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Deep Neural Networks for Image-Based Dietary Assessment

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TITLE:

Deep Neural Networks for Image-Based Dietary Assessment

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food image recognition; food image segmentation; deep neural networks; deep learning; convolutional neural networks; dietary assessment

SUMMARY:

The goal of the work presented in this article is to develop technology for automated recognition of food and beverage items from images taken by mobile devices. The technology comprises of two different approaches – the first one performs food image recognition while the second one performs food image segmentation.

ABSTRACT:

Due to the issues and costs associated with manual dietary assessment approaches, automated solutions are required to ease and speed up the work and increase its quality. Today, automated solutions are able to record a person's dietary intake in a much simpler way, such as by taking an image with a smartphone camera. In this article, we will focus on such image-based approaches to dietary assessment. For the food image recognition problem, deep neural networks have achieved the state of the art in recent years, and we present our work in this field. In particular, we first describe the method for food and beverage image recognition using a deep neural network architecture, called NutriNet. This method, like most research done in the early days of deep learning-based food image recognition, is limited to one output per image, and therefore unsuitable for images with multiple food or beverage items. That is why approaches that perform food image segmentation are considerably more robust, as they are able to identify any number of food or beverage items in the image. We therefore also present two methods for food image segmentation – one is based on fully convolutional networks (FCNs), and the other on deep residual networks (ResNet).

INTRODUCTION:

Dietary assessment is a crucial step in determining actionable areas of an individual's diet. However, performing dietary assessment using traditionally manual approaches is associated

with considerable costs. These approaches are also prone to errors as they often rely on self-reporting by the individual. Automated dietary assessment addresses these issues by providing a simpler way to quantify and qualify food intake. Such an approach can also alleviate some of the errors present in manual approaches, such as missed meals, inability to accurately assess food volume, etc. Therefore, there are clear benefits to automating dietary assessment by developing solutions that identify different foods and beverages and quantify food intake[1]. These solutions can also be used to enable an estimation of nutritional values of food and beverage items (henceforth 'food items'). Consequently, automated dietary assessment is useful for multiple applications – from strictly medical uses, such as allowing dietitians to more easily and accurately track and analyze their patients' diets, to the usage inside well-being apps targeted at the general population.

Automatically recognizing food items from images is a challenging computer vision problem. This is due to foods being typically deformable objects, and due to the fact that a large amount of the food item's visual information can be lost during its preparation. Additionally, different foods can appear to be very similar to each other, and the same food can appear to be substantially different on multiple images[2]. Furthermore, the recognition accuracy depends on many more factors, such as image quality, whether the food item is obstructed by another item, distance from which the image was taken, etc. Recognizing beverage items presents its own set of challenges, the main one being the limited amount of visual information that is available in an image. This information could be the beverage color, beverage container color and structure, and, under optimal image conditions, the beverage density[2].

To successfully recognize food items from images, it is necessary to learn features of each food and beverage class. This was traditionally done using manually-defined feature extractors[3–6] that perform recognition based on specific item features like color, texture, size, etc., or a combination of these features. Examples of these feature extractors include multiple kernel learning[4], pairwise local features[5] and the bag-of-features model[6]. Due to the complexity of food images, these approaches mostly achieved a low classification accuracy – between 10% and 40%[3–5]. The reason for this is that the manual approach is not robust enough to be sufficiently accurate. Because a food item can vary significantly in appearance, it is not feasible to encompass all these variances manually. Higher classification accuracy can be achieved with manually-defined feature extractors when either the number of food classes is reduced[5], or different image features are combined[6], thus indicating that there is a need for more complex solutions to this problem.

This is why deep learning proved to be so effective for the food image recognition problem. Deep learning, or deep neural networks, was inspired by biological brains, and allows computational models composed of multiple processing layers to automatically learn features through training on a set of input images[7,8]. Because of this, deep learning has substantially improved the state of the art in a variety of research fields[7], with computer vision, and subsequently food image recognition, being one of them[2].

In particular, deep convolutional neural networks (DCNNs) are most popular for food image

recognition – these networks are inspired by the visual system of animals, where individual neurons try to gain an understanding of the visual input by reacting to overlapping regions in the visual field[9]. A convolutional neural network takes the input image and performs a series of operations in each of the network layers, the most common of which are convolutional, fully-connected and pooling layers. Convolutional layers contain learnable filters that respond to certain features in the input data, whereas fully-connected layers compose output data from other layers to gain higher-level knowledge from it. The goal of pooling layers is to down-sample the input data[2]. There are two approaches to using deep learning models that proved popular: taking an existing deep neural network definition[10,11], referred to as a deep learning architecture in this article, or defining a new deep learning architecture[12,13], and training either one of these on a food image dataset. There are strengths and weaknesses to both approaches – when using an existing deep learning architecture, an architecture that performed well for other problems can be chosen and fine-tuned for the desired problem, thus saving time and ensuring that a validated architecture has been chosen. Defining a new deep learning architecture, on the other hand, is more time-intensive, but allows the development of architectures that are specifically made to take into account the specifics of a problem and thus theoretically perform better for that problem.

In this article, we present both approaches. For the food image recognition problem, we developed a novel DCNN architecture called NutriNet[2], which is a modification of the well-known AlexNet architecture[14]. There are two main differences compared to AlexNet: NutriNet accepts 512x512-pixel images as input (as opposed to 256x256-pixel images for AlexNet), and NutriNet has an additional convolutional layer at the beginning of the neural network. These two changes were introduced in order to extract as much information from the recognition dataset images as possible. Having higher-resolution images meant that there is more information present on images and having more convolutional layers meant that additional knowledge could be extracted from the images. Compared to AlexNet's around 60 million parameters, NutriNet contains less parameters: approximately 33 million. This is because of the difference in dimensionality at the first fully-connected layer caused by the additional convolutional layer[2]. **Figure 1** contains a diagram of the NutriNet architecture. The food images that were used to train the NutriNet model were gathered from the Internet – the procedure is described in the protocol text.

For the food image segmentation problem, we used two different existing architectures: fully convolutional networks (FCNs)[15] and deep residual networks (ResNet)[16], both of which represented the state of the art for image segmentation when we used them to develop their respective food image segmentation solutions. There are multiple FCN variants that were introduced by Long et al.: FCN-32s, FCN-16s and FCN-8s[15]. FCN-32s outputs a pixel map based on the predictions by the FCN's final layer, whereas the FCN-16s variant combines these predictions with those by an earlier layer. FCN-8s considers yet another layer's predictions and is therefore able to make predictions at the finest grain, which is why it is suitable for food image recognition. The FCN-8s that we used was pre-trained on the PASCAL Visual Object Classes (PASCAL VOC) dataset[17] and trained and tested on images of food replicas (henceforth 'fake food')[18] due to their visual resemblance to real food and due to a lack of annotated images of real food on a pixel

level. Fake food is used in different behavioral studies and images are taken for all dishes from all study participants. Because the food contents of these images are known, it makes the image dataset useful for deep learning model training. Dataset processing steps are described in the protocol text.

The ResNet-based solution was developed in the scope of the Food Recognition Challenge (FRC)[19]. It uses the Hybrid Task Cascade (HTC)[20] method with a ResNet-101[16] backbone. This is a state-of-the-art approach for the image segmentation problem that can use different feature extractors, or backbones. We considered other backbone networks as well, particularly other ResNet variants such as ResNet-50[16], but ResNet-101 was the most suitable due to its depth and ability to represent input images in a complex enough manner. The dataset used for training the HTC ResNet-101 model was the FRC dataset with added augmented images. These augmentations are presented in the protocol text.

This article is intended as a resource for machine learning experts looking for information about which deep learning architectures and data augmentation steps perform well for the problems of food image recognition and segmentation, as well as for nutrition researchers looking to use our approach to automate food image recognition for use in dietary assessment. In the following section, deep learning solutions and datasets from the food image recognition field are presented. In the protocol text, we detail how each of the three approaches was used to train deep neural network models that can be used for automated dietary assessment. Additionally, each protocol section contains a description of how the food image datasets used for training and testing were acquired and processed.

DCNNs generally achieved substantially better results than other methods for food image recognition and segmentation, which is why the vast majority of recent research in the field is based on these networks. Kawano et al. used DCNNs to complement manual approaches[21] and achieved a classification accuracy of 72.26% on the UEC-FOOD100 dataset[22]. Christodoulidis et al. used them exclusively to achieve a higher accuracy of 84.90% on a self-acquired dataset[23]. Tanno et al. developed DeepFoodCam – a smartphone app for food image recognition that uses DCNNs[24]. Liu et al. presented a system that performs an Internet of Things-based dietary assessment using DCNNs[25]. Martinel et al. introduced a DCNN-based approach that exploits the specifics of food images[26] and reported an accuracy of 90.27% on the Food-101 dataset[27]. Zhou et al. authored a review of deep learning solutions in the food domain[28].

Recently, Zhao et al. proposed a network specifically for food image recognition in mobile applications[29]. This approach uses a smaller 'student' network that learns from a larger 'teacher' network. With it, they managed to achieve an accuracy of 84% on the UEC-FOOD256[30] and an accuracy of 91.2% on the Food-101 dataset[27]. Hafiz et al. used DCNNs to develop a beverage-only image recognition solution and reported a very high accuracy of 98.51%[31]. Shimoda et al. described a novel method for detecting plate regions in food images without the usage of pixel-wise annotation[32]. Ciocca et al. introduced a new dataset containing food items from 20 different food classes in 11 different states (solid, sliced, creamy paste, etc.) and presented their approach for training recognition models that are able to recognize the food state, in addition to the food

class[33]. Knez et al. evaluated food image recognition solutions for mobile devices[34]. Finally, Furtado et al. conducted a study on how the human visual system compares to the performance of DCNNs and found out that human recognition still outperforms DCNNs with an accuracy of 80% versus 74.5%[35]. The authors noted that with a small number of food classes, the DCNNs perform well, but on a dataset with hundreds of classes, human recognition accuracy is higher[35], highlighting the complexity of the problem.

Despite its state-of-the-art results, deep learning has a major drawback – it requires a large input dataset to train the model on. In the case of food image recognition, a large food image dataset is required, and this dataset needs to encompass as many different real-world scenarios as possible. In practice this means that for each individual food or beverage item, a large collection of images is required, and as many different items need to be present in the dataset. If there are not enough images for a specific item in the dataset, that item is unlikely to be recognized successfully. On the other hand, if only a small number of items is covered by the dataset, the solution will be limited in scope, and only able to recognize a handful of different foods and beverages.

Multiple datasets were made available in the past. The Pittsburgh Fast-Food Image Dataset (PFID)[3] was introduced to encourage more research in the field of food image recognition. The University of Electro-Communications Food 100 (UEC-FOOD100)[22] and University of Electro-Communications Food 256 (UEC-FOOD256)[30] datasets contain Japanese dishes, expanded with some international dishes in the case of the UEC-FOOD256 dataset. The Food-101 dataset contains popular dishes acquired from a website[27]. The Food-50[36] and Video Retrieval Group Food 172 (VireoFood-172)[37] datasets are Chinese-based collections of food images. The University of Milano-Bicocca 2016 (UNIMIB2016) dataset is composed of images of food trays from an Italian canteen[38]. Recipe1M is a large-scale dataset of cooking recipes and food images[39]. The Food-475 dataset[40] collects four previously published food image datasets[27,30,36,37] into one. The Beijing Technology and Business University Food 60 (BTBUFood-60) is a dataset of images meant for food detection[41]. Recently, the ISIA Food-500 dataset[42] of miscellaneous food images was made available. In comparison to other publicly available food image datasets, it contains a large number of images, divided into 500 food classes, and is meant to advance the development of multimedia food recognition solutions[42].

PROTOCOL:

1. Food image recognition with NutriNet

1.1. Obtaining the food image dataset

1.1.1. Gather a list of different foods and beverages that will be the outputs of the food image recognition model. A varied list of popular foods and beverages is preferred, as that will allow the training of a robust food image recognition model.

1.1.2. Save the food and beverage list in a text file (e.g., ‘txt’ or ‘csv’).

NOTE: The text file used by the authors of this article can be found in the supplemental files ('food_items.txt') and includes a list of 520 Slovenian food items.

1.1.3. Write or download a Python[43] script that uses the Google Custom Search API[44] to download images of each food item from the list and saves them into a separate folder for each food item.

NOTE: The Python script used by the authors of this article can be found in the supplemental files ('download_images.py'). If this script is used, the Developer Key (variable 'developerKey', line 8 in the Python script code) and Custom Search Engine ID (variable 'cx', line 28 in the Python script code) need to be replaced with values specific to the Google account being used.

1.1.4. Run the Python script from step 1.1.3 (e.g., with the command: 'python download_images.py').

1.2. (Optional) Cleaning the food image dataset

1.2.1. Train a food image detection model in the same way as in section 1.4, except use only two outputs (food, non-food) as opposed to the list of outputs from step 1.1.1.

NOTE: The authors of this article used images combined from recipe websites and the ImageNet dataset[45] to train the food image detection model. Since the focus here is on food image recognition and this is an optional step for cleaning the recognition dataset, further details are omitted. Instead, more details about this approach can be found in Mezgec et al.[2].

1.2.2. Run the detection model from step 1.2.1 on the food image dataset that is the result of step 1.1.4.

1.2.3. Delete every image that was tagged as non-food by the detection model from step 1.2.1.

1.2.4. Manually check the food image dataset for other erroneous or low-quality images, and for image duplicates.

1.2.5. Delete images found in step 1.2.4.

1.3. Augmenting the food image dataset

1.3.1. Create a new version of each image from the food image dataset by rotating it by 90° using the CLoDSA library[46] (lines 19 to 21 in the included Python script).

NOTE: The Python script containing all the CLoDSA commands used by the authors of this article can be found in a file included in the supplemental files ('nutrinet_augmentation.py'). If this script is used, the Input Path (variable 'INPUT_PATH', line 8 in the Python script code) and Output Path (variable 'OUTPUT_PATH', line 11 in the Python script code) need to be replaced with paths to

the desired folders.

1.3.2. Create a new version of each image from the food image dataset by rotating it by 180° using the CLoDSA library (lines 19 to 21 in the included Python script).

1.3.3. Create a new version of each image from the food image dataset by rotating it by 270° using the CLoDSA library (lines 19 to 21 in the included Python script).

1.3.4. Create a new version of each image from the food image dataset by flipping it horizontally using the CLoDSA library (lines 23 and 24 in the included Python script).

1.3.5. Create a new version of each image from the food image dataset by adding random color noise to it using the CLoDSA library (lines 26 and 27 in the included Python script).

1.3.6. Create a new version of each image from the food image dataset by zooming into it by 25% using the CLoDSA library (lines 29 and 30 in the included Python script).

1.3.7. Save images from steps 1.3.1–1.3.6, along with the original images (lines 16 and 17 in the included Python script), into a new food image dataset (in total, 7 variants per food image). This is done by executing the command in line 32 of the included Python script.

1.4. Performing food image recognition

1.4.1. Import the food image dataset from step 1.3.7 into the NVIDIA DIGITS environment[47], dividing the dataset into training, validation and testing subsets in the NVIDIA DIGITS user interface.

1.4.2. Copy and paste the definition text of the NutriNet architecture[2] into NVIDIA DIGITS as a custom network.

NOTE: The NutriNet architecture definition text can be found in the supplemental files ('nutrinet.prototxt').

1.4.3. (Optional) Define training hyperparameters in the NVIDIA DIGITS user interface.

NOTE: Hyperparameters are parameters that are used to define the training process prior to its start. The hyperparameters used by the authors of this article can be found in a file included in the supplemental files ('nutrinet_hyperparameters.prototxt'). While experimentation is needed for each dataset to find the optimal hyperparameters, the file contains a hyperparameter configuration which can be copied into the NVIDIA DIGITS user interface. Furthermore, NVIDIA DIGITS populates the hyperparameters with default values which can be used as a baseline. This step is therefore optional.

1.4.4. Run the training of the NutriNet model.

1.4.5. After training is complete, take the best performing NutriNet model iteration. This model is then used for testing the performance of this approach.

NOTE: There are multiple ways to determine the best-performing model iteration. A straightforward way to do this is as follows. NVIDIA DIGITS outputs a graph of accuracy measures for each training epoch. Check which epoch achieved the lowest loss value for the validation subset of the food image dataset – that model iteration can be considered best-performing. An optional step in determining the best-performing model iteration is to observe how the loss value for the training subset changes from epoch to epoch and if it starts to drop continuously while the loss value for the validation subset remains the same or rises continuously, take the epoch prior to this drop in training loss value, as that can signal when the model started overfitting on the training images.

2. Food image segmentation with FCNs

2.1. Obtaining the fake-food image dataset

2.1.1. Obtain a dataset of fake-food images. Fake-food images are gathered by researchers conducting behavioral studies using food replicas.

NOTE: The authors of this article received images of fake food that were collected in a lab environment[18].

2.1.2. Manually annotate every food image on a pixel level – each pixel in the image must contain information about which food class it belongs to. The result of this step is one annotation image for each image from the food image dataset, where each pixel represents one of the food classes.

NOTE: There are many tools to achieve this – the authors of this article used JavaScript Segment Annotator[48].

2.2. Augmenting the fake-food image dataset

2.2.1. Perform the same steps as in section 1.3, but only on images from the training subset of the food image dataset.

NOTE: With the exception of step 1.3.5, all data augmentation steps need to be performed on corresponding annotation images as well. If the script from section 1.3 is used, the Input Path (variable 'INPUT_PATH', line 8 in the Python[43] script code) and Output Path (variable 'OUTPUT_PATH', line 11 in the Python script code) need to be replaced with paths to the desired folders. In addition, set the Problem (variable 'PROBLEM', line 6 in the Python script code) to 'instance_segmentation' and the Annotation Mode (variable 'ANNOTATION_MODE', line 7 in the Python script code) and Output Mode (variable 'OUTPUT_MODE', line 10 in the Python script code) to 'coco'.

2.3. Performing fake-food image segmentation

2.3.1. Perform the same steps as in section 1.4, with the exception of step 1.4.2 In place of that step, perform steps 2.3.2 and 2.3.3.

NOTE: Hyperparameters are parameters that are used to define the training process prior to its start. The training hyperparameters used by the authors of this article for the optional step 1.4.3 can be found in a file included in the supplemental files ('fcn-8s_hyperparameters.prototxt'). While experimentation is needed for each dataset to find the optimal set of hyperparameters, the file contains a hyperparameter configuration which can be copied into the NVIDIA DIGITS[47] user interface. Furthermore, NVIDIA DIGITS populates the hyperparameters with default values which can be used as a baseline.

2.3.2. Copy and paste the definition text of the FCN-8s architecture[15] into the NVIDIA DIGITS environment as a custom network.

NOTE: The FCN-8s architecture definition text is publicly available on GitHub[49].

2.3.3. Enter the path to the pre-trained FCN-8s model weights into the NVIDIA DIGITS user interface.

NOTE: These model weights were pre-trained on the PASCAL VOC dataset[17] and can be found on the Internet[49].

3. Food image segmentation with HTC ResNet

3.1. Obtaining the food image dataset

3.1.1. Download the food image dataset from the FRC website[19].

3.2. Augmenting the food image dataset

3.2.1. Perform steps 1.3.1–1.3.4.

NOTE: The Python[43] script containing all the CLoDSA[46] commands used by the authors of this article can be found in a file included in the supplemental files ('frc_augmentation.py'). If this script is used, the Input Path (variable 'INPUT_PATH', line 8 in the Python script code) and Output Path (variable 'OUTPUT_PATH', line 11 in the Python script code) need to be replaced with paths to the desired folders.

3.2.2. Create a new version of each image from the food image dataset by adding Gaussian blur to it using the CLoDSA library (lines 26 and 27 in the included Python script).

3.2.3. Create a new version of each image from the food image dataset by sharpening it using the CLoDSA library (lines 29 and 30 in the included Python script).

3.2.4. Create a new version of each image from the food image dataset by applying gamma correction to it using the CLoDSA library (lines 32 and 33 in the included Python script).

3.2.5. Save images from steps 3.2.1–3.2.4, along with the original images (lines 16 and 17 in the included Python script), into a new food image dataset (in total, 8 variants per food image). This is done by executing the command in line 35 of the included Python script.

3.2.6. Save images from steps 3.2.2–3.2.4, along with the original images (lines 16 and 17 in the included Python script), into a new food image dataset (in total, 4 variants per food image). This is done by deleting lines 19 to 24 of the included Python script and executing the command in line 35.

3.3. Performing food image segmentation

3.3.1. Modify the existing HTC[20] ResNet-101 architecture[16] definition from the MMDetection library[50] in sections 'model settings' and 'dataset settings' of the architecture definition file so that it accepts the food image datasets from steps 3.1.1, 3.2.5 and 3.2.6.

3.3.2. (Optional) Modify the HTC ResNet-101 architecture definition from step 3.3.1 to define training hyperparameters: batch size in section 'dataset settings', solver type and learning rate in section 'optimizer', learning policy in section 'learning policy' and number of training epochs in section 'runtime settings' of the architecture definition file.

NOTE: The modified HTC ResNet-101 architecture definition file can be found in the supplemental files ('htc_resnet-101.py'). Hyperparameters are parameters that are used to define the training process prior to its start. While experimentation is needed for each dataset to find the optimal set of hyperparameters, the file already contains a hyperparameter configuration which can be used without modification. This step is therefore optional.

3.3.3. Run the training of the HTC ResNet-101 model on the food image dataset from step 3.1.1 using the MMDetection library (e.g., with the command: 'python mmdetection/tools/train.py htc_resnet-101.py').

3.3.4. After the training from step 3.3.3 is complete, take the best-performing HTC ResNet-101 model iteration and fine-tune it by running the next phase of training on the food image dataset from step 3.2.5.

NOTE: There are multiple ways to determine the best-performing model iteration. A straightforward way to do this is as follows. The MMDetection library outputs values of accuracy measures for each training epoch in the command line interface. Check which epoch achieved the lowest loss value for the validation subset of the food image dataset – that model iteration

can be considered best-performing. An optional step in determining the best-performing model iteration is to observe how the loss value for the training subset changes from epoch to epoch and if it starts to drop continuously while the loss value for the validation subset remains the same or rises continuously, take the epoch prior to this drop in training loss value, as that can signal when the model started overfitting on the training images.

3.3.5. After the training from step 3.3.4 is complete, take the best-performing HTC ResNet-101 model iteration and fine-tune it by running the next phase of training on the food image dataset from step 3.2.6.

NOTE: See note for step 3.3.4.

3.3.6. After the training from step 3.3.5 is complete, take the best-performing HTC ResNet-101 model iteration and fine-tune it by again running the next phase of training on the food image dataset from step 3.2.5.

NOTE: See note for step 3.3.4.

3.3.7. After the training from step 3.3.6 is complete, take the best-performing HTC ResNet-101 model iteration. This model is then used for testing the performance of this approach.

NOTE: See note for step 3.3.4. Steps 3.3.3–3.3.7 yielded the best results for the purposes defined by the authors of this article. Experimentation is needed for each dataset to find the optimal sequence of training and data augmentation steps.

REPRESENTATIVE RESULTS:

NutriNet was tested against three popular deep learning architectures of the time: AlexNet[14], GoogLeNet[51] and ResNet[16]. Multiple training parameters were also tested for all architectures to define the optimal values[2]. Among these is the choice of solver type, which determines how the loss function is minimized. This function is the primary quality measure for training neural networks as it is better suited for optimization during training than classification accuracy. We tested three solvers: Stochastic Gradient Descent (SGD)[52], Nesterov's Accelerated Gradient (NAG)[53] and the Adaptive Gradient algorithm (AdaGrad)[54]. The second parameter is batch size, which defines the number of images that are processed at the same time. The depth of the deep learning architecture determined the value of this parameter, as deeper architectures require more space on the GPU memory – the consequence of this approach was that the memory was completely filled with images for all architectures, regardless of depth. The third parameter is learning rate, which defines the speed with which the neural network parameters are being changed during training. This parameter was set in unison with the batch size, as the number of concurrently processed images dictates the convergence rate. AlexNet models were trained using a batch size of 256 images and a base learning rate of 0.02; NutriNet used a batch size of 128 images and a rate of 0.01; GoogLeNet 64 images and a rate of 0.005; and ResNet 16 images and a rate of 0.00125. Three other parameters were fixed for all architectures: learning rate policy (step-down), step size (30%) and gamma (0.1). These parameters jointly describe how the

learning rate is changing in every epoch. The idea behind this approach is that the learning rate is being gradually lowered to fine-tune the model the closer it gets to the optimal loss value. Finally, the number of training epochs was also fixed to 150 for all deep learning architectures[2].

The best result among all the parameters tested that NutriNet achieved was a classification accuracy of 86.72% on the recognition dataset, which was around 2% higher than the best result for AlexNet and slightly higher than GoogLeNet's best result. The best-performing architecture overall was ResNet (by around 1%), however the training time for ResNet is substantially higher compared to NutriNet (by a factor of approximately five), which is important if models are continuously re-trained to improve accuracy and the number of recognizable food items. NutriNet, AlexNet and GoogLeNet achieved their best results using the AdaGrad solver, whereas ResNet's best model used the NAG solver. NutriNet was also tested on the publicly available UNIMIB2016 food image dataset[38]. This dataset contains 3,616 images of 73 different food items. NutriNet achieved a recognition accuracy of 86.39% on this dataset, slightly outperforming the baseline recognition result of the authors of the dataset, which was 85.80%. Additionally, NutriNet was tested on a small dataset of 200 real-world images of 115 different food and beverage items, where NutriNet achieved a top-five accuracy of 55%.

To train the FCN-8s fake-food image segmentation model, we used Adam[55] as the solver type, as we found that it performed optimally for this task. The base learning rate was set very low – to 0.0001. The reason for the low number is the fact that only one image could be processed at a time, which is a consequence of the pixel-level classification process. The GPU memory requirements for this approach are significantly greater than image-level classification. The learning rate thus had to be set low so that the parameters were not being changed too fast and converge to less optimal values. The number of training epochs was set to 100, while the learning rate policy, step size and gamma were set to step-down, 34% and 0.1, respectively, as these parameters produced the most accurate models.

Accuracy measurements of the FCN-8s model were performed using the pixel accuracy measure[15], which is analogous to the classification accuracy of traditional deep learning networks, the main difference being that the accuracy is computed on the pixel level instead of on the image level:

$$PA = \frac{\sum_i n_{ii}}{\sum_i t_i}$$

where PA is the pixel accuracy measure, n_{ij} is the number of pixels of class i predicted to belong to class j and $t_i = \sum_j n_{ij}$ is the total number of pixels from class i in the ground-truth labels[1]. In other words, the pixel accuracy measure is computed by dividing correctly predicted pixels with the total number of pixels. The final accuracy of the trained FCN-8s model was 92.18%. Figure 2 shows three example images from the fake-food image dataset (one from each of the training, validation and testing subsets), along with the corresponding ground-truth and model prediction labels.

The parameters to train the HTC[20] ResNet-101 model for food image segmentation were set as follows: the solver type used was SGD because it outperformed other solver types. The base learning rate was set to 0.00125 and the batch size to 2 images. The number of training epochs was set to 40 per training phase, and multiple training phases were performed – first on the original FRC dataset without augmented images, then on the 8x-augmented and 4x-augmented FRC dataset multiple times in an alternating fashion, each time taking the best-performing model and fine-tuning it in the next training phase. More details on the training phases are found in section 3.3. of the protocol text. Finally, the step-down learning policy was used, with fixed epochs for when the learning rate decreased (epochs 28 and 35 for the first training phase). An important thing to note is that while this sequence of training phases produced the best results in our testing in the scope of the FRC, using another dataset might require a different sequence to produce optimal results.

This ResNet-based solution for food image segmentation was evaluated using the following precision measure[19]:

$$P_{IoU \geq 0.5} = \frac{TP_{IoU \geq 0.5}}{TP_{IoU \geq 0.5} + FP_{IoU \geq 0.5}}$$

where P is precision, TP is the number of true positive predictions by the food image segmentation model, FP is the number of false positive predictions and IoU is Intersection over Union, which is computed with this equation:

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union}$$

where $Area\ of\ Overlap$ represents the number predictions by the model that overlap with the ground truth, and $Area\ of\ Union$ represents the total number of predictions by the model together with the ground truth, both on a pixel level and for each individual food class. Recall is used as a secondary measure and is calculated in a similar way, using the following formula[19]:

$$R_{IoU \geq 0.5} = \frac{TP_{IoU \geq 0.5}}{TP_{IoU \geq 0.5} + FN_{IoU \geq 0.5}}$$

where R is recall and FN is the number of false negative predictions by the food image segmentation model. The precision and recall measures are then averaged across all classes in the ground truth. Using these measures, our model achieved an average precision of 59.2% and an average recall of 82.1%, which ranked second in the second round of the Food Recognition Challenge[19]. This result was 4.2% behind the first place and 5.3% ahead of the third place in terms of the average precision measure. Table 1 contains the results for the top-4 participants in the competition.

FIGURE AND TABLE LEGENDS:

Figure 1: Diagram of the NutriNet deep neural network architecture. This figure has been

published in Mezgec et al.[2].

Figure 2: Images from the fake-food image dataset. Original images (left), manually-labelled ground-truth labels (middle) and predictions from the FCN-8s model (right). This figure has been published in Mezgec et al.[1].

Table 1: Top-4 results from the second round of the Food Recognition Challenge. Average precision is taken as the primary performance measure and average recall as a secondary measure. Results are taken from the official competition leaderboard[19].

DISCUSSION:

In recent years, deep neural networks have been validated multiple times as a suitable solution for recognizing food images[10–12,21,23,25,26,29,31,33]. Our work presented in this article serves to further prove this[1,2]. The single-output food image recognition approach is straightforward and can be used for simple applications where images with only one food or beverage item are expected[2].

The food image segmentation approach seems particularly suitable for recognizing food images in general, without any restriction on the number of food items[1]. Because it works by classifying each individual pixel of the image, it is able to not only recognize any number of food items in the image, but also specify where a food item is located, as well as how large it is. The latter can then be used to perform food weight estimation, particularly if used with either a reference object or a fixed-distance camera.

There has been some work done regarding the availability of food image datasets[3,22,27,30,36–42], and we hope more will be done in the future, particularly when it comes to aggregating food image datasets from different regions across the world, which would enable more robust solutions to be developed. Currently, the accuracy of automatic food image recognition solutions has not yet reached human-level accuracy[35], and this is likely in large part due to food image datasets of insufficient size and quality.

In the future, our goal will be to further evaluate the developed procedures on real-world images. In general, datasets in this field often contain images taken in controlled environments or images that were manually optimized for recognition. This is why it is important to gather a large and diverse real-world food image dataset to encompass all the different food and beverage items that individuals might want to recognize. The first step towards this was provided by the Food Recognition Challenge, which included a dataset of real-world food images[19], but further work needs to be done to validate this approach on food images from all around the world and in cooperation with dietitians.

ACKNOWLEDGMENTS:

The authors would like to thank Tamara Bucher from the University of Newcastle, Australia, for providing the fake-food image dataset. This work was supported by the European Union's Horizon 2020 research and innovation programs (grant numbers 863059 – FNS-Clouds, 769661 –

SAAM); and the Slovenian Research Agency (grant number P2-0098). The European Union and Slovenian Research Agency had no role in the design, analysis or writing of this article.

DISCLOSURES:

The authors have nothing to disclose.

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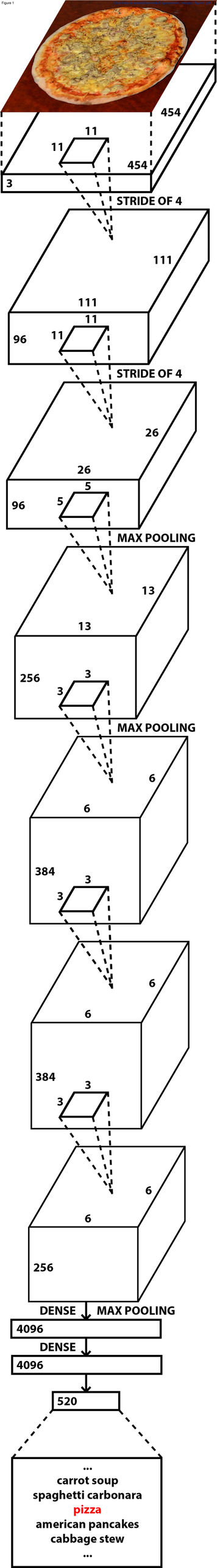
Figure 1


454
11
11
454
3
STRIDE OF 4
111
111
11
11
96
STRIDE OF 4
26
26
5
5
96
MAX POOLING
13
13
256
3
3
MAX POOLING
6
6
384
3
3
6
6
384
3
3
6
6
256
DENSE
MAX POOLING
4096
DENSE
4096
520
...
carrot soup
spaghetti carbonara
pizza
american pancakes
cabbage stew
...

Original image

Ground truth

Predictions

Training

Validation

Testing

Table 1

Team Name	Placement	Average Precision	Average Recall
rssfete	1	63.4%	88.6%
simon_mezgec	2	59.2%	82.1%
arimboux	3	53.9%	73.5%
latentvec	4	48.7%	71.1%

Table of Materials

Click here to access/download;Table of Materials;simon_mezgec_materials_revision1.xls

Name of Material / Equipment	Company	Catalog Number
HARDWARE		
NVIDIA GPU	NVIDIA	N/A
SOFTWARE		
Caffe	Berkeley AI Research	N/A
CLoDSA	Jónathan Heras	N/A
Google API Client	Google	N/A
JavaScript Segment Annotator	Kota Yamaguchi	N/A
MMDetection	Multimedia Laboratory, CUHK	N/A
NVIDIA DIGITS	NVIDIA	N/A
OpenCV	Intel	N/A
Python	Python Software Foundation	N/A
PyTorch	Facebook AI Research	N/A
Ubuntu OS	Canonical	N/A

Comments/Description

An NVIDIA GPU is needed as some of the software frameworks below will not work otherwise. https://www.nvidia.com

Caffe is a deep learning framework. https://caffe.berkeleyvision.org
CLoDSA is a Python image augmentation library. https://github.com/joheras/CLoDSA
Google API Client is a Python client library for Google's discovery based APIs. https://github.com/googleapis/google-api-python-client
JavaScript Segment Annotator is a JavaScript image annotation tool. https://github.com/kyamagu/js-segment-annotator
MMDetection is an object detection toolbox based on PyTorch. https://github.com/open-mmlab/mmdetection
NVIDIA DIGITS is a wrapper for Caffe that provides a graphical web interface. https://developer.nvidia.com/digits
OpenCV is a library for computer vision. https://opencv.org
Python is a programming language. https://www.python.org
PyTorch is a machine learning framework. https://pytorch.org
Ubuntu 14.04 is the OS used by the authors and offers compatibility with all of the software frameworks and tools above. https://ubuntu.con

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Dear All,

All the comments have been addressed in this revision of the article. Changes have been made to the manuscript using the Track Changes option in Microsoft Word, and changes can be viewed in the Simple Markup (for easier readability) and All Markup (all changes visible) modes in Word. The video has also been updated according to the comments.

Please note that in order to address all the reviewers' comments, some parts of the manuscript have been significantly updated. Consequently, the Introduction section turned out to be almost 2100 words long, which is over the 1500-word limit described in the manuscript template and instructions. In order to address this, and still include the necessary changes as outlined by the reviewers, the Introduction section has been split into Introduction and Related Work sections, where the latter includes the description of deep-learning-based food image recognition solutions and datasets. This way, the new Introduction section is around 1400 words long and the Related Work section has around 700 words. If necessary, this can be changed.

Included below are all the editor and reviewer comments (in an italic font), as well as our responses to them (in a blue font for better legibility). In them, we detail how the comments have been addressed and describe the changes that have been made to the manuscript and video.

In the hopes of a positive response I wish you all the best,

Simon Mezgec

Editorial and Production Comments:
Changes to be made by the Author(s) regarding the written manuscript:
1. Please take this opportunity to thoroughly proofread the manuscript to ensure that there are no spelling or grammar issues

The manuscript has been checked thoroughly and some errors have been corrected throughout the manuscript.

2. Please add more details to your protocol steps. Please ensure you answer the "how" question, i.e., how is the step performed?

Significant detail has been added to several protocol steps that should clarify how they are to be performed. For example, details have been added to augmentation steps (1.3.1 to 1.3.7. and 3.2.1. to 3.2.6.), to hyperparameter-defining steps (1.4.3., 2.3.1. and 3.3.2.), to training steps (3.3.4. to 3.3.7.), and others. More on this can be found in our replies to Reviewer #1 below.

3. 1.4.4/2.3.3: What does it mean to enter the definition? What are the user input commands here?

It is a copy-and-paste process from the definition text file into the NVIDIA DIGITS user interface. The instructions for both steps have been reworded to clarify this, and information on where to get the FCN-8s architecture definition text has been added as a note in step 2.3.3 (now step 2.3.2.).

4. 3.2.2: How is CLoDSA being used?

CLoDSA is being used to perform image segmentation steps (steps 1.3.1. to 1.3.7. and new steps 3.2.1. to 3.2.6.). The Python scripts containing all the CLoDSA commands are now attached to the manuscript (files 'nutrinet_augmentation.py' and 'frc_augmentation.py'). To further detail what exactly needs to be done in each of these steps, the CLoDSA library requirement and the specific CLoDSA command location in the included Python scripts for each step have been added. This allows the reader to simply copy-paste the commands, and only change the path of the image dataset.

Changes to be made by the Author(s) regarding the video:
1. Hold on all of the section titles for 2 or 3 more seconds before moving on. For example, the section 1 title at 0:43 is only on screen for a second and a half before it is gone.

The display duration of section titles has been prolonged to address this issue. New section titles are now held for 5 seconds (which is between 2 and 3 seconds more than before), with the exception of the title for section 1.2, which is held a little over 6 seconds due to the extra text present on the title card – this should allow the viewer to read everything without hurrying. Furthermore, the steps in the video have been updated to align with the new version of the manuscript. Lastly, the design of the section titles has been updated.

Please upload a revised high-resolution video here:
https://www.dropbox.com/request/chF0mlCkyvhVtOprB52d?oref=e

The revised high-resolution video has been uploaded to the above link.

Thank you for your feedback!

Reviewers' Comments:
Reviewer #1:
Manuscript Summary:
This paper describes a method for recognizing food-related images (based on a

deep neural network architecture proposed by the authors), and also two methods for segmentation of food images (down to food items). The paper presents methods for gathering the required training sets, creating the ground truth, installing and using the necessary software, and training the models. Experimental evaluation on a publicly available dataset and an in-house dataset shows promising results.

Major Concerns:
The main concern with the paper is the different levels of detail that the various steps are described. This makes it hard to identify the core audience of this work: is it machine-learning experts who want to adapt their tools and methods to food image recognition and segmentation? is it non-experts who want to apply a relatively automated method for food image recognition and segmentation? The following examples make this issue clearer.

The protocol steps have been updated significantly to equalize the level of detail across all steps. To this end, the installation steps have been removed and additional details have been added to a large number of steps. Apart from the steps mentioned below, details have been added to other steps as well (e.g., step 1.1.1., step 2.1.1., etc.). The target audience are both of the groups mentioned – machine learning experts can gain insight into what architectures and data augmentation steps perform well for the problems of food image recognition and segmentation, while non-experts can just take the provided instructions and files and run the deep learning model training as-is. To better suit the latter, significant detail has been added to the protocol steps. The target audience description has also been added to the manuscript itself (lines 147-150).

1. Software requirements: some steps in the protocol are related to installing software (python, caffe, google API client, pytorch, and more), while another step is to "write a python script that uses the google custom search API". There are some issues with this: (a) the level of detail is not consistent, (b) there is no clear definition of the underlying system (e.g. type/version of operating system, hardware requirements), (c) software requirements should be better mentioned separately, instead of listing the installation steps as part of a protocol.

The software requirements are listed in the Materials table (Excel spreadsheet file) that is attached to the manuscript. Because of this, the installation steps have been removed from the Protocol text in the manuscript to improve the consistency and help equalize the level of details in each protocol step. Furthermore, links have been added to each of the requirements in the Materials table, and three more requirements have been added to it: the OS requirement and GPU requirement (listed in a separate Hardware table section), as well as an additional software requirement (OpenCV) that was missed before.

As for step 1.1.5. (now step 1.1.3.), which contains the instruction to write a Python script – the text has been slightly altered to make it clearer that it is not mandatory to write a new Python script from scratch, as we provide our own Python script in the supplemental files of the manuscript (this is mentioned in the step 1.1.3. note).

That said, the reader who follows these steps still has the option to write their own script, and the following steps should still be applicable. This is why step 1.1.3. now reads “Write or download a Python script…”. Due to the fact that our script is included, we did not go into further details in this step – if the reader is interested in a quick way to get started with deep learning model training and maybe does not have a programming background, they can just run the script without going into details. For others, they can view the code, analyze it and either adapt it for their purpose, or write another script entirely.

2. Some steps are not clear: for example what does step 1.1.7 mean?

Upon analyzing the Python script mentioned in step 1.1.6. (now step 1.1.4.), we found that step 1.1.7. is superfluous as the script already saves the resulting images in the correct format, so there is no need for an additional step after that. Thanks for pointing out this error – it has been corrected by removing step 1.1.7.

3. Machine-learning related steps: steps of 1.3 describe a process of dataset augmentation. Additional dataset augmentations are described within 3.2. On the other hand, other parts of the machine-learning process are not adequately described. For example, the note of step 3.3.4 mentions "experimentation is needed for each dataset to find the optimal hyperparameters": this is a broader challenge and a focus of relevant research. While it might be impossible to provide an "optimal" solution, authors could suggest some approach (or specific configuration), which would be more in line with a protocol description. Step 1.4.7 mentions "take the best-performing … model": what is the best-performing? This might be clear to someone familiar with machine-learning (who understands that this is referring to validation accuracy or validation loss), but it might not be clear to someone who is not familiar and is using the paper and described protocol to implement the proposed method/system.

Step 3.3.4. (now step 3.3.2.) has been updated in multiple ways. More details have been added about what parameters exactly should be changed in the architecture definition file (if the reader wants to change them). More importantly, the note that mentions experimentation with the hyperparameters has been changed to reflect the fact that the included architecture definition file already contains a possible hyperparameter configuration that the reader can use without modifying the hyperparameters themselves. It is also now stressed that this step is optional. Since the possible hyperparameter values are already defined in the file and adding more details about the process of trying to find optimal hyperparameters would make this step very long, we did not go into further details on this topic. Steps 1.4.3. and 2.3.1. have been similarly updated.

As for step 1.4.7. (now step 1.4.5.) – this is true, and the previous step description could have confused some readers. This is why we have added a long note to this step that details how the best-performing model iteration can be determined in the

NVIDIA DIGITS software, along with an optional step that might help with overfitting. Steps 3.3.4. to 3.3.7. have been similarly updated.

Overall, the protocol described in this work follows these steps: (a) dataset and ground-truth collection, (b) dataset curation and augmentation, and (c) training of the recognition/segmentation models. Most of the steps are related to dataset augmentation and installation of various software components. As a result, the target audience as well as the desired outcome of the protocol is not clear.

As mentioned in our first reply, the installation steps were removed and the target audience are both machine learning experts and non-experts (more on this above). As for the desired outcome of the protocol – the purpose is to publicly document the methods that have led to promising results in the food image recognition field. With these instructions, other researchers (both those with machine learning expertise as well as nutrition experts who are looking to apply this approach to their own research) in the field can either take the exact approach and apply it to their own food image dataset or gather ideas from specific steps of the protocol and apply them to their own existing deep learning approach.

Thank you for your feedback!

Reviewer #2:
Manuscript Summary:
This article deals with an interesting topic image processing by the usage of deep neural networks, called 'NutriNet' with a specific application on food image classification for dietary assessment. Today, Deep neural network is considered as one of the most important topics in computer science. It is used in many studies by researchers and authors in the field of machine learning because it has achieved good results in classification and recognition.

Major Concerns:
None

Minor Concerns:
Suggestions which would improve the quality of the article but are not essential for publication:

1. Starting from the introduction authors may provide the reader with a clear picture of why automatic dietary assessment is necessary nowadays. They can discuss from health/ medical or any other point of view.

A more in-depth explanation of the usefulness of automating dietary assessment has been added to the introduction, including some applications (lines 46-49 and 52-55).

2. I suggest to add the following reference to the paper.

Hafiz, Rubaiya, et al. "Image-based soft drink type classification and dietary assessment system using deep convolutional neural network with transfer learning." Journal of King Saud University-Computer and Information Sciences (2020).

The suggested reference has been added to the paper (reference 31, cited in line 173).

Thank you for your feedback!

Reviewer #3:

Manuscript Summary:
This paper presents some deep neural networks techniques for image-based dietary assessment. This paper is well written. However, the data are newly collected but the presented techniques are not new. This paper tends to focus more on the applications instead of new technique. The novelty of this paper is fairly acceptable. I will suggest to accept this paper for publication in JoVE after the authors has successfully addressed the listed comments as below.

Major Concerns:
1. The authors should include some comparative tables of prior works considering different parameters.

NutriNet was mainly tested on a self-collected/self-acquired dataset (which includes the smaller real-world image dataset), and the fake-food image recognition solution was tested on the fake-food buffet (FFB) dataset, provided by Tamara Bucher from the University of Newcastle, Australia. Due to legal reasons, we cannot share either of the datasets, which means there are no other results on these two datasets that we can compare our results to. We could offer comparisons to other works on other datasets, but that comparison would not be fair, since the accuracy results are highly dependent on the size, quality and class distribution of the dataset, as well as the number of food classes present. NutriNet was also tested on a publicly available dataset (University of Milano-Bicocca 2016 – UNIMIB2016) and the comparison to the authors' baseline result is given in lines 497-500.

As for the ResNet-based solution for food image segmentation, which was tested on the Food Recognition Challenge benchmark dataset – we have included a table (Table 1) comparing our accuracy result to the results of the other top-4 participants.

2. Experimental results are not clear. More scientific reasoning should be added in the experimental results' explanation. What are the parameters used in the proposed system and how their values are set?

The Representative Results section of the paper has been significantly expanded to address this. For each of the three solutions (NutriNet food image recognition, FCN-8s food image segmentation and HTC ResNet-101 food image segmentation), the parameters have been described and their values given, as well as the reasoning behind their values. Additionally, the results and measures used to determine them have also been elaborated on. Lines 468-502 now contain a more in-depth description of the NutriNet food image recognition solution's parameters and results, lines 504-527 of the FCN-8s food image segmentation solution, and lines 529-566 of the HTC ResNet-101 food image segmentation solution.

3. The authors should provide some details (e.g. formula, algorithm, etc.) on the presented techniques. The presented protocol are impressive but this make this paper like a handbook if excluded the techniques' explanations and details.

Apart from the Representative Results and the Protocol sections, the Introduction section has also been significantly expanded to elaborate further on the presented techniques and approaches used. In particular, further details about the NutriNet architecture have been added, additional description of fully convolutional networks and the fake-food dataset, and the Hybrid Task Cascade has also been expanded upon. These additions are located in lines 107-145. Some formulas for accuracy measures have been added to the Representative Results section (lines 519 and 558).

Apart from that, Figure 1 already contains a complete visual representation of the NutriNet architecture, and the entire definition is included as a supplemental file to the paper ('nutrinet.prototxt'). For the FCN-8s solution, the FCN architecture was taken from the FCN paper's GitHub page, and the definition is linked in the paper (line 371). For the HTC ResNet-101 solution, the definition is also included as a supplemental file ('htc_resnet-101.py'). All the architectures' definitions are therefore either attached to or linked in the paper, so we do not think it would be beneficial to repeat them in the manuscript text as algorithms, as that would make the paper very long. Other algorithms used, such as for data augmentation, are also now included as supplemental files ('frc_augmentation.py' and 'nutrinet_augmentation.py') and described in the protocol text.

Minor Concerns:
1. Some important recent references are missing in the fields. The authors should consider more recent research done in the field of their study (especially in the year 2020 onwards).

7 recent references from the food image recognition research field, published in the last year, have been added to the paper (references 29, 31-35 and 42, described in lines 169-183 and 206-209).

Thank you for your feedback!

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Supplemental Coding Files

simon_mezgec_supplemental_files_revision1.zip