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Analysis of Odor Data Based on Mixed Neural Network of CNNs and LSTM Hybrid Model

Sang-Bum Kim[1], and Sang-Hyun Lee[2]

[1]*Prof., Department of Robotdrone Engineering, Honam University, Korea*
[2]*Prof., Department of Computer Engineering, Honam University, Korea*
2021115@honam.ac.kr[1], leesang64@honam.ac.kr[2]

Abstract

As modern society develops, the number of diseases caused by bad smells is increasing. As it can harm people's health, it is important to predict in advance the extent to which bad smells may occur, inform the public about this, and take preventive measures. In this paper, we propose a hybrid neural network structure of CNN and LSTM that can be used to detect or predict the occurrence of odors, which are most required in manufacturing or real life, using odor complex sensors. In addition, the proposed learning model uses a complex odor sensor to receive four types of data, including hydrogen sulfide, ammonia, benzene, and toluene, in real time, and applies this data to the inference model to detect and predict the odor state. The proposed model evaluated the prediction accuracy of the training model through performance indicators based on accuracy, and the evaluation results showed an average performance of more than 94%.

Keywords: *LSTM, Stink, Real Time Prediction, CNN, Data prediction*

1. INTRODUCTION

In the manufacturing industry, there is a high demand for artificial intelligence services that can detect and predict anomalies in real time [1]. In particular, in manufacturing sites that deal with chemical components or industrial sites that perform waste treatment and storage, on-site monitoring systems based on video information are being applied in real-time based on video information for odor management [2-3]. However, traditional monitoring systems do not predict the detection of anomalies, but rather detect them after they have already occurred. Mostly, this is because the existing system is not equipped with artificial intelligence-based prediction service technology. In addition, the development of artificial intelligence learning models is actively underway to provide predictive services such as odor detection [4]. In Korea, various studies are being conducted on odor generation through analysis of the cause of odor and machine learning [5-7]. In order to prevent the damage caused by diseases caused by odors and to improve public health, it is important to predict the levels at which odors may occur in advance and to inform people so that preventive measures can be taken.

In this paper, we propose a mixed neural network structure of CNN and LSTM to predict multiple time series data by fusing a linear (1D) convolutional neural network (CNN) [8] with a Long Short-term memory (LSTM) model for use in time series data analysis.

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Corresponding Author: leesnag64@honam.ac.kr
Tel: +82-62-940-5285, Fax: +82-62-940-5285
Associate Professor, Department of Computer Engineering, Honam University, Korea

In order to experiment with the proposed architecture, the data collection was carried out in a time series format in which an artificially odor occurs in an environment where an odor complex sensor is installed, and the data is collected from 120,000 Collected. The obtained datasets were used to assess the accuracy of the proposed neural networks and performance comparison models and to compare the results.

2. Design of CNN-LSTM hybrid model

In this paper, the proposed method to improve the prediction accuracy of the time series data obtained from the odor sensor is to design a CNN model with a structure that can consider multiple environmental data and a neural network model with a mixed structure in the form of adding an LSTM layer. The proposed CNN-LSTM hybrid model consists of an input layer, a CNN layer, an LSTM layer, and an output layer. Figure 1 is a structural diagram designed for a mixed neural network model of CNN and LSTM in which four types of time-series data such as hydrogen sulfide, ammonia, benzene, and toluene are inputted.

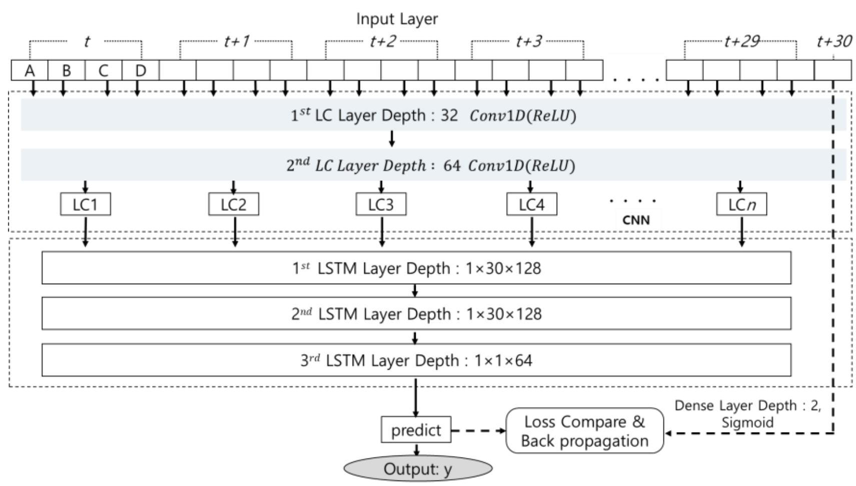

Figure 1. Structure of CNN-LSTM hybrid neural network

2.2. Data Set

For data collection, 120,000 data were collected and used by simulating a situation in which odors are artificially generated, such as in an environment where odor sensors are installed, in a time series format.

Odor-producing items include hydrogen sulfide (normal range (0.4 ± 0.3) ppm, abnormal range (40 ± 20) ppm), ammonia (normal range (9 ± 4) ppm, abnormal range (300 ± 100) ppm), benzene (normal range (0.05 ± 0.03) ppm, abnormal range (50 ± 20) ppm, toluene (normal range (12.36 ± 3) ppm, abnormal range (500 ± 200) ppm. Data items were selected and collected. The collected data consisted of 120 sets in 1 set, 600 normal data in 1 set, and 400 abnormal data in 1 set, for a total of 1,000 data sets. Table 1 and Figure 2, measures the loss rate according to the epoch, and the interval in which the loss rate was smaller, measured at 30 epochs, and then showed little change in size.

Table 1. Measure of loss rate according to epoch

Epoch	Loss	val_loss	Epoch	Loss	val_loss
Epoch 1	0.0599	0.0418	Epoch 8	0.0135	0.0021
Epoch 2	0.0442	0.0381	Epoch 9	0.0121	0.0023
Epoch 3	0.0421	0.0373	Epoch 10	0.0114	0.0023
Epoch 4	0.0393	0.0380	Epoch 11	0.0105	0.0011

Epoch 5	0.0330	0.0328	…		…
Epoch 6	0.0234	0.0119	Epoch 30	0.0078	5.0697e-04
Epoch 7	0.0160	0.0092	Epoch 31	0.0079	0.0016

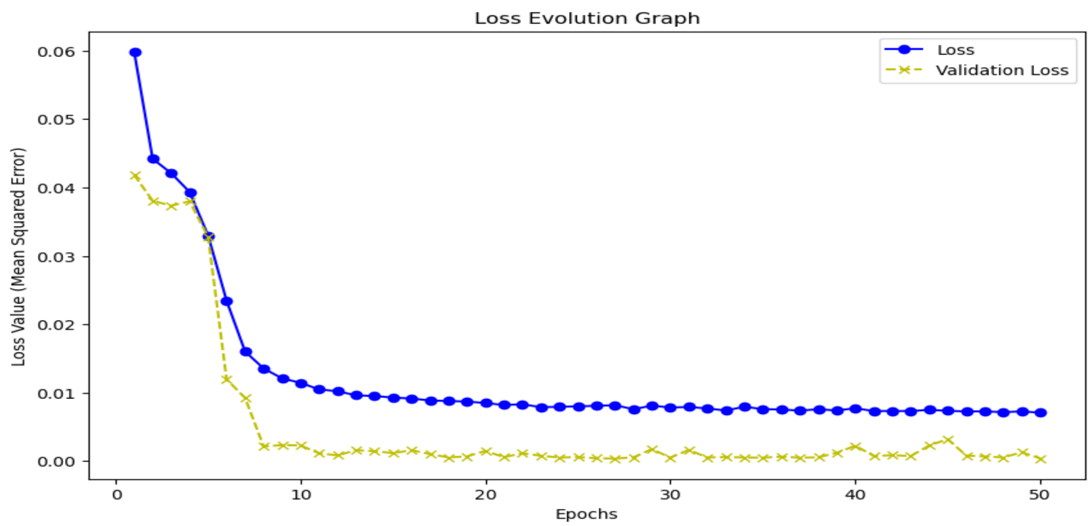

Figure 2. Measure of loss rate according to epoch related graphs

3. Implement

In this paper, the proposed method to improve the prediction accuracy of the time series data obtained from the odor sensor is to design a CNN model with a structure that can consider multiple environmental data and a neural network model.

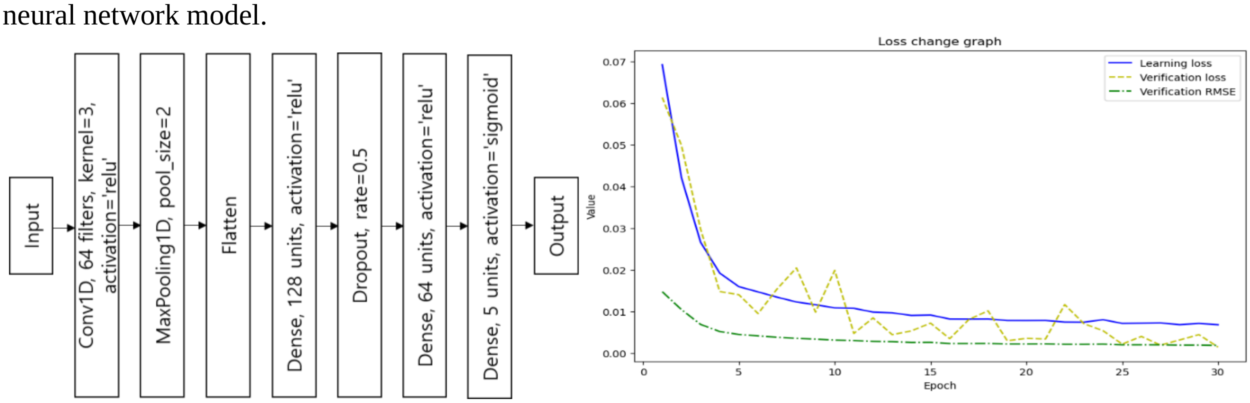

Figure 3. Structure of 1D CNN Model

Figure 3 shows the connection and structure of each layer to the CNN model. In the convolutional layer, 1D convolutional operations and pooling are performed, followed by a flatten layer, and then a fully connected layer. Dropout layers were used to prevent overfitting. Finally, in the output layer, a sigmoid activation function is applied to five neurons to perform multiclass classification. The code for each parameter used in the CNN model is as follows: compile (optimizer='adam', loss='binary_crossentropy', metrics=['mean_squared_error']). Here, Adam uses an optimizer to optimize the model, loss='binary_crossentropy' uses binary cross-entropy as a loss function for the binary classification problem, and 'mean_squared_error' uses mean square error as an indicator to evaluate the model's performance.

Figure 4 shows the structure of the sequential model, including the LSTM layer. The LSTM layer has 64 units, followed by a dropout layer, a dense layer, and an output layer with a sigmoid-enabled function.

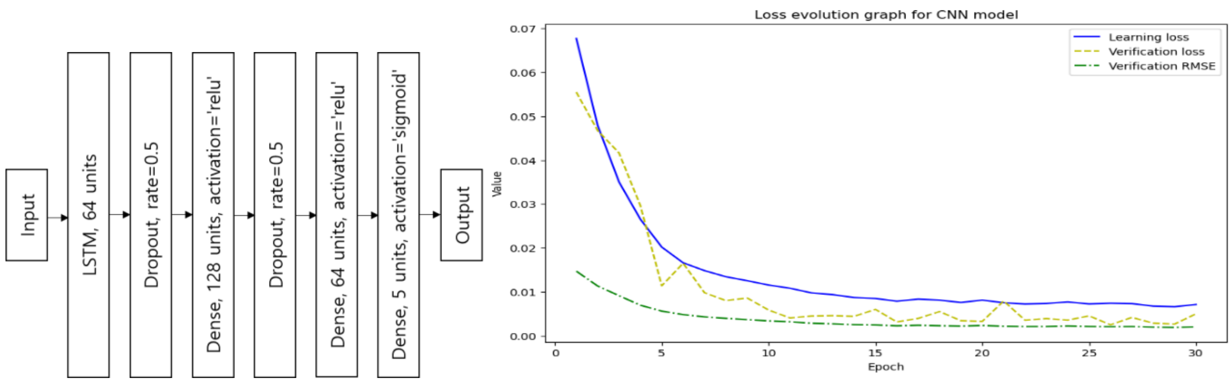

Figure 4. Structure of LSTM Model

Figure 5 shows the structure of the model, which includes a convolutional layer, a pooling layer, an LSTM layer, a dropout layer, and a dense layer. The Conv1D layer and MaxPooling1D layer perform 1D convolution and pooling, while the LSTM layer processes sequential data. Dropout layers were used to prevent overfitting. In the final output layer, a sigmoid-activation function is applied to five neurons to perform a multiclass classification.

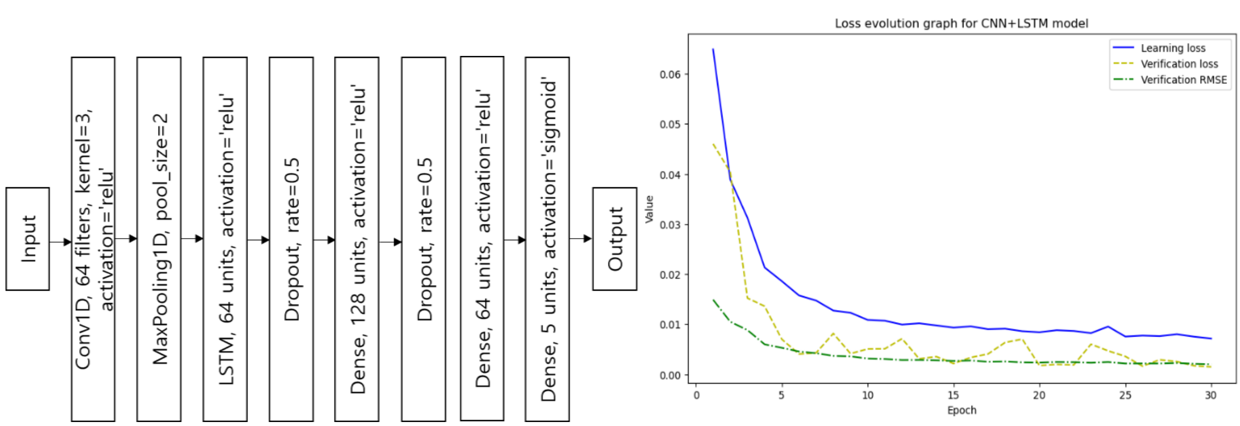

Figure 5. Structure of CNN-LSTM Hybrid Model

4. Result

Table 2. Performance Analysis by Model

Division	Epochs	Accuracy	RMSE	mAP
CNN Model	30	0.94	0.07	0.99
LSTM Model	30	0.96	0.52	0.99
CNN-LSTM hybrid Model	30	0.99	0.09	0.99

The contents of Table 2 are analyzed as follows. As a result of the CNN model, the CNN model trained for

30 epochs showed a high overall accuracy of 94%, with a low RMSE value of 0.07, which means that the model's prediction is close to the actual value. The high mAP value was 99%, indicating that the object detection model performed well. The LSTM model trained for 30 epochs showed a high accuracy of 96%, but compared to the other two models, the relatively high 0 RMSE value was 0.52, confirming that the prediction differed slightly from the actual value. It was confirmed that 99% of object detection performance is excellent with a high mAP value. In addition, the CNN-LSTM hybrid model that combines CNN and LSTM presented in this paper showed a high accuracy of 99% and high object detection performance, a low RMSE value of 0.09 showed that the model's prediction was close to the actual value, and a high mAP value 99% showed that the object detection model performed well.

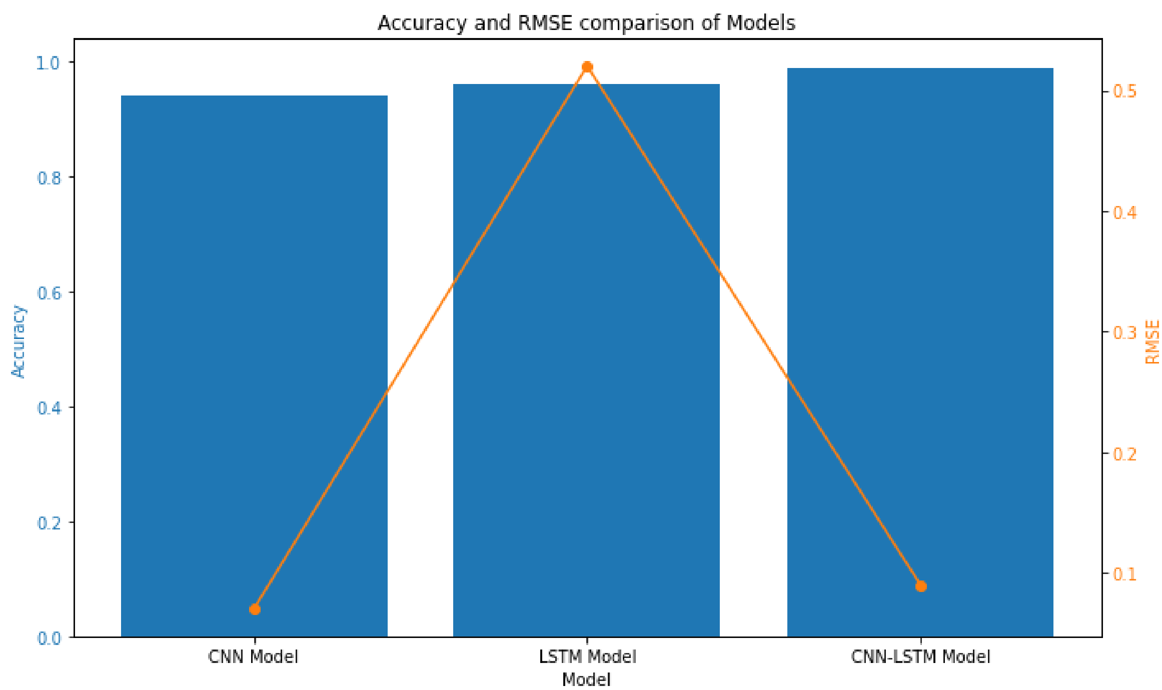

Figure 6. Comparison of the three models

Based on the model performance shown in Figure 6, the CNN, LSTM, and CNN-LSTM models perform well according to their respective characteristics.

5. Conclusion

In this paper, we proposed a mixed neural network structure that combines CNNs and LSTMs to improve the accuracy of time series predictions of various environmental data collected from compound sensors. As a result of the experiments, the proposed CNN-LSTM hybrid model showed high accuracy, low RMSE values, and excellent object detection performance. In particular, the CNN model was 94% accurate, the LSTM model was 96% accurate, and the CNN-LSTM hybrid model was 99% accurate. This model presents an important advance in exploring the applicability of odor detection and prediction in real-world industrial settings. By anticipating ahead of time and taking appropriate precautions, we can contribute to the prevention of diseases caused by odors and the improvement of public health. Furthermore, based on the results of the experiment, it can be confirmed that the CNN, LSTM, and CNN-LSTM hybrid models perform effectively according to their respective characteristics.

Therefore, this paper demonstrates the effectiveness of CNN-LSTM hybrid model structure as a predictive model for compound sensor data.

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