Research Article

Identification of Passion Fruit Nutrients for Elderly People Using Network in Network Architecture: An Empirical Study in Thailand

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DOI: 10.14416/j.asep.2024.07.007
Received: 21 March 2024; Revised: 6 May 2024; Accepted: 30 May 2024; Published online: 9 July 2024

Abstract
The growing elderly population has led to a rise in health issues, particularly chronic diseases. Passion fruits contain numerous nutrients that may help in the treatment of chronic diseases. However, specific recommendations for daily passion fruit nutrient intake for the elderly are currently lacking in the literature. This research aimed to identify passion fruit groups and to suggest the appropriate daily passion fruit nutrient intake for elderly people using network in network (NiN) architecture. This research demonstrates that the NiN model can be effectively applied to identify passion fruit groups for the elderly. It is more efficient than other convolutional neural network (CNN) architectures. The results show that NiN can correctly identify passion fruit groups and suggest the appropriate amount of nutrient intake for the elderly, achieving + 96.76% accuracy in the training dataset and 95.89% accuracy in the validation dataset, surpassing 84.6% accuracy achieved by EaglAI. Sensitivity analysis of the NiN model using mean absolute error (MAE) for geometric transformations revealed consistent training image results and model robustness. This research benefits elderly people with chronic diseases by providing tailored recommendations for daily passion fruit intake, based on the analysis of sugar nutrients using the NiN model.

Keywords: Convolutional neural network, EaglAI software, Elderly people, Network in network, Passion fruit

1 Introduction

At present, the world's population is increasingly entering the elderly age bracket. According to the World Population Prospects 2022 report by the United Nations [1], the world's population is estimated to grow to 8 billion people, with approximately 10 percent being over 65 years of age, which is expected to increase to 16 percent by 2050. The number of people aged 60 and above in Thailand reached 13.1 million in 2021, representing 20% of the country's total population [2]. The growing population of the elderly creates risks and health issues. The Ministry of Public Health of Thailand [3] highlighted the high frequency of the elderly suffering from chronic non-communicable diseases, including cardiovascular disease (15.55%), diabetes (9.84%), high blood pressure (7.72%), dementia (0.88%), and falls (3.12%). According to the population development plan for the long-term national development of 2022–2037 in Thailand [4], reducing the premature death rate from chronic non-communicable diseases is essential. This plan emphasizes prevention, treatment, and the promotion of mental health and well-being. Promoting mental health and well-being begins with the consumption of nutritious foods, especially fruits and vegetables. The impact of nutritional factors on cognitive functions is significant, particularly in the elderly population [5]. According to Zhou *et al*. [6], the beneficial effects of fruits and vegetables on cognition in elderly people are attributable to their antioxidant content. Fruits and vegetables provide vitamins and minerals, making them a vital component of a healthy diet, which aids in chronic disease prevention. Therefore, selecting the right types of food is crucial for maintaining good health [7].

Passion fruit is rich in vitamins and minerals, such as vitamins C, A, E, B2, and B3, folic acid, calcium, magnesium, carbohydrate, and dietary fibers [8], [9]. Regular consumption of passion fruit juice reduces the level of inflammatory cytokines in elderly individuals [7], owing to its antioxidant properties, encompassing anti-hypertensive, anti-tumor, anti-diabetic, and hypolipidemic effects [8], [10], [11]. Nutrients in passion fruits also offer skin protection from sunlight [12]. Nutrient compositions in passion fruit may vary over time following the post-harvesting period [13], [14].

Kengpol and Klunngien [15] applied a decision support system using a multi-layer perceptron neural network (MLPNN) model to classify health beverage preferences among the elderly. However, this approach is limited by its time-consuming dataset training and limited dataset size. While the MLPNN method can be used for selecting the type of passion fruit for elderly individuals [16], it is incapable of making classifications based on images and recommending daily nutrient intake for these individuals. Krizhevsky *et al*. [17] suggested the use of the convolutional neural network (CNN) for processing big data and high-resolution images, making it suitable for multiclass classification. CNN-ANN hybrid can apply cost evaluation to the plastic injection industry [18]. A network-in-network (NiN) convolutional neural network is another model that can be applied to identify passion fruit groups for the elderly. Although ResNet (Residual Networks) outperformed GoogLeNet and AlexNet [19], Visual Geometry Group (VGG) correctly identified pneumonia images with greater accuracy than ResNet [20]. However, Yanai *et al*. [21] highlighted that the NiN model is highly efficient in reducing the dimensions of input images, thereby minimizing memory consumption. Thus, NiN is easier to build than AlexNet, GoogLeNet, and VGG.

Currently, the growing elderly population is facing health challenges, particularly chronic diseases. Passion fruit contains nutrients known to alleviate these ailments, yet daily intake recommendations tailored to the specific needs of elderly individuals are lacking in the existing literature. This research fills this gap by demonstrating the use of the NiN model to identify passion fruit groups and propose the appropriate passion fruit nutrient intake for elderly individuals. The NiN model offers efficiency and simplicity compared to other CNN architectures. Therefore, this research aimed to identify passion fruit groups, suggest appropriate nutrient intake for the elderly using the NiN architecture and compare these results with commercial software outputs.

2 Materials and Methods

2.1 *The benefits of passion fruit for elderly people*

Passion fruit, also known by its scientific name, *Passiflora edulis*, is widely cultivated. It is rich in nutrients, such as vitamin C, vitamin A, fiber, calcium, and antioxidants [8], [9]. Regular consumption of passion fruit juice increases vitamin A and vitamin E intakes in elderly individuals, reducing inflammatory cytokines levels in their bodies [7]. Furthermore, the health benefits of passion fruit extracts, juices, and isolated components stem from their antioxidant, anti-hypertensive, anti-tumor, anti-diabetic, and hypolipidemic properties [8], [10]. Additionally, these components help mitigate the adverse effects of sunlight exposure on skin aging [8]. According to Prasertsri *et al*. [11], the consumption of passion fruit juice among healthy subjects significantly lowers their blood sugar levels. Pertuzatti *et al*. [13] asserted that the nutrient compositions in the passion fruit varied over time following the post-harvesting period. The organically cultivated passion fruit contains more tocopherols, carotenoids, and ascorbic acid than the conventionally grown passion fruit.

Previous research has focused on the impact of time and storage conditions on the physical and physico-chemical properties of passion fruit. Passion fruits stored post-harvest at varying durations differ in their nutritional values [14]. Therefore, determining the optimal intake of passion fruit nutrients for the elderly is important, which is lacking in existing literature.

2.2 *The application of CNN to classify passion fruits*

Recent advancements in AI technology and deep learning have facilitated the classification of passion fruits based on quality. The Red-Green-Blue Dense Scale Invariant Features Transform Locality-constrained Linear Coding (RGB-DSIFT-LLC) features [22], Histogram Oriented Gradients (HOG) and color features in outdoor scenes [23], and an electronic nose sensor have been applied to classify fruits [24]. Tu *et al*. [22] developed machine vision algorithms to detect passion fruit by surface color at different maturation stages. Lu *et al*. [25] conducted a deep learning-based analysis of passion fruit surface 3D features. Deep learning algorithms, especially CNNs, have outperformed classical methods. Computer vision (CV) technologies are being replaced by deep learning for fruit quality classification. Scholars have initiated the classification of fruits and their quality using similar methods. The result is a nondestructive method for more accurate and efficient automatic acquisition of comprehensive phenotypic traits of passion fruit, which has the potential to be extended to more fruit crops. However, this research does not cover the suggestion of passion fruit nutrition. Gill *et al*. [26] trained several neural networks or algorithms, such as K-nearest neighbors (KNN), SVM (Support Vector Machine), random forests (RF), and multilayer perceptron (MLP), on a high-quality dataset of fruit images to compare differences among different sorting methods. CNN achieved the highest accuracy at 98.35%, while SVM had the lowest at 86.11%. CNN proves to be more powerful than SVM and other traditional classifiers. CNN was compared to KNN, SVM, and decision trees by Joseph *et al*. [27]. CNNs outperformed classic CV and deep learning methods in these comparisons. CNN learns features independently, enhancing variety and accuracy, with GPUs enabling their utilization. CNN structures have been applied to more CV algorithms. Liu *et al*. [28] emphasized that fruit quality classification is crucial for reducing waste and ensuring consumer satisfaction. The ATC-YOLOv5 (You Only Look Once, version 5) model, based upon deep learning, is applied to detect passion fruit and classify its quality. However, it does not identify the passion fruit by post-harvest age and does not provide nutrition recommendations. Each stage of passion fruit after harvesting provides different nutritional values [13]. Thus, consumers, especially the elderly, are unaware of the optimal passion fruit intake for health benefits. Previous research has found that the nutrients contained in passion fruit can alleviate symptoms of high blood pressure and diabetes [8]–[11], which are prevalent non-communicable diseases among the elderly [3]. Conversely, excessive consumption, particularly of passion fruit with a long after-harvest period and high sugar content, could have adverse effects on consumers. The new trend is the production of sugar-free fruit beverages can be sugar-free fruit beverages to enhance mood and brain health [29].

Further academic research focuses on passion fruit yield estimation and ripening detection in complex natural environments [30]–[32]. There is only a limited amount of related work on deep learning for identifying the nutrients in passion fruit. The application of CNN to classify fruits and passion fruits is shown in Table 1.

Table 1: Comparison of the literature reviews regarding the application of CNN to classify passion fruits.

Title	Techniques	Focused Topics	Reference
Passion Fruit Disease Detection using Image Processing	ANN/K-Means clustering	Identify passion fruit diseases accurately	[22]
Nondestructive 3D phenotyping method of passion fruit based on X-ray micro-computed tomography and deep learning	U-Net convolutional model	Extracts the complete morphological traits of passion fruit	[25]
Fruit Image Classification Using Deep Learning	SVM, FFNN, CNN, RNN, Neuro-Fuzzy Inference System	Fruit image classification	[26]
Fruit Classification Using Deep Learning	CNN	Fruit classification	[27]
ATC-YOLOv5:Fruit Appearance Quality Classification Algorithm Based upon the Improved YOLOv5 Model for Passion Fruits	YOLOv5	Classification by defects in shape, defects of the skin, and defects in the coloring of passion fruit	[28]
Passion fruit detection and counting based upon multiple scales faster R-CNN using RGB-D images	MS-FRCNN, R-CNN	Detection and counting passion fruits	[30]
Classification of Fruits Using Deep Learning	VGG16	Fruit classification	[31]
Fruit Classification and Detection Application Using Deep Learning	YOLOv3, ResNet50, VGG16	Fruits classification	[32]

Remark: ANN = Artificial Neural Network, FFNN = Feed Forward Neural Network, RNN = Recurrent Neural Networks, YOLO = You Only Look Once, R-CNN = Region-based Convolutional Neural Networks, MS-FRCNN = A Multi-Scale Faster Region-based Convolutional Neural Networks.

From Table 1, the convolutional neural network (CNN) emerges as a deep learning model for classifying big data and high-resolution images of passion fruit [17], such as the U-Net convolutional model, YOLOv5, ResNet50, VGG16, MS-FRCNN, and R-CNN. It is optimal for multiclass classification. While previous studies have shown that ResNet outperformed GoogLeNet and AlexNet [19], VGG demonstrates superior accuracy in identifying all pneumonia images compared to ResNet [20]. However, Yanai *et al*. [21] highlight the efficiency of the NiN model in reducing the dimensions of input images, thereby minimizing memory consumption. NiN is also easier to build than AlexNet, GoogLeNet, and VGG. Another model capable of identifying passion fruit groups for the elderly is a decision support system using a network-in-network convolutional neural network.

In literature reviews, grading the quality of passion fruit has primarily focused on achieving high detection efficiency for fruit quality classification by evaluating defects in shape, skin, and color [28]. Lu *et al*. used samples from three widely grown passion fruit cultivars, differing significantly in fruit shape, size, and other morphological traits, to generate 3D models of passion fruit using a Micro-CT system [25]. Similarly, Gill *et al*. [26] applied the enhanced fruit images to extract and label optimal features for fruit classification. However, these studies have not considered the amount consumed, the nutrient intake, or the post-harvest age for classifying the quality of passion fruit. The research gap lies in the lack of consideration for the amount consumed or the nutritional value of passion fruit, and the identification of passion fruit by post-harvest age, which influences its nutritional compositions. This study addresses this gap by proposing a method for the identification of passion fruit by post-harvest age and the determination of the nutrient contents of each group. In addition, the results provide suggestions on the daily intake of passion fruit nutrients for the elderly, particularly those with chronic diseases. Therefore, this research aimed to identify passion fruit groups by post-harvest age and suggest the appropriate daily intake of passion fruit nutrients for elderly individuals using CNN, specifically a network in network (NiN) architecture, and to compare the results with those obtained from EaglAI software.

2.3 *The NiN model*

The convolutional neural network (CNN) architecture, known as a network in network (NiN), employs a specific configuration, introduced by Lin *et al*. [33]. NiN enhances model discriminability for local patches within the receptive field, by utilizing micro-neural networks, which are multilayer perceptron within the filters of the convolutional layer. These filters are then passed through a nonlinear activation function to scan the input, generating feature maps. Subsequently, these feature maps are passed as input to the subsequent layer. Deep NiN can be efficiently realized through the process of stacking multiple instances of the aforementioned structure by employing micro-networks, which can improve local modeling. It applies global average pooling to the feature maps within the classification layer. This approach is more interpretable and less susceptible to overfitting compared to conventional, fully connected layers [19], [33], [34]. The key components of the NiN structure are the multilayer perceptron convolutional (mlpconv) layer and the global averaging pooling layer.

Multilayer perceptron is compatible with the structure of backpropagation-trained convolutional neural networks and can be a deep model, consistent with the concept of feature reuse [20]. The calculation performed by multilayer perceptron is given by Equation (1).

$$f_{i,j,k_n}^{n} = \max\left(w_{k_n}^{n\,T} f_{i,j}^{n-1} + b_{k_n}, 0\right). \tag{1}$$

Based upon this equation, i, j is the pixel index in the feature map, x_{ij} is the input patch centered at the location i, j, k is applied to index the channels of the feature map and n is the number of layers in the multilayer perceptron. Rectified linear unit (ReLU) is applied as the activation function in the multilayer perceptron [19], [33], [35]. The computation of the ReLU activation function is simplified. It does not have the same exponentiation operation as the sigmoid activation function [19].

The final convolutional layer's feature maps are vectorized and input into fully connected layers, which are followed by a softmax logistic regression layer for classification [33]. The propensity of the fully connected layers to overfit hinders the generalization of the entire network. NiN uses global average pooling to substitute the conventional fully connected layers within CNNs [19], [33], [36]. The global average pooling layer does not have any parameters to tune, which helps prevent overfitting. Moreover, the utilization of global average pooling effectively aggregates spatial information, resulting in enhanced resilience to spatial translations within the input. Figure 2 illustrates a NiN with three multi-layer perceptron convolutional layers. In each mlpconv layer, a three-layer perceptron is present. The flexibility of the number of layers in both the NiN and the micro-networks allows for customization and optimization specific to assigned tasks [33], [34], [37]. In addition, Yanai *et al.* [21] asserted that the NiN model can be built better than CNN architectures commonly applied for object recognition, such as AlexNet, GoogLeNet, and VGG-16, as it is devoid of fully connected (FC) layers and consists only 12 convolutional (conv) layers. The number of parameters and computation times in the NiN model are less than in other architectures. Table 2 shows the 7.6 million parameters and 1.1 billion computation times, with an error of 10.9%, in the NiN model. MLPNIN (Mlpconv-wise supervised pre-training network in network) outperforms other models in terms of classification tasks [38]. Furthermore, the NiN model applies the linear exponential unit (eLU) called DNiN (Deep Network in Network), instead of ReLU, to solve the vanishing gradient problem in the classification of the CIFAR-10 (the Canadian Institute for Advanced Research). This model shows a low error compared to other models [19]. Kim *et al*. [39] highlighted that NiN can classify polyp images in colonoscopy more accurately than four other methods using AlexNet. NiN was also developed for mobile applications based on voice recognition to drive wheelchairs for disabled users [40]. NiN is suitable for mobile apps as it allows users to adjust the speed and accuracy without altering the network's weight. The NiN model can take on image classification tasks and voice recognition, as shown in Table 3. However, the development of the NiN model for recommending daily nutrient intake based on fruit images has not been reported. Therefore, this research aimed to fill this gap, by developing the NiN model for the classification of passion fruit and the recommendation of its daily intake among the elderly.

2.4 *Methods*

This section presents the workflow describing the research methodology, as illustrated in Figure 1. The first section was recognizing and categorizing passion fruit images using the NiN model and EaglAI software. The procedure started with describing how to collect and classify the passion fruit images, followed by describing the dietary reference intakes among Thai elderly people. Next, the architecture of the developed NiN model and the EaglAI software used in this study were addressed. Finally, the outputs from the NiN model and EaglAI software were compared. The NiN model can identify passion fruit groups and recommend the appropriate daily intake among elderly people.

Table 2: Comparison of CNN architectures regarding the number of layers, weights, and computation [14].

Model		Alex	VGG-16	GoogLeNet	NiN
Convolutional	Layer	5	13	21	12
	Weight	3.8M	15M	5.8M	7.6M
	Computation	1.1B	15.3B	1.5B	1.1B
Fully Connected	Layer	3	3	1	0
	Weight	59M	124M	1M	0
	Computation	59M	124M	1M	0
Total	Weight	62M	138M	6.8M	7.6M
	Computation	1.1B	15.5B	1.5B	1.1B
ImageNet	Top-5 error	17.0%	7.3%	7.9%	10.9%

Table 3: Comparison of the literature reviews regarding the application of NiN.

Title	Techniques	Focused topics	Reference
Deep network in network	DNiN	Image classification	[19]
Batch-normalized Mlpconv-wise supervised pre-training network in network	MLPNIN	Image classification	[38]
New polyp image classification technique using transfer learning of network-in-network structure in endoscopic images	NiN	Image classification	[39]
Steering a Robotic Wheelchair Based upon Voice Recognition System Using Convolutional Neural Networks	NiN	Voice recognition	[40]

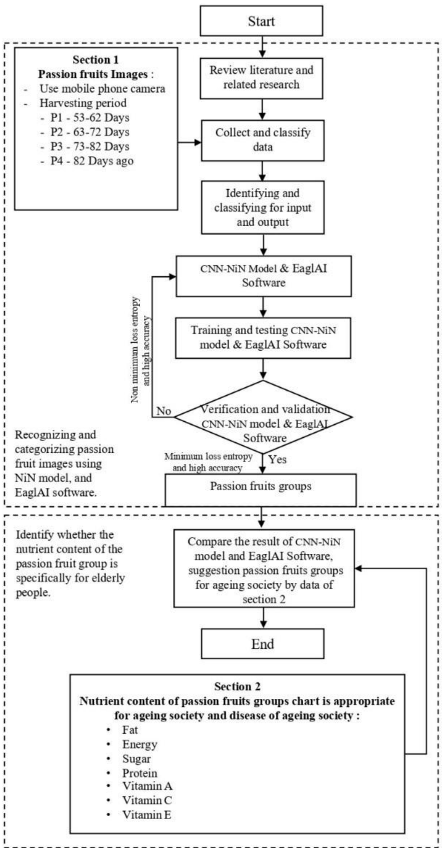


Figure 1: The proposed methodology to identify passion fruit.

2.4.1 The collection and classification of passion fruit images

The present study focused on the collection and analysis of data pertaining to passion fruit, *Passiflora edulis* [8], specifically the Tainong variety. It is a sweet variety, commonly grown for consumption, with most of them having mild purple skin. The harvest period for passion fruit was in August 2021, during which the productivity was the highest in northern Thailand [41]. The passion fruits were subjected to imaging after a minimum of 53 days post-flowering harvest. The images were taken at four distinct time points using three different types of cameras. The passion fruit images were divided into four groups based on the duration after harvesting: P1 (53–59 days), P2 (60–66 days), P3 (67–73 days), and P4 (74 days and beyond) [14]. Each group of passion fruit consisted of 2,400 images. The remaining 200 passion fruits were subjected to chemical analysis.

2.4.2 The dietary reference intakes for Thai elderly people

The Bureau of Nutrition, Department of Health, and Ministry of Public Health of Thailand [42] have established the dietary reference intakes for Thai people in the year 2020. This reference recommends a daily intake of seven nutrients, namely vitamin A, vitamin C, vitamin E, total fat, carbohydrate, sugar, and protein among the Thai elderly. Research divides Thai elderly people into three age groups: Group 1 (60–69 years old), Group 2 (70–79 years old), and Group 3 (80 years and older) [43]. Therefore, the information on the dietary reference intakes for six Thai elderly separates men and women, as shown in Table 4. The first elderly group comprises men aged between 60 and 69 years; the second group is men between 70 to 79 years; the third group is men of 80 years or older; the fourth group is women between 60 to 69 years; the fifth group is women between 70 and 79 years; the sixth group is women of 80 years and older [43].

2.4.3 The architecture of the NiN model

Figure 2 shows the design of the NiN model used in this research. The initial and input layers of the NiN model consisted of a dataset of photos of passion fruit. The shape of the convolution window in the second layer was 11×11. To effectively capture objects, it is necessary to employ a large convolution window. Additionally, a stride of four was implemented to significantly decrease the dimensions of the output in terms of height and breadth. The convolution window in the third layer was reduced to 5 × 5, and subsequently to 3 × 3. According to a previous study [44], the initial convolution employs a 96-channel configuration, followed by a second convolution with 256 channels, and finally, a third convolution with 384 channels. After each convolutional layer, the network incorporates maximum pooling layers featuring a window dimension of 3 × 3 and a stride of two. In each convolution, a rectified linear unit (ReLU) was employed as the activation function [19], [33]. The NiN model is distinct from other CNNs as it does not incorporate fully connected layers [19], [33], [36], [44]. Instead, the NiN architecture employs a NiN block with a number of output channels equivalent to the total number of label classes. A global average pooling layer produces a vector of logits [44]. The NiN block was equipped with a total of four output channels.

The output layer was comprised of passion fruit groups identified via the global average pooling layer.

2.4.4 Training and testing

The NiN model, depicted in Figure 2, was examined using a Python program. The input dataset was partitioned into training (70%) and validation (30%) sets [19], [33], [44], [45]. The NiN model was implemented using the Python 3.7 programming language and trained with the TensorFlow and Keras libraries. RMSprop, short for Root Mean Square Propagation, is a commonly employed optimization algorithm for training neural network models. This algorithm obviates the manual tuning of the learning rate by invoking automated adaptation during the training process. Moreover, this algorithm selects a distinct learning rate for every parameter, as asserted in a previous study [46]. RMSprop employs the concept of the exponentially weighted average of gradients, similar to gradient descent with momentum, but differs in parameter update. In the RMSProp optimization algorithm, the exponentially weighted average (EWA) of gradients is computed and subsequently utilized to update the model parameters. During each iteration *t*, the calculation of *dw* and *db* was performed on the current mini-batch, as V_{dw} and V_{db}, respectively, using Equations (2) and (3).

$$V_{dw} = \beta V_{dw} + (1-\beta)dw^2 \tag{2}$$

$$V_{db} = \beta V_{db} + (1-\beta)db^2 \tag{3}$$

where *db* and *dw* are the gradients of the cost function concerning the weight and β is a moving average parameter (a good value is 0.9) [47].

The parameters were updated after calculating the exponentially weighted averages, putting the values of *db* and *dw* in the respective Equations (4) and (5).

$$W = W - \propto . \frac{dw}{\sqrt{V_{dw+\epsilon}}} \tag{4}$$

$$b = b - \propto . \frac{db}{\sqrt{V_{db+\epsilon}}} \tag{5}$$

The training model used a learning rate ($\propto$) of 0.001 and β of 0.9, with 20 epochs [40].

Table 4: The dietary reference intakes for Thai elderly people [42].

Elderly Groups	Nutrition						
	Vitamin A (mg/day)	Vitamin C (mg/day)	Vitamin E (mg/day)	Total Fat (g/day)	Carbo-hydrate (g/day)	Sugar (g/day)	Protein (g/day)
Men/60-69 years	700	100	13	64.73	244-353	16.2	59
Men/70-79 years	700	100	13	64.73	239-345	15.7	56
Men/≥80 years	700	100	13	64.73	239-345	15.7	56
Women/60-69 years	600	85	11	64.73	213-304	14.1	50
Women/70-79years	600	85	11	64.73	210-304	13.9	49
Women/≥80 years	600	85	11	64.73	210-304	13.9	49

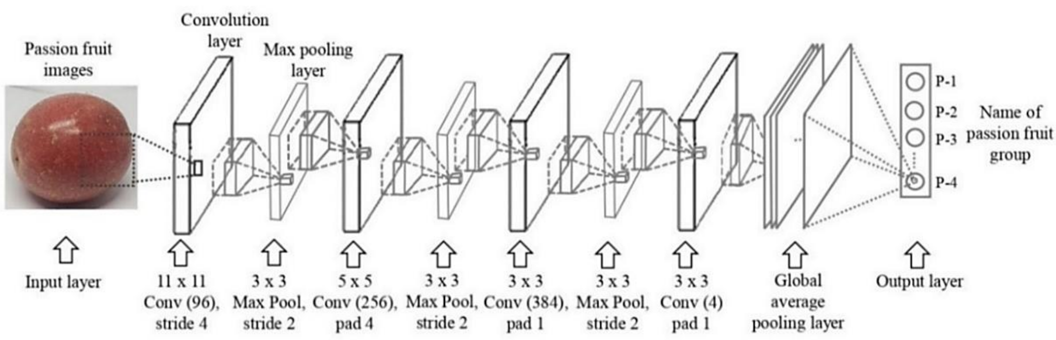


Figure 2: The architecture of the NiN model to identify passion fruit.
(Remark: Conv = convolutional layers, Stride = a parameter that dictates the movement of the kernel, or filter, across the input data, such as an image, Pad = padding is essential to convolutional neural network architecture and function in machine learning [44].)

2.4.5 Verification and validation

The NiN models were verified and validated based on the categorical cross-entropy loss function. A loss function measures how far the model deviates from the correct prediction [45]. The categorical cross-entropy loss function is commonly employed for multi-class classification applications. The categorical cross-entropy is advantageous for classification tasks because it allows instances to be assigned to one category with a probability of 1 and to another with a probability of 0. The categorical cross-entropy loss function was calculated by Equation (6) [45], [46], [48].

$$\text{Loss}=\sum_{i=1}^{\substack{\text{output}\\ \text{size}}} y_i \cdot \log\widehat{y_i} \tag{6}$$

where $\widehat{y_i}$ is the i scalar value in the model output, y_i is the corresponding target value, output size is the number of scalar values in the model output, and Loss is the difference between the predicted probability distribution and actual distribution of classes in categorical data. The categorical cross-entropy measures prediction accuracy in classification tasks, guiding neural network training.

2.4.6 The training of EaglAI software models

The training of EaglAI software models is proprietary to the company [49], and access requires a registered account name and password. The process of EaglAI training using passion fruit was explained in a video in the supplementary materials. The video was designed for illustrative purposes, guiding viewers through the entire workflow and highlighting the precision of the platform. The EaglAI software model uses the plot of sensitivity, called the receiver operating characteristic (ROC) curve, and the area under the curve (AUC), as effective measures of accuracy.

2.4.7 A comparison of the NiN model and EaglAI software performance and the identification of passion fruit nutrients for elderly people

A validation was performed after generating the two CNN models. The accuracy and error of the NiN model and EaglAI software were compared. The appropriate intake of nutrients from each passion fruit group for elderly people and diseases was determined based on the dietary reference intakes for Thai elderly people in 2020.

3 Results and Discussion

An empirical case study was conducted to identify the passion fruit group based upon nutrient contents, for the consumption of Thai elderly people. The case study involved recognizing and categorizing passion fruit images using the NiN model and EaglAI software. The input data was collected and analyzed based on purple passion fruit, which is a Tainong variety, harvested in August 2021. The details of each section are illustrated in Figure 1 and explained as follows:

3.1 *The input data*

The input variables for this research were the purple passion fruit images. The total number of passion fruit images was 9,600, collected from four groups. Each group comprised 2,400 images. The fruit was classified according to the post-harvesting period [14], as illustrated in Figure 3. The input dataset was divided into 70% of training and 30% of validating datasets. Each passion fruit image was resized to 300 × 300 pixels [44], [45].

3.2 *The NiN model generated in the Python program*

The Network in Network model (NiN) was applied to identify the passion fruit images of four passion fruit groups. The input comprised 9,600 images of the passion fruit. The output was computed as the group name and nutrition contents of the passion fruit. The input dataset was divided into 70% for training and 30% for validating [19], [33], [44], [45]. The NiN was applied to learn the data, which comprised passion fruit images and the passion fruit group. The NiN model comprises four convolutional layers, three spatial pooling layers, a dropout layer for regularization between NIN blocks, and a global average pooling layer. Softmax is applied to the output layer [38].

The convolution layer is defined as (height) × (width) × (number of units) and presents the convolution layer's stride (st), padding (pad), batch normalization (BN), and activation function. A softmax layer is applied to the output layer [38].

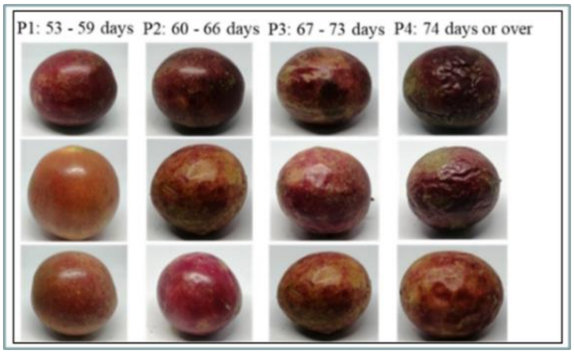


Figure 3: The passion fruit images are categorized by the post-harvesting period.

Table 5: Parameter settings for the proposed NiN architecture applied in the experiments.

Layers	Lists the Parameters
Conv-1	11×11×96 / st. 4/ pad 0/ BN / Act.ReLu
Max.Pool	3×3 / st.2/BN
Dropout	0.5
Conv-2	5×5×256 / st.1/ pad 4/ BN / Act.ReLu
Max.Pool	3×3 / st.2/BN
Dropout	0.5
Conv-3	3×3×384 / st. 1/ pad 1/ BN / Act.ReLu
Max.Pool	3×3 / st.2/BN
Dropout	0.5
Conv-4	3×3×4 / st. 1/ pad 1/ BN
Avg. Pool	4×4
Output	Softmax

Table 5 details the parameter settings. RMSprop and learning rate, among other factors, optimized this model (not shown here). NiN was built into the Python program version 3.7. The application optimizes the training of neural network models in terms of loss function and accuracy. The output layer denotes the name of a passion fruit group. The model predicted the nutritional content of the passion fruit in each group. Global average pooling prevents overfitting at this layer as there is no parameter to optimize. Furthermore, global average pooling sums out the spatial information, making it more robust to spatial translations of the input [33].

3.3 *Verification and validation*

The categorical cross-entropy loss function was applied to verify and validate the NiN models. The NiN model is a multi-class classification. This model defines more than two labels or classes, which usually start with Class 0 until Class +1. The model indicates the confidence in the prediction of each class. The sum of all classes is equal to 1.0. This model uses the categorical cross-entropy loss from the Keras framework [45]. The categorical cross-entropy is the average of cross-entropy resulting from two different types of probability distributions: the desired probability distribution (actual) and the probability distribution estimated by the model (predicted) for various classes (0, 1, 2, 3). The smaller the average, the better the prediction. Categorical cross-entropy loss in Keras applies the logarithm to base e and binary cross-entropy loss [45].

3.4 *The outputs from the NiN model*

The results of passion fruit image testing by the NiN model are shown in Figure 4. The highest value below each image denotes the group to which the passion fruit belongs. For example, at position zero is the P1 group; at position one is the P2 group; at position two is the P3 group; and at position three is the P4 group. Figure 4 (a) depicts the passion fruit in the P1 group, as denoted by the highest value below the image, with its position at zero. The results also depict the nutrient contents in the passion fruit of this group: vitamin A (0.2 mg/100 g), vitamin C (9.19 mg/100 g), vitamin E (15.11 mg/100 g), total fat (1.47 g/100 g), carbohydrate (12.11 g/100 g), sugar (1.69 g/100 g), and protein (1.56 g/100 g). This group of passion fruit is appropriate for elderly people aged 60 and over. However, the consumption should be limited to less than 0.9 kg/day and 0.8 kg/day in men and women, respectively. Figure 4 (b), presents the results obtained for the passion fruit in group P2, with the highest value at position one. The corresponding nutrient contents of group P2 (60–66 days post-harvest) includes vitamin A (0.26 mg/100 g), vitamin C (31.28 mg/100 g), vitamin E (21.54 mg/100g), total fat (1.75 g/100 g), carbohydrates (11.34 g/100 g), sugars (1.78 g/100 g), and protein (1.63 g/100 g). This passion fruit group is appropriate for elderly people aged 60 and over. However, the consumption should be limited to less than 0.85 kg/day and 0.75 kg/day in men and women, respectively. Figure 4 (c) presents the results obtained for the passion fruit in group P3, with the highest values at position two. The corresponding nutrient contents of this group (67–73 days post-harvest) include vitamin A (0.26 mg/100 g), vitamin C (33.36 mg/100 g), vitamin E (0.10 mg/100 g), total fat (1.77 g/100 g), carbohydrate (9.98 g/100 g), sugar (2.07 g/100 g), and protein (1.57 g/100 g). This passion fruit group is appropriate for elderly people aged 60 and over. However, the consumption should be limited to less than 0.7 kg/day and 0.6 kg/day in men and women, respectively. Finally, Figure 4 (d) shows the results obtained for the passion fruit in group P4, with the highest results positioned at position three. The nutrient contents in the group P4 (more than 74 days post-harvest) include vitamin A (0.24 mg/100 g), vitamin C (35.44 mg/100 g), vitamin E (0.10 mg/100 g), total fat (1.84 g/100 g), carbohydrates (9.35 g/100 g), sugar (2.72 g/100 g), and protein (1.78 g/100 g). This passion fruit group is appropriate for elderly people aged 60 and over. However, the consumption should be limited to less than 0.55 kg/day and 0.45 kg/day in men and women, respectively.

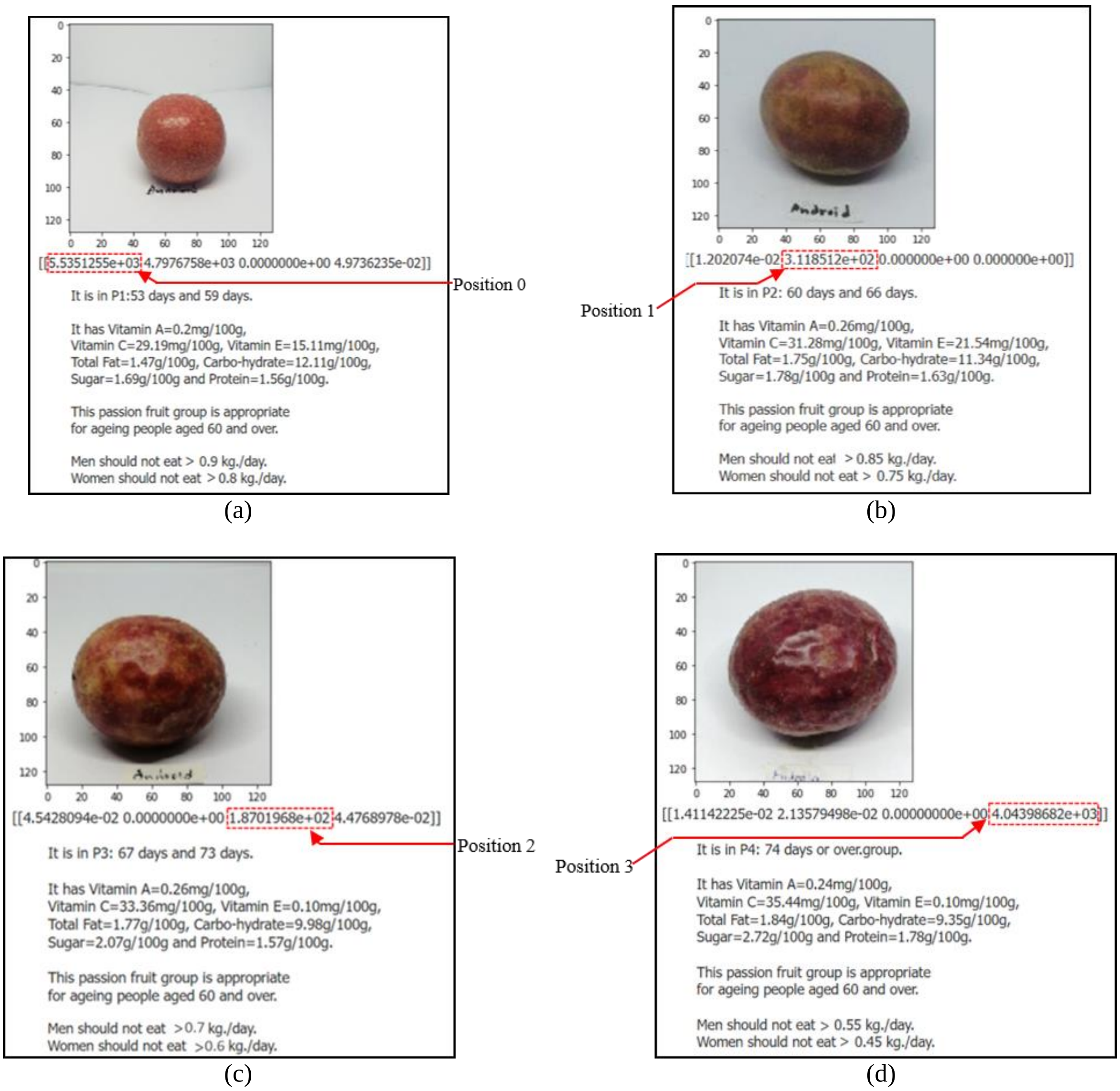


Figure 4: The results of passion fruit image testing from the program. (a) The prediction results indicate that passion fruit is in the P1 group (the value of the result in position 0 is the highest).; (b) The prediction results indicate that passion fruit is in the P2 group (the value of the result in position 1 is the highest).; (c) The prediction results indicate that passion fruit is in the P3 group (the value of the result in position 2 is the highest). and (d) The prediction results indicate that passion fruit is in the P4 group (the value of the result in position 3 is the highest).

Table 6: The nutritional composition of passion fruit per 100 grams from the Food Chemistry Laboratory of the Lampang Agricultural Technology Research Institute and from the Central Laboratory (Thailand) Company Limited (CLT) are analyzable following the standards of the American Association of Analytical Chemists (AOAC) 941.5, 967.21, 2003.05, 992.23, 2011.25 (2016), and KHON KAEN AGR.J.42 SUPPL.1: (2014).

Passion Fruit Groups	Nutrition						
	Vitamin A (mg/100g)	Vitamin C (mg/100g)	Vitamin E (mg/100g)	Total Fat g/100g	Carbo-hydrate (g/100g)	Sugar (g/100g)	Protein (g/100g)
P1, from 53–59 days	0.2	29.19	15.11	1.47	12.11	1.69	1.56
P2, from 60–66 days	0.26	31.28	21.54	1.75	11.34	1.78	1.63
P3, from 67–73 days	0.26	33.36	0.10	1.77	9.98	2.07	1.57
P4, from 74 days up	0.24	35.44	0.10	1.84	9.35	2.72	1.78

Figure 4 depicts the common nutrient contents in passion fruit across all groups, namely vitamin A, vitamin C, vitamin E, total fat, carbohydrate, sugar, and protein, which offer health benefits to the elderly. However, the consumption of sugar from this fruit exceeding the recommended serving by the Ministry of Public Health may lead to chronic diseases in the elderly, e.g., diabetes and high blood pressure. Table 6 shows that the sugar content is high (2.72 g/100 g) in the passion fruit group P4. Thus, this group is deemed unsuitable for consumption among the elderly. Therefore, elderly people, both men and women aged 60 years and over, are recommended to consume freshly harvested passion fruit, as it contains less sugar, as observed in the group P1 (1.69 g/100 g). However, the consumption should be limited to 900 g/day and 800 g/day in elderly men and women, respectively.

When benchmarking related research for this study, it was found that various CNN models have been applied for passion fruit classification and grading [22], [23], [25], [26]. However, there is still a lack of passion fruit classification that considers post-harvest stages and provides nutrition recommendations for elderly individuals in each group. A distinctive feature of this research lies in emphasizing the importance of developing models capable of both passion fruit classification and recommending suitable nutrition for the elderly. Clear research is presented to prevent harm and ensure the safety of food consumption for diverse target groups with varying health issues. The NiN model is capable of determining the appropriate amount of passion fruit nutrients for the elderly. The elderly also gain supplies of vitamin C, vitamin E, and adequate amounts of carbohydrates to provide energy. Furthermore, vitamins A and E can reduce the level of inflammatory cytokines in their bodies [7]. Passion fruit juices are rich in antioxidant, anti-hypertensive, anti-tumor, antidiabetic, and hypolipidemic agents, which may aid in the treatment of diseases, such as high blood pressure, diabetes, and osteoarthritis [8], [10]. Moreover, the consumption of passion fruit among the healthy elderly lowers blood sugar levels. Therefore, based upon the recommendation by the Ministry of Public Health [3] provided in Table 7, each group of elderly people can determine their appropriate passion fruit consumption.

Table 6 shows the results obtained from the chemical test of the passion fruit in each group, performed in the chemical laboratory that complied with the international standards: ISO/IEC 17025 underlines the general requirements for testing and calibration laboratories; ISO/IEC 17043 underlines the general requirements for proficiency testing; ISO/IEC 17065 and ISO/IEC 17021-1 underline the standards for Certification Bodies (CB) from the National Bureau of Agricultural Commodity and Food Standards. Each value was calculated and compared to the amount of 100 grams of passion fruit, which considered juice and pulp only. The analysis was conducted following the standards of the American Association of Analytical Chemists (AOAC) 941.5, 967.21, 2003.05, 992.23, 2011.25 (2016), and KHON KAEN AGR.J.42 SUPPL.1: (2014). The nutritional content of each sample in the table demonstrates notable variations, with prolonged storage resulting in increased levels of vitamin C, fats, sugars, and proteins. These changes generally enhance the benefits, except for the potential negative impact that stems from the increased sugar levels that can lead to chronic diseases. It is important to analyze and interpret the nutritional changes in each sample, particularly their sugars, vitamins, carbohydrates, fats, and proteins, which can significantly affect consumer health.

All 9,600 passion fruit images were processed using a mathematical model called NiN using convolutional windows. Maximum pooling using global average pooling calculations. The NiN model increases the learning rate and takes larger steps in the horizontal direction, converging faster with RMSProp. The accuracy of the training was 96.76%, and the validation was 95.89%, as shown in Figure 5.

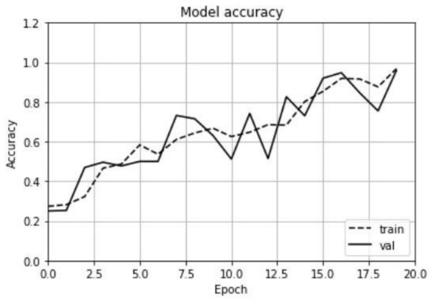


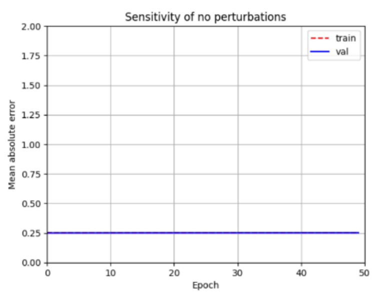
Figure 5: The training and validation accuracy results of the NiN model.

			
no perturbations	left right flip	90° rotation	upside down flip

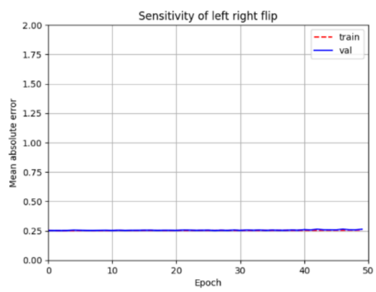
Figure 6: Image noise and geometric transformations by Roboflow (https://roboflow.com/).

To enhance the understanding and confidence in the accuracy and reliability of models or systems used for prediction or decision-making, sensitivity analysis is crucial [50]. Rodner *et al*. [51] highlighted that sensitivity analysis of parameters considers image noise and geometric transformations including random translations, rotations, and flips. Figure 6 shows geometric transformations of the image. The sensitivity analysis of the NiN model compares the mean absolute error (MAE) values [50] for geometric image transformations.

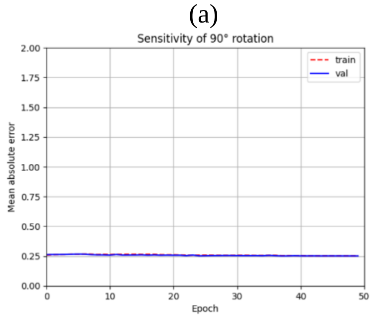
Figure 7 illustrates the influence of parameters on the convergence speed of the NiN model, with the red line signifying the training convergence speed and the blue line indicating the validating convergence speed. The convergence of the NiN model remained unchanged when the input images underwent no perturbations or remained unmodified (Figure 7(a)). However, when the input images were subjected to geometric transformations, such as left-right flips (Figure 7(b)), 90° rotations (Figure 7(c)), or upside-down flips (Figure 7(d)), slight changes in the convergence of the NiN model were noted. To mitigate the sensitivity to these transformations, data augmentation techniques can be employed by introducing perturbations to the training images. Interestingly, the mean absolute error (MAE) of training images subjected to geometric transformations remained consistent and overlapped with that of images with no perturbations, indicating the robustness of the model [50], [51].



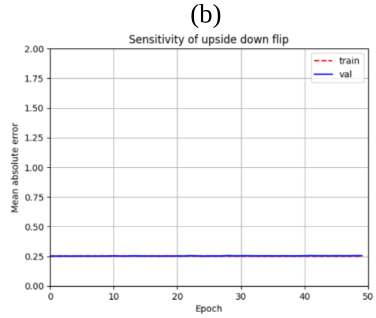
(a)



(b)



(c)



(d)

Figure 7: The relationship between the mean absolute error and the epoch. (a) Sensitivity of no perturbations; (b) Sensitivity of left-right flips; (c) Sensitivity of 90° rotations and (d) Sensitivity of upside-down flips. (Remark: train = the training convergence speed, val = the validating convergence speed.).

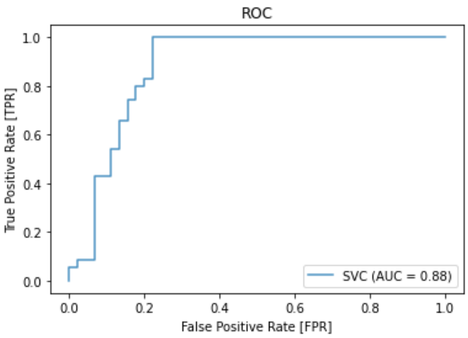


Figure 8: The results of the EaglAI software's Receiver-Operating Characteristic analysis.

3.5 *The outputs of the EaglAI software regarding Receiver-Operating Characteristics analysis and passion fruit image testing*

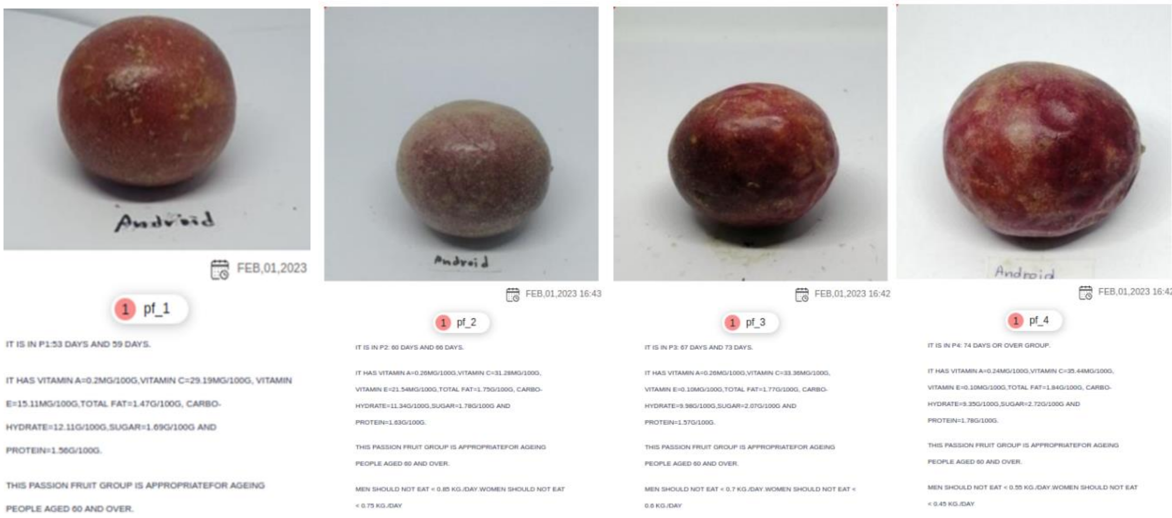
Concurrently, an analysis of 9,600 images of passion fruit was conducted using the EaglAI software. The dataset was partitioned into two—70% for training and 30% for testing. The analysis yielded an AUC of 0.88, as shown in Figure 8. The AUC is commonly applied to assess the accuracy of diagnostic tests. The performance of EaglAI is considered good. According to Nahm [52], for a diagnostic test to be meaningful, the AUC must be greater than 0.5. Generally, an AUC of ≥ 0.8 is considered acceptable [52]. For the testing model with 39 passion fruit images, the true positive number was 33 and the true negative number was six. The accuracy of the model was 84.6%.

The EaglAI software was analyzed, followed by the steps in the workflow outlined in the EaglAI platform video to train and test the passion fruit image dataset. According to company confirmation, EaglAI has achieved an impressive precision rate ranging between 85% and 90%. Notably, this precision is poised to experience a substantial enhancement over time, as stated in the letter received directly from the company.

The outputs from the passion fruit image testing using the EaglAI software are shown in Figure 9. The results demonstrate the capability of EaglAI in identifying passion fruit images, specifying their nutrient contents, and recommending the appropriate intake for elderly people as recommended by the Ministry of Public Health of Thailand. For instance, Figure 9(a) shows the results obtained for the passion fruit in the P1 group (53–59 days). The contents include vitamin A (0.2 mg/100 g), vitamin C (29.19 mg/100 g), vitamin E (15.11 mg/100 g), total fat (1.47 g/100 g), carbohydrate (12.11 g/100 g), sugar (1.69 g/100 g), and protein (1.56 g/100 g). Figure 9(b) shows the nutrient contents of passion fruits in P2 (60 and 66 days). This group contains vitamin A (0.26 mg/100 g), vitamin C (31.28 mg/100 g), vitamin E (21.54 mg/100g), total fat (1.75 g/100 g), carbohydrates (11.34 g/100g), sugar (1.78 g/100 g), and protein (1.63 g/100 g). Figure 9(c) shows the nutrient contents in P3 (67–73 days). This group contains vitamin A (0.26 mg/100 g), vitamin C (33.36 mg/100 g), vitamin E (0.10 mg/100 g), total fat (1.77 g/100 g), carbohydrate (9.98 g/100 g), sugar (2.07 g/100 g), and protein (1.57 g/100 g). Figure 9(d) shows the nutrient contents in P4 (74 days or over). This group contains vitamin A (0.24 mg/100 g), vitamin C (35.44 mg/100 g), vitamin E (0.10 mg/100 g), total fat (1.84 g/100 g), carbohydrates (9.35 g/100 g), sugar (2.72 g/100 g), and protein (1.78 g/100 g). All groups are deemed appropriate for the consumption of elderly people aged 60 and over. The passion fruit image testing by the EaglAI software was similar to the passion fruit image in each group in Figure 3.

3.6 *Comparison of the accuracy of the NiN model and EaglAI software*

In a validation comparison of the NiN model and EglAI software based on accuracy, the NiN model outperformed EaglAI software. Therefore, the identification of passion fruit groups and suggestion of the appropriate daily amount of passion fruit nutrients for elderly people by the NiN model is deemed more accurate. The training and validation accuracy of the NiN model was 96.76% and 95.89%, respectively. In contrast, the accuracy of EaglAI software was 84.6%. EglAI software has identified groups without requiring an interpretation. The results obtained from the twice-model illustrate the nutrition of each passion fruit group using the information from a chemical laboratory in Table 6.



(a) (b) (c) (d)

Figure 9: The results of passion fruit image testing from the EaglAI software. (a) The prediction results indicate that passion fruit is in the P1 group; (b) The prediction results indicate that passion fruit is in the P2 group; (c) The prediction results indicate that passion fruit is in the P3 group and (d) The prediction results indicate that passion fruit is in the P4 group.

3.7 *The amount of passion fruit intake for elderly people per day*

Information on the nutritional values in Tables 4 and 6 was used to calculate the appropriate intake of passion fruit nutrients that both elderly men and women of each age group should consume according to the recommendations of the Ministry of Public Health of Thailand. Table 7 presents nutrition columns, including the recommended amount of nutrients that the elderly should receive per day as recommended by the Ministry of Public Health of Thailand and a column for the amount of nutrients contained in each group of passion fruit, labeled as P1, P2, P3, and P4. The remaining columns include the age range for elderly men and women. In the rows section, which contains information about vitamins and various nutrients, there are a total of seven essential nutrients—vitamin A, vitamin C, vitamin E, total fat, carbohydrates, sugar, and protein. Each row of the nutrition table details the amount of dietary reference intake (DRI) and the amount of vitamins or nutrients contained in each group of passion fruit, including the recommended amount of passion fruit for elderly men and women in each age group. Most vitamins and nutrients are beneficial to the elderly, except for sugar, which requires special consideration. Typically, dietary sugar intake should not exceed the amount recommended by the Ministry of Public Health of Thailand. Excessive sugar intake may lead to diabetes, high blood pressure, etc. [42]. Thus, Table 7 highlights the importance of sugar amount in passion fruit. Furthermore, it is used as a criterion to limit the consumption of passion fruit by elderly people in each age group, across genders.

The maximum intake of passion fruit nutrients by the elderly in each group, based upon sugar contents, has the following details: elderly men aged 60–69 years should consume no more than 16.20 g/day, and those aged 70 years and over should receive no more than 15.70 g/day. The amount of nutrients that elderly women aged 60–69 years should consume is no more than 14.10 g/day, and those aged 70 years and over should consume no more than 13.90 g/day, as recommended by the Ministry of Public Health of Thailand. Therefore, based upon the analysis of sugar content in passion fruit from each group in comparison with the recommended daily nutrient intake, the following recommendations are made: elderly men aged 60–69 years should consume no more than 959 g/day of passion fruit in P1, no more than 910 g/day of P2, no more than 783 g/day of P3, and no more than 596 g/day of P4. The elderly men aged 70 years and over should consume no more than 929 g/day of passion fruit in P1, no more than 882 g/day of P2, no more than 758 g/day of P3, and no more than 577 g/day of P4. The elderly women aged 60–69 years should consume no more than 834 g/day of passion fruit in P1, no more than 792 g/day of P2, no more than 681 g/day of P3, and no more than 518 g/day of P4. The elderly women aged 70 years and over should consume no more than 822 g/day of passion fruit in P1, no more than 781 g/day in P2, no more than 671 g/day in P3, and no more than 511 g/day in P4. Sheikh [53] asserted that passion fruit is generally safe without a specific safety limit, but multiple fruits may be necessary for a full serving due to their small size. In light of its fiber content, it is imperative to consider the consumption of passion fruit, particularly for individuals unaccustomed to high-fiber diets, to prevent digestive discomfort. Concerns about sugar overload are unwarranted when consuming whole fruit, as the gradual release of sugar into the bloodstream is minimal compared to fruit juice. Despite the recommended intake of 0.6–1 kg of passion fruit for each elderly individual, this safety aspect remains paramount.

Table 7: Amount of passion fruit nutrients intakes for elderly people per day.

Nutritional	Dietary Reference Intakes (DRI)*	Elderly Groups / Amount of Passion Fruit Nutrients Intakes					
	Passion fruit groups per 100g sample	Men, 60–69years	Men, 70–79years	Men, ≥80 years	Women, 60–69years	Women, 70–79years	Women, ≥80 years
Vitamin A (mg/day)	**DRI**	**≤ 700**	**≤ 700**	**≤ 700**	**≤ 600**	**≤ 600**	**≤ 600**
	P1 = 0.20 mg	350,000,000**	350,000,000	350,000,000	300,000,000	300,000,000	300,000,000
	P2 = 0.26 mg	269,230,769	269,230,769	269,230,769	230,769,231	230,769,231	230,769,231
	P3 = 0.26 mg	269,230,769	269,230,769	269,230,769	230,769,231	230,769,231	230,769,231
	P4 = 0.24 mg	291,666,667	291,666,667	291,666,667	250,000,000	250,000,000	250,000,000
Vitamin C (mg/day)	**DRI**	**≤ 100**	**≤ 100**	**≤100**	**≤ 100**	**≤85**	**≤85**
	P1 = 29.19 mg	342,583	342,583	342,583	291,196	291,196	291,196
	P2 = 31.28 mg	319,693	319,693	319,693	271,739	271,739	271,739
	P3 = 33.36 mg	299,760	299,760	299,760	254,796	254,796	254,796
	P4 = 35.44 mg	282,167	282,167	282,167	239,842	239,842	239,842
Vitamin E (mg/day)	**DRI**	**≤ 13**	**≤ 13**	**≤ 13**	**≤ 13**	**≤ 11**	**≤ 11**
	P1 = 15.11mg	86,036	86,036	86,036	72,799	72,799	72,799
	P2 = 21.54mg	60,353	60,353	60,353	51,068	51,068	51,068
	P3 = 0.10mg	13,000,000	13,000,000	13,000,000	11,000,000	11,000,000	11,000,000
	P4 = 0.10mg	13,000,000	13,000,000	13,000,000	11,000,000	11,000,000	11,000,000
Total Fat (g/day)	**DRI**	**≤ 64.73**	**≤ 64.73**	**≤ 64.73**	**≤ 64.73**	**≤ 64.73**	**≤ 64.73**
	P1 = 1.47 g	4,403	4,403	4,403	4,403	4,403	4,403
	P2 = 1.75 g	3,699	3,699	3,699	3,699	3,699	3,699
	P3 = 1.77 g	3,657	3,657	3,657	3,657	3,657	3,657
	P4 = 1.84 g	3,518	3,518	3,518	3,518	3,518	3,518
Carbo-hydrate (g/day)	**DRI**	**≤ 299**	**≤ 1,392**	**≤ 292**	**≤ 259**	**≤ 259**	**≤ 259**
	P1 = 12.11 g	2,465	11,495	2,411	2,135	2,135	2,135
	P2 = 11.34 g	2,632	12,275	2,575	2,280	2,280	2,280
	P3 = 9.98 g	2,991	13,948	2,926	2,590	2,590	2,590
	P4 = 9.35 g	3,193	14,888	3,123	2,765	2,765	2,765
Sugar (g/day)	**DRI**	**≤16.20**	**≤15.70**	**≤15.70**	**≤14.10**	**≤13.90**	**≤13.90**
	P1 = 1.69 g	959	929	929	834	822	822
	P2 = 1.78 g	910	882	882	792	781	781
	P3 = 2.07 g	783	758	758	681	671	671
	P4 = 2.72 g	596	577	577	518	511	511
Protein (g/day)	**DRI**	**≤ 59**	**≤ 56**	**≤ 56**	**≤ 50**	**≤ 49**	**≤ 49**
	P1 = 1.56 g	3,782	3,590	3,590	3,205	3,141	3,141
	P2 = 1.63 g	3,620	3,436	3,436	3,067	3,006	3,006
	P3 = 1.57 g	3,758	3,567	3,567	3,185	3,121	3,121
	P4 = 1.78 g	3,315	3,146	3,146	2,809	2,753	2,753

Remark: * Dietary Reference Intakes (DRI) come from the Bureau of Nutrition, Department of Health, and Ministry of Public Health of Thailand [42]. ** 1 kg. = 1,000 g. = 1,000,000 mg.

4 Conclusions

There is a need for the recommendation of daily nutrient intake from passion fruit for the elderly, which is lacking in the existing literature. The objective of this research was to identify passion fruit groups and suggest the appropriate daily intake of passion fruit nutrients for elderly people using network in network (NiN) architecture. The NiN model is capable of identifying passion fruit groups based on the elderly requirement efficiently compared with CNN and EaglAI software. Furthermore, the NiN model is easier to build than CNN architectures, commonly applied for object recognition. The results show that the NiN model can correctly identify passion fruit groups and suggest the appropriate daily intake of passion fruit nutrients for the Thai elderly with 96.76% accuracy in the training dataset and 95.89% accuracy in the validation dataset. These values are higher than that of EaglAI software with an accuracy of 84.6%. The sensitivity analysis of the NiN model involved comparing mean absolute error (MAE) values across geometric image transformations. Consistent MAE values in geometrically transformed training images underscore the robustness of the model. This experiment expands on the quality grading of passion fruit, emphasizing the high detection efficiency for fruit quality classification based on shape, skin, and coloring defects. Beyond ensuring that consumers can access high-quality passion fruit, it is equally important to consider the quantity consumed and the nutrients obtained from passion fruit consumption. Previous research does not consider the amount consumed, the nutrients obtained from passion fruit consumption, or the post-harvest age when classifying the quality of passion fruit. This research aimed to address this gap by proposing a method for identifying passion fruit by its post-harvest age and specifying the nutrient contents in each group. The results offer recommendations on the daily amount of passion fruit nutrients that elderly individuals should consume.

This research demonstrates that the NiN model can effectively identify passion fruit groups and suggest the appropriate amount of passion fruit nutrients for Thai elderly individuals. This model is highly efficient and easier to build compared to other CNN architectures and commercial software like EaglAI. It achieved an accuracy of 96.76% on the training dataset and 95.89% on the validation dataset, outperforming the accuracy achieved in EaglAI software at 84.6%. The NiN model generated using the Python program has identified four categories of purple passion fruit based on its post-harvest age, more accurately than the commercial software. This study focused on identifying passion fruit by its post-harvest age and nutrient contents specific to each group using the NiN model. The results offer recommendations on the daily amount of passion fruit nutrients and whole fruit consumption for elderly individuals. These recommendations benefit the Thai elderly with chronic diseases across all age groups, as the NiN model considers the sugar contents in the passion fruit. The advantage of this research is that it provides valuable information on the daily intake of passion fruit nutrients for elderly individuals. This advantage enables Thai elderly people in each age group, particularly those with chronic diseases, to consume passion fruit nutrients in appropriate amounts tailored to their specific needs. However, this research faced several limitations, including difficulties in collecting images of passion fruit harvested from the farm. Some fruits did not reach the desired age and the color of their peels differed from the others, hampering the identification. In addition, this model did not consider the identification of hybrid passion fruit or those of colors other than purple. Furthermore, the accuracy of the model could be improved if 100,000 passion fruit images were used as input data for training. Future studies should consider incorporating the NiN model into a mobile application. This incorporation will offer an advantage to Thai elderly individuals due to its convenience for real-time identification of passion fruit. The application of the NiN model can be expanded to identify other fruits, important for providing sufficient nutrients for Thai elderly people. The assessment of precision, F1 score, or recall for both the NiN model and EaglAI shall be performed in the next phase.

Acknowledgments

The authors would like to thank King Mongkut's University of Technology North Bangkok (KMUTNB) for their support. The authors are very grateful to the Food Chemistry Laboratory of the Lampang Agricultural Technology Research Institute at Rajamangala University of Technology Lanna and the Central Laboratory (Thailand) Company Limited (CLT) for testing the nutritional content of the passion fruit. This research is funded by the Faculty of Engineering at King Mongkut’s University of Technology North Bangkok, Thailand. The authors thank the agricultural foundation and their staff,

whose names unfortunately cannot be revealed due to the confidentiality agreement.

Author Contributions

A.K.: conceptualization, investigation, reviewing and editing; A.D.: investigation, methodology, writing an original draft. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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