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APPLYING MACHINE LEARNING TO IDENTIFY COUNTERFEIT FOODS

Abstract: Currently, the shelves of shops and supermarkets are filled with food that people consume daily, with many products coming from abroad. However, are all these products useful for the human body, and do they meet the standards? In this article, we will talk about how to identify low-quality products using modern machine learning. Recognition and classification of images and text based on machine learning can be a key technology in the fight against low-quality food. Automatic image and text recognition and classification of product information enable end customers to identify counterfeit products accurately and quickly by comparing them to trained templates. However, it is clear that this does not apply to all food processing enterprises. In food production, low-quality and non-standard products are used to reduce the cost of the product. Manufacturers can change their products by replacing higher quality products with lower quality ones. They may use confusing terms on the label to mislead you. When buying and serving counterfeit products, consumers suffer in different ways. First, they may not be getting the nutrients they need, adulterated foods may not be safe for their health, and may also be an economic loss for consumers. We evaluate the technical feasibility of the components of this food fraud detection architecture using a real-world scenario, including machine learning models to distinguish multiple products from each other. It allows you to control the circulation of food products at the state level, thereby protecting the end consumer from purchasing low-quality and potentially dangerous goods. In this article, we used the MobileNetV2 model and multiclass classification and evaluated the model we received from different angles.

Keywords: convolution neural network, classification, counterfeit foods, image, and text recognition, MobileNetV2.

Introduction

Food is made from plant or animal materials that enter the body in raw, processed, or semi-processed forms in order to support a variety of biochemical and physiological activities. In most cases, these products are spoiled or adulterated foods that harm the health of consumers. It includes false or misleading product claims for financial gain and intentional substitution, addition, adulteration, or misrepresentation of food, food ingredients, or food packaging. A specific sort of fraud occurs when actual ingredients are removed, replaced, or fake compounds are added without the buyer's awareness in order to give the seller a financial advantage. Sometimes these nutrients in many of these outlets may have been prepared using quality ingredients to appeal to and satisfy the palate, rather than providing a complete nutritious meal. These consumers' health has severely worsened as a result. Researchers, the government, and regulatory authorities have focused their attention on the quality and safety of food, as well as the variables that may affect them, as important growing areas within the food supply chain. Among these various newly developing scientific fields is the adulteration of food. The term "adulteration" can be interpreted in a variety of ways, including by mixing or substituting inferior substances for those that are superior to the adulterants or by removing some important components from a particular food product [1]. Any harmful or dangerous ingredients that could make the food harmful to your health are also included. Examples include adding water to milk, animal carcasses to meat items other than those from the animal intended for consumption, or grain goods with stones, gravel, or animal hairs. Customers are always either at least victims of being cheated or even suffer from disease as a result of adulteration of food stuffs, and death is the worst, so knowing the common types of foods to be adulterated, the common adulterants, and the health implications of the different adulterants is very important to the consumer. We realized that the consumption of such products is evil [2]. We all need to avoid this. Every year, April 7th is celebrated as World Health Day around the world, and according to reports, WHO aims to raise general awareness of food fraud, motivate, and inspire everyone to eat healthy and balanced. In this article, we will explore how modern machine learning can prevent food adulteration. We must first appropriately categorize the data using images of foods and dishes. Thus, when we take a product, we will know what the probability is that this product will meet the standards. One of the researchers in this field, i.e., food and nutrition researcher Misgana Banti, studied this topic and wrote an article titled "Food Adulteration and Some Detection Techniques, Review"[3]. But in this article, he only theoretically showed the detection methods and what kind of disease a person will have if he uses such products. For example, a mixture of water and milk, etc. And we'll show how accurately our machine learning models classify foods to protect human health.

Image recognition

In order to recognize images and texts in our project, we will need Python libraries. Of these, a library for recognition like TensorFlow is perfect for us. The Google Brain created new library for Python, this is Tensorflow. TensorFlow will enable the use of algorithms and models for deep learning. The ego can be used for recognition, to classify images, and for word processing. A "graph" is the term for the collection of all the processing nodes that make up the sophisticated framework TensorFlow. Each node in the graph represents a different mathematical operation [4].

Keras uses TensorFlow features. Keras was designed with convenience and modularity as guiding principles. In terms of sometimes complex features in TensorFlow being maximally simplified in Keras, it is configured to work with Python without modification. This work uses Google's Tensorflow framework and the MobileNetV2 convolutional network model for food recognition. The experiment was carried out using an already assembled set of images; the number of images is 10100. ResNet, CNN, and MobileNetV2 models were tested for food recognition. The highest transfer learning accuracy was achieved using the MobileNet model and was 42.71%. The purpose of this work is to create a food recognition system using the MobileNetV2 neural network.

MobileNetV2 is the network with the deepest convolution. These applications require comparable recognition accuracy in timely computations. MobileNetV2, this model uses the rectified linear modulus activation function and defines convolution constructions. The main key points in it are: inverted residuals and linear bottlenecks. The first one is depth convolution, it performs filtering by applying a convolutional filter. The second is a 1×1 convolution, called

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point convolution, and creates new features by computing linear combinations between channels. MobileNetV2 contains a convolutional layer with 32 filters, followed by 19 levels of residual bottlenecks. The ReLU activation function is used in this work. The network is implemented using the Tensorflow model library.

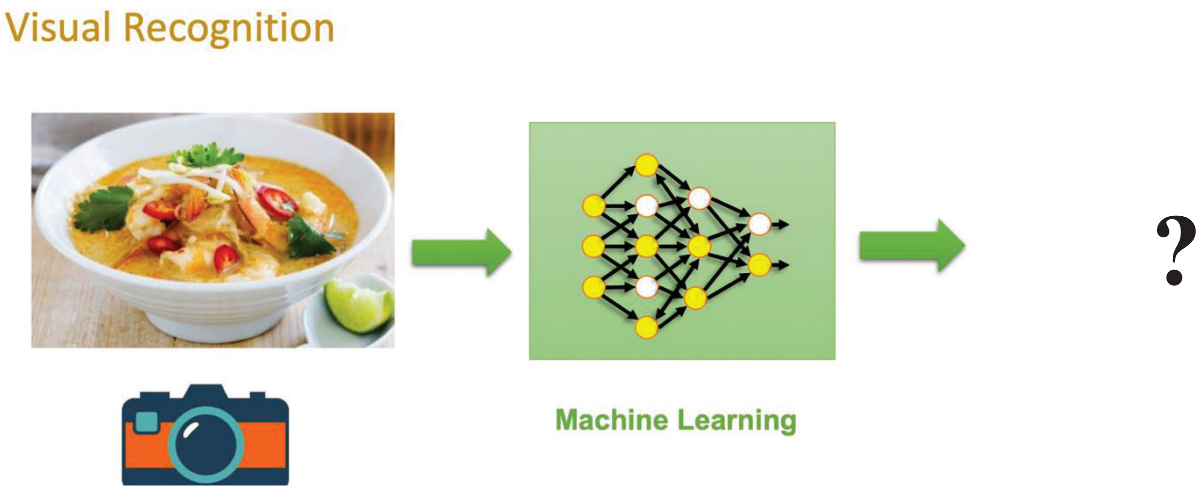

Figure 1. Image Recognition Process

The image recognition process looks simple, but it really isn't. After receiving an image using a machine image, you need to extract from it all the features that will help with recognition. After that, we will need to choose a classification algorithm. Train the model and, if necessary, select several algorithms and use the assembly of algorithms to find the overall accuracy. There is a case when our data is insufficient to obtain high recognition accuracy. Then you need to supplement the data and once again train the resulting model with us.

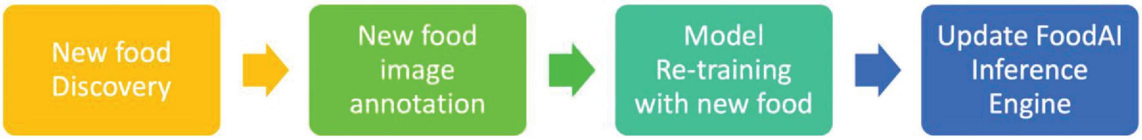

Figure 2. Retraining process with new data

Extract function

The neural network extracts features in order to recognize and classify images. Characteristics are the data components that the neural network will transmit and which are of the greatest interest. If you accurately consider these characteristics, such as points and lines, you can also note pixels in the image; they are used to find dependencies. Feature extraction is the extraction of the desired elements from the input image; they are used for analysis. Many images have notes and features; they help the neural network find the details it needs [5].

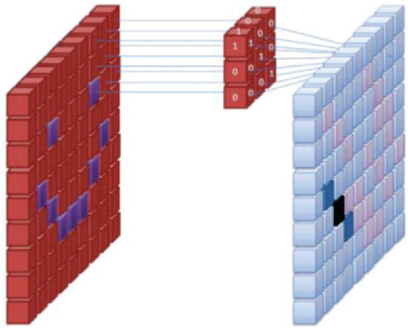

Figure 3. Feature extraction using filters

The first layer of the neural network receives all image pixels. Once all the input data has been entered into the network, the image is subjected to a series of filters that help the network capture the individual components of the image. This feature extraction process produces "feature maps". This process of removing features from an image is done with a "convolution layer", and the convolution simply creates a representation of a portion of the image. Convolutional neural networks, a category of neural networks often used for image classification and recognition, get their name from this idea of convolution. Imagine looking at an image through a light in a dark place to get a clear idea of how object mapping works. You can reveal the details of an image by aiming a beam at it. In this metaphor, the filter represents light, and the network uses it to create an image. Just as the width of your light beam affects how much of an image you can see at once, neural networks have a parameter called filter size. How many pixels are checked at the same time depends on the size. The filter looks for a 3 × 3 pixel region since the CNN filter's overall size is 3 [6].

The values that constitute an image are sent via an activation function or activation layer once the feature map of the picture has been produced. Since the pictures themselves aren't linear, the function takes these values, which are linear because of the convolution layer, and makes them more non-linear.

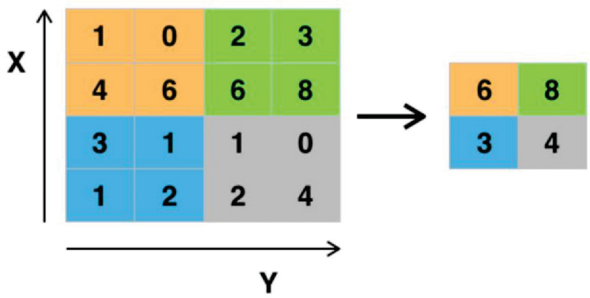

Figure 4. Example Merging Layers

Work algorithm

The steps listed below can be used to implement this model:

1. Using a digital source image to train the program (food image).
2. For image processing, matplotlib and open resume are used to extract source program features.
3. A target is used to test the model. (soup, juice, coffee).
4. The traits of the source and the target are similar.

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5. Then we determine the probability of matching features.

6. If more than 75% match, display a label indicating that this product does not meet the requirements, or display a label indicating that this product is eligible.

The following library is opencv, which supports multiple high level programming languages like python and is an open-source library used in CV for image processing. Specifically, here we are importing opencv2, which has a Python bindings library designed to solve CV problems. All OpenCV array structures are converted to Numpy arrays, and images are converted using this package. This makes it easy to integrate with libraries that use Numpy, such as SciPy and Matplotlib. A tool for plotting is called Matplotlib. It can create 2D plots in various environments. The primary function of matplotlib is data exploration and well-defined conclusion-making utilizing precise graph models. We use the pyplot set of object-style features in this article. The pyplot functions each perform a certain transformation on an image or shape, such as creating a figure and plotting an area on the figure, drawing some lines in the plot area, decorating a plot with markers, etc. Here, we employ Pyplot to create line-matching graphs that compare aspects of the various photos [7].

Types of counterfeit foods

In order to discuss food falsification and its methods, it is necessary to consider several prerequisites that must be met to determine whether food has been adulterated or not. The following provides a summary of these points.

1) A component is introduced that lowers the food's quality or renders it dangerous.

2) Whole or several components are substituted with less expensive or inferior materials.

3) Food is largely or entirely exported, which lowers the quality of the food.

4) Dangerous drugs have been used to make food presentable or to improve its appearance. Its hue is altered.

5) Everything that subtracts from or devalues food quality gets added to it.

Food adulteration can take four main forms. Intentional adulteration is when chemicals that are similar to a food's components are added to it to make it heavier and more profitable. As an illustration, consider combining polluted water, pebbles, stones, marble, sand, dirt, and other materials. Accidental adulteration: negligence in food handling might lead to accidental adulteration. For example, pesticide residues in cereals, larval development, rat droppings, etc. Adulterating food with metallic substances like lead or mercury is known as metal adulteration. This may happen by mistake or even with intent. Packaging Hazards: The packaging materials in which food is packaged can also interfere with and mix with food constituents, resulting in packaging hazards [8].

Food adulteration methods

The following are several types of food adulteration:

1) Blending: Blending food particles with sand, dust, clay, dirt, and pebbles.

2) Substitution: Some nutritious components are swapped out with less expensive, lower-quality alternatives, changing the food's nutritional value and perhaps posing a health risk.

3) Using decomposing foods: This technique entails combining unhealthy meals with decaying ones. Food that even conceals flaws or subpar qualities is deemed adulterated. Additionally, the purposeful blending of nutritious food with food of dubious quality results in the falsification of the finished product.

4) Adding Toxic Chemicals: Another method of food adulteration is to combine food with harmful substances in an effort to boost sales and profits. Adding color, dyes, or dangerous unauthorized preservatives, for instance.

5) Misbranding: Modifying the manufacturing and expiration dates, ingredient listings, or using deceptive ingredient derivatives, etc.

6) Artificial Ripening: Chemically accelerating the ripening of fruits and vegetables is another form of food adulteration. To fulfill the need for commercial supply, mango, for instance, is ripened using carbide [9].

Consequences of food adulteration on our health

Our health is significantly impacted by food adulteration. Long-term ingestion of this kind of food is extremely detrimental to the body, regardless of deception. Consuming these foods makes the body more poisonous. Falsified food loses nutritional value with time, rendering it unfit for human consumption. Chemical adulterations and dyes frequently prove lethal because they are both carcinogens and health risks. Some fabrications can also negatively impact our interior organs, which can result in heart, kidney, liver, and many other organ malfunctions. We will now forecast fake goods using the data we have collected [10].

Training a machine learning model

Our data is from images such as: pork_chop, bread_pudding, club_sandwich, french_fries, beef_tartare, creme_brulee, hummus, clam_chowder, caprese_salad, foie_gras. The amount of data we used in our models is 10100 and we used data from 101 classes. In our counterfeit food detection model, a multi-class classification was made because we divide the image dataset weight into several classes.

```
image_df['Label'].value_counts()
```

```
pork_chop        100
bread_pudding    100
club_sandwich    100
french_fries     100
beef_tartare     100
                ... 
creme_brulee     100
hummus           100
clam_chowder     100
caprese_salad    100
foie_gras        100
Name: Label, Length: 101, dtype: int64
```

Figure 5. Number of data and our classes

And we shared the data in order to train and test the model (data for training, validation and testing).

```
Found 5656 validated image filenames belonging to 101 classes.
Found 1414 validated image filenames belonging to 101 classes.
Found 3030 validated image filenames belonging to 101 classes.
```

Figure 6. Amount of data in each segment

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For image recognition or image classification, the neural network has feature recognition. Signs are elements that are of the greatest interest and are transmitted through the neural network. In the expected cases, signs are like lines and points that will analyze the presence of patterns. Feature recognition is the process of assimilating the features of an input image so that they can be evaluated. Many detection cases or metadata that trigger neural networks cause temporary symptoms.

With the help of machine learning, we will extract features from the image in order to distinguish them from each other. The image was set to 28 × 28 pixels in 256 shades of color.

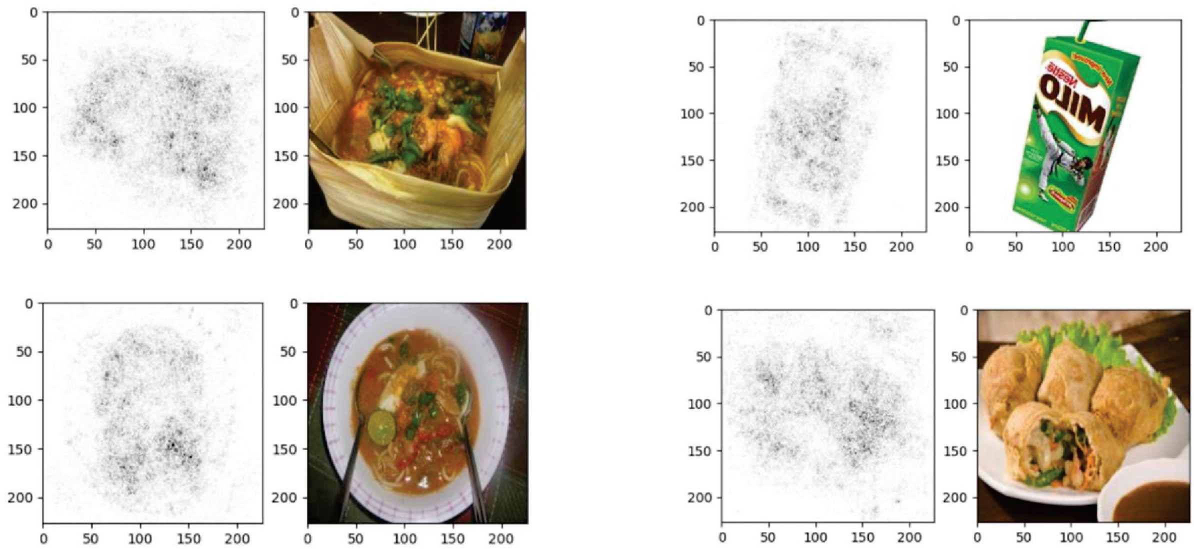

Figure 7. Here are some steps in food recognition

Now consider the accuracy of the obtained models. We have to view at least a few thousand images, familiarize the device with all the possible required features, and fully train this model to get an accuracy of 1, so this volumetric data can be processed and analyzed with machine learning and opencv in a more efficient way. In order to find the accuracy, we need the error matrix. After data purification, preprocessing, and processing, the first thing we do is input newly acquired data into an excellent model, which naturally produces probabilities as its output. Better effectiveness and performance are exactly what we seek. The confusion Matrix now becomes clear in this context. A performance indicator for machine learning classification is the confusion matrix [11].

We categorize actual values as true or false and anticipated values as positive or negative. Confusion matrices show counts between expected and observed values. The output “TN” stands for “True Negative” and displays the total number of cases that were correctly identified as negative. Similarly, “TP” stands for “True Positive” and denotes the quantity of correctly identified positive cases. A false positive is defined as the number of real negative cases that were mistakenly categorized as positive, while a false negative is defined as the number of real positive examples that were mistakenly classified as negative. Accuracy is one of the most often used measures in classification.

$$accuracy = \frac{TN + TP}{TN + FP + FN + TP} \tag{1}$$

$$recall \ = \frac{TP}{FN + TP} \tag{2}$$

$$precision \ = \frac{TP}{FP + TP} \tag{3}$$

All these formulas (1), (2), and (3) are used as the main indicators of the model. With their help, we estimated how accurately our model predicts counterfeit products that will spoil the human body. Next, we showed the accuracy of the model and other indicators of our model [9].

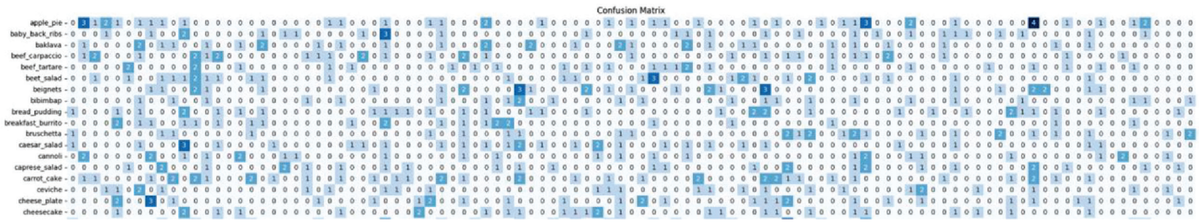

Figure 8. Confusion matrix for our product adulteration models

```
Epoch 1/100
177/177 [==============================] - 72s 401ms/step - loss: 1.4190 - accuracy: 0.6243 - val_loss: 2.5008 - va
l_accuracy: 0.4059
Epoch 2/100
177/177 [==============================] - 76s 427ms/step - loss: 1.0923 - accuracy: 0.7056 - val_loss: 2.4580 - va
l_accuracy: 0.4243
Epoch 3/100
177/177 [==============================] - 77s 438ms/step - loss: 0.8376 - accuracy: 0.7707 - val_loss: 2.6106 - va
l_accuracy: 0.4024
Epoch 4/100
177/177 [==============================] - 78s 442ms/step - loss: 0.6321 - accuracy: 0.8373 - val_loss: 2.7404 - va
l_accuracy: 0.3960
Epoch 5/100
177/177 [==============================] - 79s 446ms/step - loss: 0.4582 - accuracy: 0.8913 - val_loss: 2.7505 - va
l_accuracy: 0.4144
```

Figure 9. Training our model

We trained our models and got accuracy. The obtained accuracy is shown in the 10th image. Next, we test the model in a test set. And the accuracy obtained in it is 42.71%. If the resulting accuracy is small, then we need to supplement our data in order to get higher accuracy. In addition to accuracy, the model estimation also uses the area under the ROC curve for multiclass classification problems. The AUC ROC (the area under the ROC curve) is often used to assess the quality of the ordering by the algorithm of objects of several classes. It is clear that this value lies in the segment [0, 1]. The ideal corresponds to the ROC curve passing through the point (0, 1), the area under it is 1. The worst is the ROC curve passing through the point (1, 0); the area under it is 0 [12]. Random - something similar to the diagonal of a square; the area is approximately equal to 0.5. In our cases, the average value of the AUC ROC is 4.2. You can mail it easily and simply through the libraries from sklearn.metrics import roc_auc_score. Currently, due to the lack of the necessary data set, the accuracy of the model is not enough. At a later stage, with the improvement of higher resolution cameras that can capture microscopic images of products, machine learning can be applied to a larger dataset, and predictions can be made with greater accuracy, which is the most important thing for me. Consequently, consumers can buy safe and authentic fruits and vegetables [13]. All they have to do is look over the fruits and vegetables they are about to buy. See its adulteration percentage and shop accordingly. This can lead to a change in the health of society and reduce the number of premature deaths and fatal diseases due to genuine food [14]. Authentication of products will critically depend on the establishment of databases and their characterization of data containing comprehensive and standardized information on the origin of foodstuffs, including species/subspecies, production methods and other important information and methods of obtaining. Most studies to date are exploratory or selective-classifying in nature - they analyze preliminary data and show that the data can be divided into classes [15].

Conclusion

This article, "Applying machine learning to identify counterfeit foods," based on open source digital imaging and computer vision technology, can provide a permanent solution to the acute problem of adulteration of fruits and vegetables through an in-depth study of the necessary data sets and experiments and save consumers from an unnecessary consumption of toxic impurities, which will lead to many diseases and premature death. The results displayed by this model will be more accurate as it is designed with the latest "opencv2" technology and modern tools and libraries such as "numpy, pyplot,tensorflow,keras,mobilenetv2". As mentioned above, this in-app model will be helpful to every consumer and dealer in their daily routine of checking the items they buy. This article is also a valuable source of information for scientists who would like to become familiar with the various analytical and technical technologies used to authenticate products. The ability to work with multiple falsification methods is essential for food authentication research, as they provide more descriptors and signs of falsification, thus facilitating better classification. Analytical chemists, IT specialists, and all mankind, based on their knowledge of methodology, lead the research and development of technologies for food authentication. However, food authentication is the most important interdisciplinary field, which includes instrumentation, biology, computer science, mathematics and statistics, agriculture, and food technology, and is important for all people.

References

1. AL-Mamun, M., Chowdhury, T., Biswas, B., & Absar, N. (2018). Food Poisoning and Intoxication: A Global Leading Concern for Human Health. *Food Safety and Preservation*, 307–352. https://doi.org/10.1016/b978-0-12-814956-0.00011-1
2. Zeng, G. (2017, October). Fruit and vegetables classification system using image saliency and convolutional neural network. In *2017 IEEE 3rd Information Technology and Mechatronics Engineering Conference (ITOEC)* (pp. 613-617). IEEE. https://doi.org/10.1109/ITOEC.2017.8122370
3. Banti, M. (2020). Food adulteration and some methods of detection, review. *International Journal of Nutrition and Food Sciences*, *9*(3), 86–94.https://doi.org/10.11648/j.ijnfs.20200903.13
4. Zenkov. D. et al. (2019, January 1). *DSpace at Saint Petersburg State University: Machine learning methods in the problem of image recognition*. DSpace at Saint Petersburg State University: Machine Learning Methods in the Problem of Image Recognition. http://hdl.handle.net/11701/25909
5. Atienza, R. (2020). *Advanced Deep Learning with TensorFlow 2 and Keras* (2nd ed.). Packt Publishing. Retrieved from https://www.perlego.com/book/1388452/advanced-deep-learning-with-tensorflow-2-and-keras-apply-dl-gans-vaes-deep-rl-unsupervised-learning-object-detection-and-segmentation-and-more-2nd-edition-pdf (Original work published 2020)
6. Ganegedara, T. (2018). *Natural Language Processing with TensorFlow* (1st ed.). Retrieved from https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwiKmYDNqcn-AhXrpYsKHUx8D94QFnoECA4QAQ&url=https%3A%2F%2Fpdfcoffee.com%2Fdownload%2Fnatural-language-processing-tensorflowpdf-4-pdf-free.html&usg=AOvVaw2qehScB8cUSrm4e8E_Ph9A

7. Wilson, J.N., & Ritter, G.X. (2000). *Handbook of computer vision algorithms in image algebra* (2nd ed.). CRC press. 145-153. https://doi.org/10.1201/9781420042382
8. Podstawka, E., Świątłowska, M., Borowiec, E., & Proniewicz, L.M. (2007). Food additives characterization by infrared, Raman, and surface-enhanced Raman spectroscopies. *Journal of Raman Spectroscopy: An International Journal for Original Work in all Aspects of Raman Spectroscopy, Including Higher Order Processes, and also Brillouin and Rayleigh Scattering*, *38*(3), 356-363. https://doi.org/10.1002/jrs.1653
9. Hemanth, D.J., & Smys, S. (Eds.). (2018). *Computational vision and bio inspired computing* (Vol. 28). Springer. https://doi.org/10.1007/978-3-319-71767-8
10. Aung, M.M., & Chang, Y.S. (2014). Traceability in a food supply chain: Safety and quality perspectives. *Food control*, *39*, 172-184. https://doi.org/10.1016/j.foodcont.2013.11.007
11. Olaf Ronneberger, Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. *Lecture Notes in Computer Science*, 9351, 234-241. https://doi.org/10.1007/978-3-319-24574-4_28
12. Uddin, S.M.K., Hossain, M.M., Chowdhury, Z.Z., & Johan, M.R. (2021). Detection and discrimination of seven highly consumed meat species simultaneously in food products using heptaplex PCR-RFLP assay. *Journal of Food Composition and Analysis*, *100*, 103938. https://doi.org/10.1016/j.jfca.2021.103938
13. Arcuri, E.F., El Sheikha, A.F., Rychlik, T., Piro-Métayer, I., & Montet, D. (2013). Determination of cheese origin by using 16S rDNA fingerprinting of bacteria communities by PCR–DGGE: Preliminary application to traditional Minas cheese. *Food Control*, *30*(1), 1-6. https://doi.org/10.1016/j.foodcont.2012.07.007
14. Ouyang, Q., Zhao, J., & Chen, Q. (2014). Instrumental intelligent test of food sensory quality as mimic of human panel test combining multiple cross-perception sensors and data fusion. *Analytica chimica acta*, *841*, 68-76. https://doi.org/10.1016/j.aca.2014.06.001
15. Zou, S., Chen, W., & Chen, H. (2020). Image classification model based on deep learning in internet of things. *Wireless Communications and Mobile Computing*, *2020*, 1-16. https://doi.org/10.1155/2020/6677907