Integration of biosensors and deep learning for assessing food quality

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November 18, 2022

Abstract

With the rapid expansion of food trade, there is a growing concern about health issues. As a result, consumer demand for high quality food is increasing and food quality analysis has become a very important and interesting area of research. The application of biosensors in food analysis is promising because specific biosensors can be used to easily access the nutritional composition inside food products, including macronutrients, trace elements and other bioactive substances. Deep learning includes many different types of artificial neural networks, and convolutional neural networks can be used to extract external features of food products from images, such as shape, size, color, etc. Deep neural networks are able to generate predictive models using different food properties. In this paper, we aim to show how to combine biosensors and deep learning to assess food quality. We first focus on the process of generating predictive models by deep neural networks and the datasets required to train the models. Secondly, we focus on how to use convolutional neural networks to extract external features of food products and representative research work on biosensors for food nutrient content analysis. Finally, the paper summarizes and looks at the challenges and possible solutions of the approach in the field of food quality assessment.

Introduction

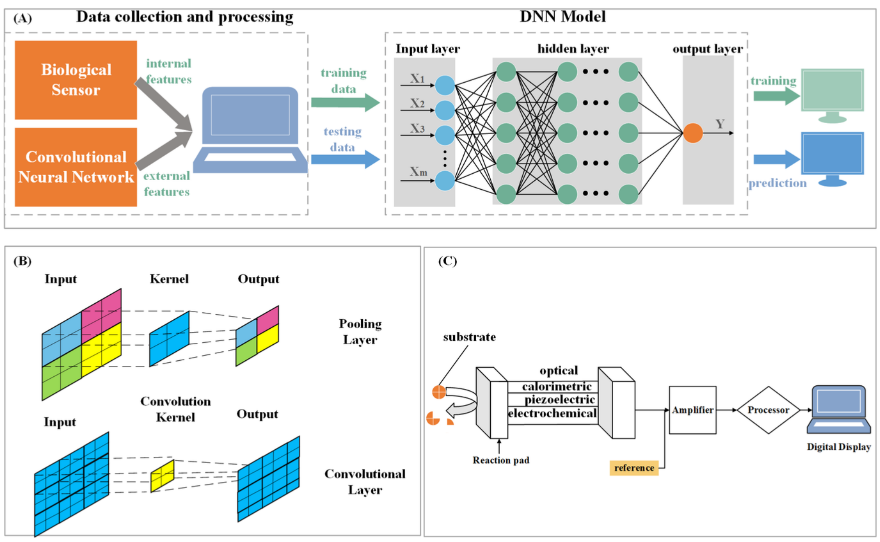
Food is closely related to human health and culture. Food-related research has always been a current research hotspot. With the rapid development of economy and society, people pay more attention to their own health problems. Food quality has received widespread attention as an important part of safeguarding human health. At the same time, the rapid growth of the food trade has made high-quality food the basis for success in a highly competitive market. Therefore, simple and effective food quality assessment technology can be effectively applied in food production, transportation, storage and other links. At present, food quality evaluation still relies heavily on manual inspection, which is cumbersome, laborious, and costly, resulting in subjective and inconsistent evaluation results. In order to ensure the quality inspection of food during production, transportation, and storage, and to meet demands for different quality food, researchers have proposed a variety of advanced strategies for food quality inspection, including artificial intelligence methods [1, 2, 3], infrared spectroscopy and biosensors [4, 5, 6, 7, 8]. However, a single biosensor can only extract the content of specific components in food, and cannot comprehensively evaluate food quality.

In recent years, artificial intelligence technology has been used in different fields [9, 10, 11, 12], using artificial neural network to accurately and quickly evaluate food quality. In addition to the advantage in detection speed, artificial neural network can automatically extract the intrinsic features of the target using its own network structure. It constructs stable feature combinations through a process of abstraction from low to high levels, which weakens the subjectivity of manual feature selection and can save a lot of time and workload. The generation of the predictive model is mainly dependent on data collection and algorithm determination.

In this method, food quality data is collected from convolutional neural networks and different types of biosensors. Instead of focusing on how feature extraction is performed inside the neural network, we only need to use the collected food quality data and food quality grade as the input and output of the model, respectively. This approach is complex, but it is also flexible. Although artificial intelligence technology can automatically and accurately evaluate food quality through training, the training process requires a large amount of food characteristic data. Therefore, in order to take into account the detection speed and the acquisition speed of food characteristic data, this paper proposes to combine artificial neural network and biosensor to evaluate food quality.

This article will show how to combine biosensors and deep learning to assess food quality. First, we focus on the training of prediction models and the required datasets. Secondly, we present representative research work on convolutional neural networks and biosensors for extracting food quality features. Finally, the paper summarizes and discusses the challenges and possible solutions of the approach in the field of food quality assessment.

Predictive model generation



The generation of predictive models relies heavily on data set collection and model determination. DNN is an end-to-end network. Its internal neural network layers can be divided into three categories: input layer, hidden layer and output layer. The input layer takes the characteristic parameters of the collected food as input. The training process of the DNN model mainly includes forward propagation and back propagation. The forward propagation algorithm is to use several weight coefficient matrices $\omega^i(i = 1, 2 \ldots n)$, bias vector b to perform a series of linear operations y^i,$y^i = \omega^i \times x^i + b^i$, At the same time, the activation function is used to complete the transformation from linear to nonlinear, the process is done in the hidden layer. After completing the forward propagation, the difference between the predicted output and the actual output can be used to generate the loss function$L\left(\theta\right)$, $L\left(\theta\right) = \frac{1}{n}\sum_{i=1}^{n}\left(y - \hat{y}\right)$. After the loss function is obtained, the weight w^i and the bias vector b^i are continuously updated through the gradient descent method. By repeating this process over and over, the model gets optimal weights and biases. Therefore, this process requires a large amount of data for the model to learn. As shown in Figure 1(A)

Figure 1 (A) Predictive model generation process (B) Convolutional and Pooling Layers (C) Schematic diagram of biosensor components

Using deep neural networks to predict food quality, we no longer pay attention to how the low-level features are transformed into high-level features. We only need to use a large amount of statistical real-time feedback data to train a mathematical model with a specific structure containing unknown parameters. This method takes into account both the detection speed and the comprehensiveness of the evaluation.

Collecting external data

The training of the predictive model requires the acquisition of a large amount of data, so the speed of data collection needs to be guaranteed. If the external quality characteristics of food are extracted in an artificial way, it will undoubtedly consume a lot of time. As a branch of deep learning, computer vision [13, 14, 15, 16, 17, 18, 19] has been widely used in food classification and feature extraction. For every food features are figured out for which the quality is either directly or inversely varied.

Computer vision technology is a branch of artificial intelligence that aims to eventually replace the human visual decision-making process with automated programs. Computer vision technology is a mechanism that artificially simulates the human thinking process. Through continuous learning, it can make accurate, fast and complex judgments. At present, the more mature solution in computer vision technology is CNN (convolutional neural network). The difference from ANN is that CNN introduces the operation of convolution. CNN are mainly composed of these types of layers: input layer, convolutional layer, pooling layer and fully connected layer. The core part is the convolution layer and the pooling layer. The function of the convolutional layer is to extract the information in the input image, which is called image features. These features are reflected by each pixel in the image in a combined or independent way, such as texture features and color features of the image. The function of the convolution layer is to perform convolution operations. The convolution operation is to perform the cross-correlation operation from left to right and from top to bottom through the convolution check of the matrix of each channel, and slide from the upper left corner to the lower right corner step by step. The sliding step size is a hyper parameter. It means that the corresponding positions are multiplied and then added, and finally the values of the three channels are also added together to obtain a value. The role of the pooling layer is to select the features extracted from the convolutional layer. The basic structure of the convolutional layer and the pooling layer is shown in Figure 1(B)

The convolutional neural network can not only improve the detection speed of acquiring the external features of food, but also realize automatic detection based on this technology. Therefore, convolutional neural network becomes a new solution for food external feature extraction

Collecting internal data

It is not comprehensive to evaluate the quality of food simply by using its external characteristics, so the nutrient content, microorganisms, and other substances inside the food also need to be produced as data sets. Biosensors are low cost and fast, and have been widely used for food composition testing. Biosensors are composed of two parts, the biological progenitor and the sensing element [20], the schematic diagram of its components is shown in Figure 1(C). The biological element is the receptor of the sensor, while the sensing element is the transducer that transmits the signal through thermal, electrical or optical reactions. When a specific bioelement reacts with a specific analyte, a physicochemical reaction occurs on the sensor surface, producing a visible output.

According to different detection components, various types of biosensors have appeared, including Glucose [21], Vitamin C [22], Tyramine [23, 24, 25], Bisphenol A [26, 27], L-glutamic acid [28], Aflatoxin [29], etc. Reasonable selection of different types of biosensors can not only obtain the content of macro elements in food, but also the content of trace elements and other biologically active substances.

The biosensor detection method realizes the automatic detection of the internal components of food, greatly simplifies the tedious steps of manual detection, and improves the detection efficiency. Therefore, biosensors have broad application prospects in rapidly generating training datasets required for predictive models

Discussion

As shown above, this method combining biosensors and deep learning has many advantages such as high efficiency, low cost, and automation, and is expected to be applied in the field of food quality assessment. However, there are many challenges in these applications. First, in the long run, it is necessary to develop effective sensing systems that are cheap, reliable, and fully functional. Since different foods contain different nutrients, how to choose A suitable biosensor to construct a sensing system is still a problem, which needs to be selected according to the needs of users, or according to the general formula for food quality evaluation. Second, the generation of predictive models requires a large amount of training data. Different models may need to be trained for different types of food. Therefore, the amount of data is huge, which requires specific hardware for data processing, model training and evaluation. Therefore, combining technologies such as cloud computing, 5G networks can effectively address the challenges.

Future prospects

Deep learning and biosensors have exciting potential in the field of food quality inspection. (a).On the one hand, biosensors can quickly acquire internal features of food due to their unique sensing capabilities, and convolutional neural networks can quickly acquire external features of food, which can provide sufficient data for the training of predictive models. On the other hand, deep learning can automatically extract features of the target through its own network structure and transform low-level features into high-level features, avoiding the subjectivity of manual feature selection and saving a lot of time and workload. (b).In future research, it is expected to produce different food quality assessment systems based on this method. Food quality can be effectively and efficiently tested during the production, transportation, storage and sale of food. (c).Due to the embeddability of computer vision technology, by developing corresponding mobile applications and embedding convolutional neural networks into mobile applications, consumers can simply and accurately judge the quality of food to meet their own needs.

Conclusion

This paper describes how biosensors and deep learning can be combined to assess food quality. By presenting representative work on convolutional neural networks and biosensors, the effectiveness and reliability of convolutional neural networks and biosensors in extracting food quality features are shown. Finally, the paper discusses the possible challenges of the method in assessing food quality and the future prospects of the development.

Conflict of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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