge can be obsolete and useless (Ansari et al., 2012). Therefore, organizations need to implement processes to manage their knowledge (OuYang, 2014). KM is comprised of systematic processes ranging from data processing to information, and knowledge, as well as the experience of people to create knowledge, and this must be stored in a manner in which people can use it and that can be accessed through a convenient channel. These processes comprise the application of knowledge, enabling the transfer of knowledge and circulating throughout the organization (Iskander et al., 2017).

Figure 1. Stages of knowledge management. Source: Kumar, 2015

Knowledge management research is presented in the following. Luiza and Daniela (2014) have proposed, analyzed, and generated recommendations for food process knowledge management in order to achieve the highest level of competitiveness by offering a method for knowledge management with advanced information technology. (Luiza & Daniela, 2014). Sompong and Rampai (2015) have used knowledge management of Thai food in 14 northern provinces with high potential for tourism promotion. The study found that local tourism organizations should use this knowledge to promote local tourism through integrated media. The suitability of the media that is used to convey and share knowledge comes from the needs of the tourists (Sompong & Rampai, 2015). Firlej and Zmija (2017) analyses knowledge management issues in Poland’s food industry. The result found that customer and supplier collaboration, as well as outside training, are not possible. The lack of collaboration with universities and research centers can attest to the impossibility of applying them in practical applications in the enterprise (Firlej & Zmija, 2017). Hsieh et al. (2020) has investigated the factors that influence success through effective KM and has forecasted the likelihood of KM’s success in the post-epidemic era. The KM conceptual framework employs a hierarchical prediction model based upon preference relationship in order to assist the franchised service sector in realizing the influencing criteria (Hsieh et al, 2020). Knowledge management can move food organizations to understand and maintain their knowledge sources and activities. This new knowledge is applied both to the management of food organizations and to develop new products and new services, or to make significant changes regarding business or individual decisions.

As the elderly population grows, consumption is one of the most important factors and disease resistance in this group. Food knowledge management for the elderly can reduce chronic disease
statistics and create a decrease in the number of patients. Therefore, knowledge management is critical for comprehending vegetarian food for the elderly.

**Vegetarian Food**

Vegetarian food is a kind of diet that involves little or non-consumption of any meat or its products. There are many types of vegetarian food which exist today, but none follows a specific pattern (Mehta, 2017). Vegetarian food is healthy. It consists of vegetables, fruits, whole grains, legumes, and oils, which are rich in nutrients (Cramer et al., 2017).

**Deep Convolutional Neural Network**

Vegetarian food is presented as follows. Juan et al. (2015) indicate that a vegetarian diet provides better quality of food with lower energy consumption compared to the non-vegetarian diet. Vegetarian diet planning can be helpful for losing weight or managing weight without degrading the quality of the diet (Juan et al., 2015). Government agencies and health/nutrition organizations emphasize that regular consumption of plant foods provides health benefits and helps to prevent certain diseases. A well-planned vegetarian diet, which includes a wide variety of plant foods provides adequate nutrition (Agnoli et al., 2017). Plant-based diets are associated with lower blood pressure, lower blood lipids, and lower platelet aggregation than non-vegetarian diets, and are helpful in weight control, reducing the risk of metabolic disease and type 2 diabetes (Kahleova et al., 2018). Lacto, lacto-ovo, and semi-vegetarian diets are associated with lower chances of developing diabetes (Agrawal et al., 2014). Most vegetarians and plant-based diets have relatively favorable risk factors and a lower risk of ischemic heart disease (IHD). The many nutritional properties of a plant-based diet have protective properties regarding heart disease (Mann, 2017). In the vegetarian diet, mortality from ischemic heart disease is found to be lower, possibly due to lower blood cholesterol levels, lower obesity prevalence, and higher intake of antioxidants (Ginter, 2008).

Vegetarian food is considered healthy and can prevent or reduce the risk of chronic disease, but some older people are not fully aware of the properties or benefits of vegetarian food. If appropriate knowledge or menus is introduced to the elderly, it may make them more satisfied and consume more vegetarian food. The deep convolutional neural network is part of a popular machine learning that can identify food suitability for the elderly and is capable of image learning.

The DCNN is a machine learning method based upon artificial neural network (ANN) research. The aim of ANN is to create a neural network that can simulate the human brain to analyze and understand information. ANN is used in conjunction with the particle swarm optimization (PSO) method to assess customer satisfaction with the aroma and taste of beverages (Ounsrri et al., 2020). The DCNN is especially applied to image classification (Pan et al., 2017). ANN covers a number of architectures, including convolutional neural networks (CNN). The CNN is a type of feedforward of ANN. It contains different layers, including the convolutional layer, the pooling layer, and the fully-connected layer. These layers are stacked on top of each other according to the CNN architecture in order to do recognition tasks. The CNN is developed and performs better than traditional computer vision techniques in terms of cognitive performance. CNN can extract and classify image attributes such as colors, textures, and shapes. It is currently considered one of the most popular machine intelligence models for big image data analysis in various research areas (Termritthikun et al., 2017). The DCNN is an addition to the CNN layer class for solving problems that are more complex. (Ravi et al., 2017). The basic architecture of CNN is shown in Figure 2.

Convolutional layers: a convolution is the fundamental layer of computing. When the data reach a convolution layer, it convolves each filter across the spatial dimensionality of the data to produce a 2D activation map. The output of neurons connected to local regions of the input can be verified by using the convolution layer for calculating the scalar between their weights and the area connected to the input volume. Neurons with the same feature map share weights, reducing network complexity
by limiting the number of parameters. However, these are optimized by using three hyperparameters: depth, stride, and zero-padding.

The following is the formula for calculating the spatial dimension of the convolution layer output:

\[
\frac{V - R - 2Z}{S + 1}
\]  

(1)

Here \(V\) represents the input volume size, (i.e., height x breadth x depth), \(R\) represents the receptive field size, \(Z\) is the amount of zero padding set, and \(S\) is the stride. Convolution is trained by using the backpropagation algorithm. It is associated with convolution operations involving spatially flipped filters. The individual neuron in the output can represent the gradient of which may be lost across the depth, so only one set of weights is upgraded, rather than all of them. Next, the most common activation functions in this layer are the sigmoid, tanh, and rectified linear units (ReLU). Rectified linear units (ReLU) are preferred because they can train neural networks several times faster. The result of the ReLu is that if the value is less than zero, it forwards the output zero; if the value is greater than or equal to zero, it forwards the output greater than zero. At the end of the final layer, Softmax activation is used to improve network performance. The ReLu equation is expressed as equation (2) and the Softmax equation is expressed as equation (3).

\[
g(y) = \begin{cases} 
0 & \text{for } y < 0 \\
y & \text{for } y \geq 0 
\end{cases}
\]  

(2)

\[
\alpha(c)_j = \frac{e^{c_j}}{\sum_{i=1}^{N} e^{c_i}}
\]  

(3)

\(C\) is the input vector of the softmax function, \(N\) is the number of classes in the multi-class classifier, \((c)_j\) is the elements of the input vector of the Softmax function, and they can take any real value, positive, zero or negative. \(e^{c_j}\) is the standard exponential function that is applied to each element of the input vector. This gives a positive value above 0, which will be very small if the input
is negative, and very large if the input is large. \( \sum_{N=1}^{N^c} e^{N/k} \) is the normalization term being the term at the bottom of the formula. It ensures that all of the function’s output values sum up to 1 and are in the range of \([0, 1]\), resulting in a valid probability distribution (Sakib et al., 2015). The result of the convolution is identified as the feature map, and it is passed on to the pooling layer.

The pooling layer: pooling operations reduce the dimensions of feature maps in order to summarize sub-regions, such as taking the average or maximum value. It gradually reduces the size of the data and the complexity of the model process, as well as controls the overfitting problem. The pooling layer applies the “max” function to each activation map in the input and scales its dimensionality. The stride and filters of the pooling layers are typically set to 2 x 2, allowing the layer to spread across the entire area of the input’s spatial dimensionality, as seen in Figure 3.

Figure 3. Max pooling operation

Fully connected layer: Neurons are a fully connected layer, as seen in conventional multilayer perceptron (MLP). As a result, their activations are computed by using a matrix operation followed by a bias offset. Because it can extract high-level features from the output of the convolution and pooling layers, adding a fully-connected layer is also a cheap way to learn the non-linear combinations of these features. The softmax or sigmoid function can be used to predict the input for single-label, multiclass classification. A fully connected layer sends a two-dimensional output to the output layer. The fully connected layer’s main objective is to flatten the high-level features learned by convolutional layers and to mix all of the elements.

CNN is developed for the following research in food: Kagaya and Aizawa (2015) classify food / non-food according to three CNN datasets. The dataset is compiled from publicly available images and social media. The result is a high accuracy of 96%, 95%, and 99% in the three datasets, respectively (Kagaya and Aizawa, 2015). Amatul et al. (2018) use CNN to image classifiers. Due to the previously proposed methods for recognizing food have low classification accuracy. CNN learns and distinguishes features better than other methods, such as histograms of oriented gradients (HOG), local binary patterns (LBP), or speeded up robust features (SURF) (Amatul et al., 2018). Gianluigi et al. (2018) evaluate CNN-based features for food classification and retrieval. The features learned from the database Food-475 are better than those learned from other food databases, and are better than those in ImageNet’s very large image database. The result shows that the higher the
food’s database domain, the more accurate the retrieval accuracy can be compared to other methods (Gianluigi et al., 2018). Park et al. (2019) detect and recognize Korean food images on mobile devices in order to estimate accurately food intake using the DCNN method and to compare the results to AlexNet, GoogLeNet, the deep convolutional neural network, the visual geometry group (VGG), and the residual network (ResNet) for large image recognition (Park et al., 2019). Saeed et al. (2019) propose a powerful machine learning algorithm-based method for forecasting fire using images from CCTV camera data based upon the Adaboost-MLP model. This model’s purpose is to search for emergencies in images and to generate the region of interest (ROI) of the detected objects. The results show that the model is more efficient and becomes more accurate with training (Saeed et al., 2019). Lu (2019) studies the application of CNNs to ten-class small-scale food image data. The food images with a small data set of 5,822 images and 10 food groups are recognized by the CNN model. The five-tier CNN model is built with the best testing accuracy to 74 percent, which is higher than the bag-of-features (BoF) method’s accuracy of 56 percent. The overfitting problem is fixed from model training by expanding the training data through correlation, which test accuracy to more than 90% (Lu, 2019). Pan et al. (2020) create a new blended network by combining two convolutional subnets. The network complexity is optimized by adapting and modifying existing convolutional networks for automatic classification of food ingredients. The results show that CBNet, which employs VGGNet, ResNet, and DenseNet, can be thoroughly examined and evaluated on the Food-41 dataset, with top 1 accuracy above baseline. Two subnets are combined to achieve better results. (Pan et al., 2020).

According to the above, the DCNN simulates the vision of a human being that views a sub-area and merges a group of sub-regions to see what it is seeing, which is highly accurate. The DCNN network is capable of extracting image features and classifying images efficiently. Therefore, the objective of this research is to apply knowledge management for identifying food from the images of vegetarian food appropriately according to the chronic disease by using the deep convolution neural network.

**Methodology**

The method of operation in KM is separated into four stages: knowledge creation, knowledge storing, knowledge sharing, and use of the knowledge. KM of vegetarian food is shown in Figure 4.

![Figure 4. Knowledge management of vegetarian food in research (adapted from Kumar, 2015 and developed by the authors).](image-url)
Knowledge Creation

The knowledge of vegetarian food is created to provide information for the elderly on the consumption of vegetarian food. The material uses in cooking has different nutritional values and health benefits. The questionnaire is created for the data collection. The questionnaire consists of two parts: personal information and vegetarian food preferences. It consists of gender (male (M)/female (F)) questions and chronic disease, with ten disease options, with the most common among the elderly in Thailand being high blood pressure, osteoarthritis, cataract, high cholesterol, diabetes, dementia, cardiovascular disease, depression, stroke, and emphysema. Ten foods chili sauce with tamarind, red curry with chakram, spice vegan soup, spicy fruit salad, Thai rice and herb salad, deep fried spring rolls, Thai spicy mixed mushroom salad, stir-fried tempeh with cashew nuts, spicy winged bean salad, fried ivy gourd leaf with spicy cream dressing are selected in this research (Yokoyama et al., 2014). The food menus are popular menus in vegetarian restaurants in Thailand and have the dietary properties specified by the Institute of Nutrition (Chanchanakit, 2017). After the questionnaire is created, the questionnaire quality is validated with a measure of validity which is measured to match the intended research objectives by using a conformity index of item-objective congruence (IOC). This is a method for finding a conformity index between each question and the objective or measure. The IOC formula is shown in Equation 4, where \( \sum R \) is the sum of all of the expert opinion scores and \( n \) is the number of experts. The results of the IOC assessment criteria are less than 0.50, which means that the questions in that question can be measured in terms of what needs to be measured (Pasunon, 2015).

\[
IOC = \frac{\sum R}{n}
\]  

(4)

Table 1. The results of the survey of vegetarian food menu and appropriate food for the elderly.

<table>
<thead>
<tr>
<th>Chronic disease</th>
<th>Favorite food menu</th>
<th>Appropriate food</th>
</tr>
</thead>
<tbody>
<tr>
<td>High blood pressure</td>
<td>(M) Chili sauce with tamarind (F) Red curry with chakram</td>
<td>• Spicy winged bean salad</td>
</tr>
<tr>
<td>Osteoarthritis</td>
<td>(M) Spice vegan soup (F) Spice vegan soup</td>
<td>• Stir-fried tempeh with cashew nuts</td>
</tr>
<tr>
<td>Cataract</td>
<td>(M) Spicy fruit salad (F) Spice vegan soup</td>
<td>• Red curry with chakram</td>
</tr>
<tr>
<td>High cholesterol</td>
<td>(M) Thai rice and herb salad, chili sauce with tamarind, spice vegan soup, spicy fruit salad (F) spicy fruit salad</td>
<td>• Spicy fruit salad</td>
</tr>
<tr>
<td>Diabetes</td>
<td>(M) Spicy fruit salad (F) Thai spicy mixed mushroom salad</td>
<td>• Spice vegan soup</td>
</tr>
<tr>
<td>Dementia</td>
<td>(M) Chili sauce with tamarind (F) Red curry with chakram</td>
<td>• Thai rice and herb salad</td>
</tr>
<tr>
<td>Depression</td>
<td>(M) Spice vegan soup (F) Red curry with chakram</td>
<td>• Deep fried spring roll</td>
</tr>
<tr>
<td>Stroke</td>
<td>(F) Stir-fried tempeh with cashew nuts</td>
<td>• Thai spicy mixed mushroom salad</td>
</tr>
</tbody>
</table>
Knowledge Storing

Data Collection

In this study, 100 elderly people who consume vegetarian food in a vegetarian restaurant in Thailand are interviewed. The majority of the elderly are 84 percent female and 16 percent male.

Data Analysis

The analysis of the data is divided into two parts: the first is a statistical method to find the correlation of gender, disease, and favorite food. The second part uses the DCNN in order to identify vegetarian food based upon chronic disease.

Part I: Survey of vegetarian food for the elderly. The elderly is analyzed using statistical principles of the relationships among gender, chronic disease, and vegetarian food. The results of the analysis are shown in Table 1 (favorite food menu) by statistical (chi-squared test) significance at the level 0.05 from previous research of a survey of vegetarian food menu for the elderly (Kengpol & Punyota, 2020). According to a survey of vegetarian food preferences among the elderly, the majority of the elderly consume food based upon their favorite flavor, ignoring dietary benefits and chronic disease.

Part II: Identification of food using the DCNN. The input is vegetarian food images and the output is chronic disease, which is food-appropriate. All of the vegetarian food images in the dataset belong to eight classes, including spicy winged bean salad, stir-fried tempeh with cashew nuts, red curry with chakram, spicy fruit salad, spice vegan soup, Thai rice and herb salad, deep fried spring roll, and Thai spicy mixed mushroom salad as shown in Table 1 (appropriate food). Examples of food images are shown in Figure 5. This research collects images from two sources: web images and mobile phone photos. Some of the images have blurry, of low resolution, or excessive noise, which is inappropriate for classification. Therefore, the image quality is improved and properly prepared by adjusting the resolution and by sharpening the food images. Vegetarian food images are performed reduce/ enlarge, rotate left/ right, flip left/ right/ top/ bottom, corner crop, light/ dark adjustment, contrast adjust until gets good quality images. The resolution of each image is 128 * 128 in order to reduce the time to separate the feature and to recognize the food image. An illustration of DCNN architecture is shown in Figure 6.

Figure 5. Examples of food images in spicy fruit salad class.
The experiments are performed on Intel (R) Core (TM) i7-10510 U CPU @ 1.80 Ghz 2.30 GHz RAM 8GB. The data are analyzed by using the Python program version 3.7 and the pre-trained network model of Keras applications. Keras is a library for deep learning and provides an easy-to-use interface with a focus on cutting-edge deep learning. Because of the advantages of Keras, it is selected for this experiment.

The experimental results of the DCNN are presented this section. The DCNN extracts feature vegetarian food images in order to identify suitability, food images, and chronic diseases. According to Lu (2019) research, a basic 5-layer model is used. The depth or complexity of the network has an effect on the extraction feature by which the images are distinguished. The VGG 16, VGG 19, and MobileNet network, which have different network depths and complexity, are selected in this experiment. VGG is the CNN architecture used to win the 2014 ILSVR (Imagenet) competition; it is widely regarded as one of the best visual modeling architectures currently available. MobileNet is a type of convolutional neural network that is created to allow the model to be deployed on small computing devices such as smartphones while maintaining performance comparable to a large deep neural network. If this research applies in real-time, it would require the use of a smartphone, which is why the MobileNet network is selected for this experiment. The VGG16, VGG19, and MobileNet network structures are as follows. The structure of DCNN for identification of vegetarian food is shown in Figure 7.

The VGG16 has 13 convolutional layers and three fully connected layers, while VGG19 has 16 convolution layers and a total of three fully connected layers. This architecture is uniform. There are a few convolution layers followed by a pooling layer which reduces the height and width of the volume. It has 64 filters and then this double to 128, then to 256, and the last layer uses 512. The number of filters is doubled with every step or doubled across all convolution layers. The neural network VGG19, which is larger than the VGG16, has 19 layers. This increases the depth of the network and contributes to the learning of more complex properties. The impressive VGG results reveal that network depth is a key factor in achieving high classification accuracy (Hu et al., 2015). MobileNet replaces expensive convolutional layers with depth wise separable convolutional blocks. Each block consists of a 3x3 deep convolutional layer that filters the input, followed by a convolutional 1x1 pointwise layer that joins these filtered values in order to create new properties. It is much faster than normal convolution, yielding approximately the same results. MobileNet is a compact model that delivers fast, low latency, and low power consumption. It is designed for tasks with limited resources. VGG16, VGG19, MobileNet have a depth of 23, 26, 88 layers respectively (Michele, 2019). MobileNet has a simple structure, good in-depth separation of properties, and reduces processing time, so MobileNet is selected for this experiment.

In the experiment, the parameters are set as follows: number of food categories = 10, number of epochs = 20, size of input image = 128 × 128, number of training images = 4,000, and number of testing images = 1,000. The model separates the data with 80% and 20% optimal ratios for training.

**Experiment and Results**

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and testing, respectively (Kengpol & Neungrit, 2014). The input shape has the dimensions \((k \times k \times n)\) 128 \times 128 \times 3, indicating that the vegetarian food image is 128 \times 128 pixels in RGB color, so \(n\) is 3 if the image is white and black \(n\) is 1. The batch size is the number of images in the train 1 cycle. In this experiment, 4,000 training images are split up into batches and trained to a complete 1 epoch. If the batch size is 40, then 4,000/40 equals 100 iterations. Therefore, 100 iterations equal 1 epoch completed by completing 100 iterations or 1 run batch performs a weight 1 update. The activation function is the softmax function. softmax outputs equate to one, and the interpretation is that each output estimates the probability or confidence that the class exists. The learning rate and the momentum are adjusted from 0-1 (Shamsaldin et al., 2019). The optimum and greatest performance values of this model are the learning rate of 0.01 and momentum of 0.9. In general, the optimizations have three types: momentum, root mean square propagation (RMSprop), and adaptive moment estimation (Adam). Momentum is a speed boost for stochastic gradient descent (SGD) optimization by focusing on a near-center direction and is able to adjust the learning rate and automate the adjustment. RMSprop automatically adjusts the learning rate as well as selects a different learning rate for each parameter. Adam is a combination of momentum and root mean square propagation (Wibowo et al., 2019). RMSprop and Adam optimization algorithms are chosen for this study because RMSprop and Adam are more prominent and stable than Momentum (Jiang et al., 2020). The number of cycles is set to train in 20 epochs because the visuals for data training are large and take a long time to train, so the number of training cycles is set merely to present the trend of the results.

In terms of model evaluation, the model is evaluated by using loss function and accuracy. A loss function assesses the compatibility between the network’s forward propagation output predictions and given ground truth labels. Cross-entropy loss is the loss function that is most commonly used for multiple classifications. In the experiments, the Adam optimization and RMSprop optimization methods are compared in terms of the number of training and testing of 20 epochs. According to Table 2, the loss function in VGG16, VGG19, and MobileNet networks using Adam optimization

![Figure 7. The structure of DCNN for identification of vegetarian food (a) VGG 16 (b) VGG 19 (c) MobileNet (adapted from Hu et al., 2015 & Michele et al., 2019 and developed by the authors)](image-url)
The accuracy is inversely proportional to the loss function. The model has a low loss function, which results in high accuracy. Because the loss function is the difference between the model’s output and the target, it is a measure of the model’s error. The model is more accurate if the loss function value or error is low (the resulting value from the model is close to the target value). If the accuracy approaches 1, it means that the model is excellent. In this experiment, the MobileNet network with Adam optimization has the lowest loss function (0.37) and the highest accuracy (0.84), implying that the vegetarian food identification model identifies images of vegetarian food and chronic diseases with good accuracy. However, the model in this study is more than 80% effective; its efficiency is comparable to that of Lu (2019), who created a CNN model for 10 classes of food image recognition with 90% efficiency. Pan et al. (2020) discover that when two subnets network are combined, the best accuracy performance is 95%, which is slightly better than the performance in this study that only uses one subnet network. The model in this study can be used to solve other classification problems with small or medium datasets. According to Pan et al. (2020) research, increasing the network’s complexity is necessary if the dataset is large or complex. Figure 8 shows a loss function and accuracy in training with 20 epochs. The initial loss function is large, but as the number of training cycles increases, the loss function value approaches zero. If the loss function approaches zero, the model has a small error. As a result, as the number of cycles is increased, the performance of the model is improved. After completing the model training, the model is tested on the new food image data, and the model identifies vegetarian food for chronic disease in 10 seconds, which is considered a long time.

<table>
<thead>
<tr>
<th>Deep Learning Model</th>
<th>Optimization</th>
<th>RMS-prop</th>
<th>Adam</th>
</tr>
</thead>
<tbody>
<tr>
<td>VGG16</td>
<td>Loss Function</td>
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<tr>
<td></td>
<td>Accuracy</td>
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<tr>
<td>VGG19</td>
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<td>Accuracy</td>
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<tr>
<td>MobileNet</td>
<td>Loss Function</td>
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<tr>
<td></td>
<td>Accuracy</td>
<td>0.37</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Knowledge Sharing
After obtaining a vegetarian identification model for the elderly, the model is tested with knowledge sharing data with 20 elderly people that consume vegetarian food in a vegetarian restaurant. At this stage, an experiment is performed to demonstrate to the elderly that when the food image is fed into the model, the model assigns a name for the chronic disease that is appropriate to the food in order to display the test model results for the elderly. The results of the knowledge sharing revealed that 60 percent (or 12 people) of elderly are satisfied with specifying the vegetarian food and stated that the models are capable of recommending food well, while another 40 percent (or 8 people) are dissatisfied because the recommended food did not meet their needs.
Use of the Knowledge

The vegetarian food identification model is developed for the elderly as a recommendation and alternative for the elderly to consume vegetarian food. It also provides information on the suitability of vegetarian food for a particular chronic disease among the elderly. From the perspective of manufacturers, they can design food menus that meet the tastes of the elderly and modify the ingredients in each menu to suit their tastes and preferences.

Figure 8. Experiment results for identifying foods for chronic disease with loss and accuracy of training data (a) Adam optimization (b) RMSprop optimization.

Conclusion

The objective of this research is to apply knowledge management in identifying appropriate vegetarian food for individuals with a chronic disease by using the deep convolutional neural network. The contribution of this research is the suggestion of the ability to use knowledge management and to collect knowledge in order to create a machine learning algorithm system so that the elderly with a chronic disease can access knowledge about vegetarian food that is appropriate for them. This research is in agreement with a knowledge management process that consists of four steps: knowledge creation, knowledge storage, knowledge sharing, and use of the knowledge. The first part, knowledge creation, is to generate a large amount of vegetarian food knowledge that can be used with the elderly and to collect disease-specific food data. Next, knowledge storage is comprised of a collection of 500 images of 10 classes of images of food that is appropriate for chronic disease and popular food dishes in restaurants. The experiment uses a total of 5,000 images. The DCNN model identifies vegetarian food images, and the results of the DCNN architectures VGG16, VGG19, and MobileNet are compared. The results show that MobileNet is the most effective in identifying vegetarian food for individuals with a chronic disease with an accuracy greater than 80%. The model correctly identifies vegetarian food for chronic diseases for the elderly at 80%. Although this model is created using a basic DCNN model, the solution of this model is more efficient than 80%; the efficiency of our model is similar to that of Lu (2019) using the CNN method. The CNN model recognizes food images containing 5,822 image data sets and 10 food groups, which is roughly the same size as the data set in this research. The next step, knowledge sharing, is to promote vegetarian food knowledge among the elderly. Without the assistance of a dietitian, the elderly can assess the suitability of dishes for any chronic disease on
their own. The final step, use of knowledge, is the application of vegetarian food knowledge. Food identification vegetarian food that is appropriate for the chronic disease group to the elderly affects vegetarian food perception and understanding. One of the most important tools for communicating with or persuading the elderly to consume vegetarian foods is food information. Food producers can allocate resources, select raw materials such as vegetables and fruits, and produce vegetarian food that meets the needs of the elderly. Finally, knowledge of vegetarian food for chronic disease is easily accessible by the elderly.

The challenge in this research is the composition of the vegetarian food. The majority of vegetarian food includes fruits and vegetables that are very similar in color and feature. The model has an extreme difficulty in distinguishing the characteristics of vegetarian images due to the complexity of these images. Another challenge is the scarcity of vegetarian food images of high-quality. The limitation of this study is that various types of vegetarian food are suitable for individuals with a given chronic disease. Only 10 types of vegetarian foods that are sold in Thailand are selected as models and for the experiments. The results of the model suggest that MobileNet provides the best results for these ten vegetarian foods. If this model is used in other food research, it must be modified to produce effective results. The future research should improve the recognition efficiency and classification of fruit and vegetable color separation in vegetarian food more thoroughly and accurately by incorporating CNN characterization methods such as YOLO-CNN, Mark-CNN, and others. The suitability of vegetarian food for chronic diseases necessitates more careful consideration and analysis of the nutrients in the dishes. Furthermore, vegetarian food should have selected as a variety of vegetarian foods (more than ten menus) or select the most comprehensive and appropriate for chronic disease conditions.

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