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장단기 기억 신경망 및 RF 에너지 소거능을 사용한 정확한 식품 품질 추정

도후중[1], 김동언[1], 정완영[1,*]
[1]부경대학교 전자공학과

Accurate Food Quality Estimation Using Long Short-Term Memory Neural Networks and RF Energy Scavenging

Huu-Dung Do[1], Dong-Eon Kim[1], Wan-Young Chung[1]
[1]Department of Electronic Engineering, Pukyong National University, Busan, 48513, South Korea

Abstract Estimating food quality based on the data from battery-free food monitoring systems is still a challenge due to its low accuracy and reliability. Recently, many deep learning (DL) models have been proposed to solve these problems and have shown exceptional promise. However, all the existing DL methods treat the food sensor data as separate data points and ignore temporal characteristics which lead to a complex network but limited recognition accuracy. In this study, for the first time, the sensor data gathered from a battery-less food monitoring system is treated as a time series sequence. Hence, we proposed a long short-term memory (LSTM) model for food quality classification. A set of the experiment is conducted with different sorts of food such as pork, chicken, and fish to obtain the food data set for training and testing. Some other classification models are also developed to compare the accuracy such as CNN, MLP, and SVM. Experimental results show that the proposed LSTM classifier achieves the best accuracy of above 99% on all three datasets. The food classification performance is investigated based on training accuracy and testing confusion matrix.

• Key Words – Food quality prediction, radio-frequency energy harvesting, air pressure sensor, Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Support Vector Machine (SVM), Multilayer Perceptron (MLP).

Ⅰ. INTRODUCTION

Food safety is becoming a top concern in the world because it is directly related to human health. According to World Health Organization statistics, about 550 million people are poisoned each year because of unsafe food consumption [1]. One of the leading causes of foodborne illnesses is the consumption of rotten and expired foods. Therefore, the need to develop a food quality monitoring system is essential.

In recent years, many studies have focused on developing battery-free food monitoring systems based on RFEH technology due to its benefits such as durability, low cost, and safety for stored food [2] - [5]. However, due to energy limitations, the RFEH system is designed with sensors with low energy consumption, such as gas sensors, air pressure, temperature, and humidity. Evaluating food quality based on these data remains a challenge. Deep learning models have been proposed in the study [3] to classify food quality based on TVOCs data obtained during food preservation and show significant results. However, gas sensors' disadvantages of energy consumption make this system's feasibility not high. These studies also consider the input data as discrete points and ignore the temporal characteristics of food data lead to a complicated network but limited recognition accuracy.

Unlike these studies, we consider food monitoring data as a time sequence and propose an LSTM classifier network to classify and evaluate the food during storage. A battery-free food monitoring system based on RF energy harvesting technology is designed to collect training and testing data. Air pressure sensor is selected to collect data from food containers from overcoming the conventional systems' weaknesses using gas sensors [5]. A set of experiments are conducted with different sorts of food, including pork, chicken, and fish. Each type of food is stored for seven consecutive days under variable ambient temperature conditions. To evaluate and compare the proposed LSTM model's effectiveness, we also developed other popular classification models such as CNN, MLP, and SVM. The classification results show that the LSTM model achieved the highest accuracy on all three data sets. The classification models' performance is investigated based on training accuracy and testing confusion matrix.

The rest of the paper is organized as follows: the deep learning architectures and preparation of training data are described in section II. Experimental results and classification performance are presented in section III. Finally, section IV concludes this article.

II. SYSTEM DESIGN

2.1. Battery-free food monitoring system

A battery-less food surveillance system based on far-field RF energy harvesting technology is proposed to collect food data for the training process. The overview architecture of the system is depicted in Figure 1.

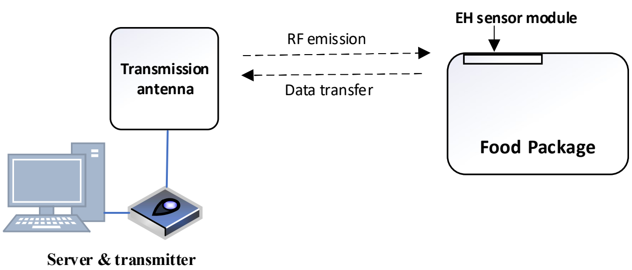


Fig.1 The conceptual model of the battery-free food monitoring system.

Firstly, the complete system incorporates a food storage package utilized to hold foods for tracking quality, such as pork, chicken, and fish. The self-powered sensor tag is attached beneath the top of the food package. The radiofrequency wave is radiated persistently by a transmitter placed at a certain distance from the food container. A profoundly accurate integrated sensor chip detects the information on air pressure and temperature measured inside the food package. At that point, these data are handled by the microcontroller and transmitted to the server through the backscatter protocol. Information about the air pressure and temperature inside the food storage packages is sent to the server every two minutes and continuously for seven days. The raw data is then preprocessed and labeled to build the training and testing datasets for supervised learning models.

2.2. The proposed LSTM model for food quality estimation.

Long Short-Term Memory (LSTM), an augmented model of the Recurrent Neural Network (RNN), plays a vital role in sequence data and natural language processing. Unlike feed-forward systems, RNNs include feedback loops and can extract information of the time series data. The LSTM model was born to overcome gradient vanishing and explosion problems during the training of conventional RNN networks [6]. Figure 2 shows the overall architecture of the proposed LSTM network for food classification. The proposed network includes three main layers: the input layer, hidden layers, and the output layer. The input class consists of an LSTM class with the dimension of the inner cells selected of 50. The dropping-out rate of the LSTM layer is adjusted to 40% for preventing the overfitting phenomenon. A fully connected with 100 nodes layer is added to convert the feature matrix in the previous layer into a vector containing the probabilities of the objects to be predicted. The output layer consists of 3 layers corresponding to three food states, and the Softmax is selected as the activation function for this layer. To evaluate the model's performance after each epoch, cross-entropy was chosen as a function loss function. The Adam algorithm is selected as the optimal method to update the weights of the network.

Table 1. The number of training and testing data

States	Number of samples					
	Training			Testing		
	Pork	Fish	Chicken	Pork	Fish	Chicken
Freshness	719	719	619	72	72	62
Warning	1280	1280	1179	128	128	118
Rotting	3041	3040	2842	304	304	284

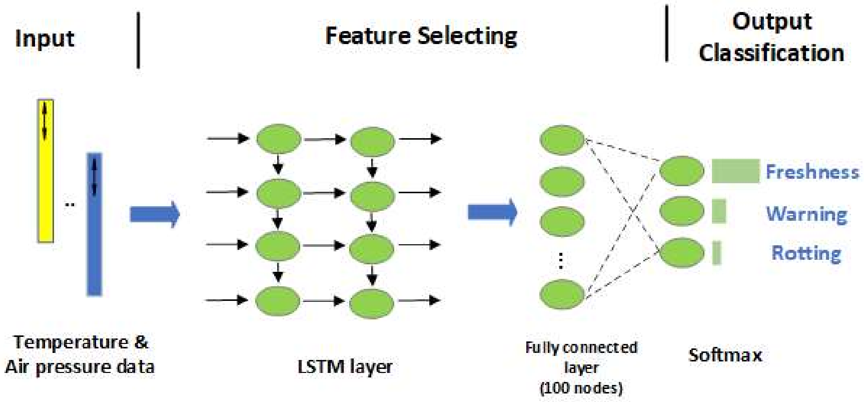


Fig.2 The proposed architecture of an LSTM model for food quality classification.

Ⅲ. EXPERIMENT RESULTS

3.1 Dataset preparation

The food dataset, including the air pressure and the air temperature, was treated as time-series data with a sampling rate of 2 min. In order to evaluate the classification performance correctly, the train set and test set data must be collected separately. Therefore, we conducted a few more experiments on each food to gather data for the test set. Table 1 describes the sample number of the training and test sets for each kind of food.

3.2 Food Classfication Results

The use of cross-validation techniques in classification problems helps limit overfitting when making predictions on test sets. This mechanism is also a strategy for optimizing hyperparameters for deep learning models. We use the 5-fold cross-validation to test all proposed models' performance, including LSTM, CNN, MLP, and SVM. The average accuracy of 5-folds is used to select the best architecture for each model. Finally, the entire trainset is used for training to avoid missing data. The early-stopping technique is implemented to choose the best performance weight set. All models were built, trained, and evaluated by using Python programming language and TensorFlow framework. Figure 3 depicts the LSTM classifier model's training and validation loss on the pork and chicken dataset. Each model was trained in 500 epochs. In general, the training results show that the number of samples in the food data set is sufficient for the training phase. The training and evaluation process is conducted similarly for the fish cases.

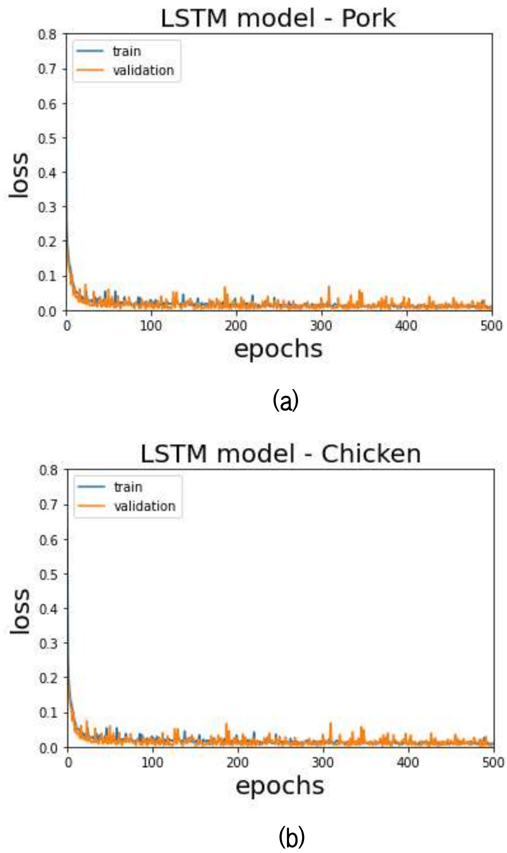
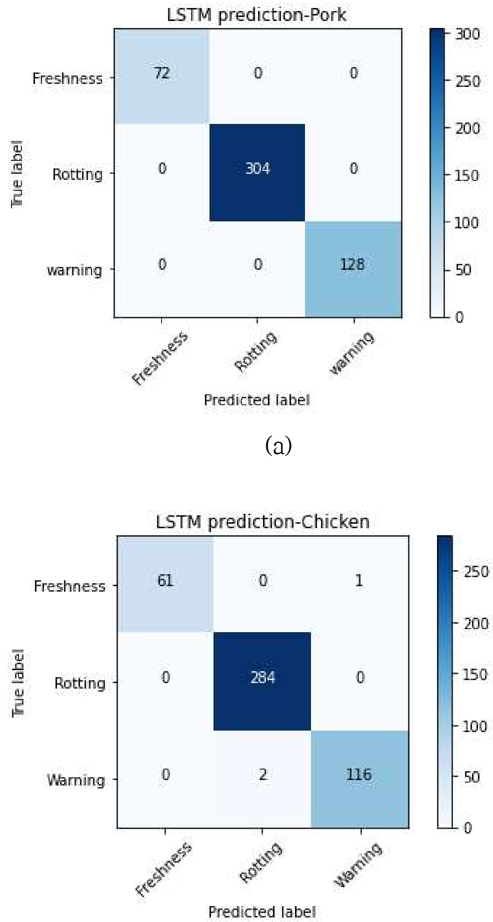


Fig.3 The training and validation loss of LSTM model: (a) pork and (b) chicken dataset.

Figure 4 presents the classification performance of the LSTM model on the pork and chicken test set in terms of confusion matrix. The result shows that the predicted pattern between the freshness-warning and warning-rotting are relatively easy to be confused. This is predictable since these are the food quality transitions and the pressure and temperature values at these points are quite similar.



(a)

(b)

Fig.4 The performance of LSTM classifier on (a) pork and (b) chicken dataset by confusion matrix.

Table 2. Accuracy comparison of different models

Model	Accuracy(%)		
	Pork	Fish	Chicken
MLP	98.61	99.36	99.54
CNN	98.21	97.89	99.49
SVM	97.60	96.23	96.55
LSTM	99.21	99.53	99.4

To demonstrate the model's feasibility, we investigate three more machine learning models, CNN, SVM and MLP. The results of the model comparison are shown in Table 2. From the obtained results, the LSTM model demonstrated superiority on both test and train sets. The ability to extract information from time-series data allowed this model to outperform the others which are popular in classification problems. Besides, the use of LSTM makes it possible to reduces the complexity of the model and the number of parameters.

IV. CONCLUSION

In this paper, we have developed an LSTM neural network that uses food data obtained from a batteryless sensor system to predict different food states. The model achieved the best accuracy of above 99% on all three food datasets. The results indicate that the proposed LSTM network architecture is well-suited to extract global temporal features in food monitoring data. Simultaneously, the performance of our proposed method has demonstrated the feasibility of a battery-free food monitoring system based on RF energy harvesting.

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