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Study on Real-time Detection Using Odor Data Based on Mixed Neural Network of CNN and LSTM

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Abstract

In this paper, we propose a mixed neural network structure of CNN and LSTM that can be used to detect or predict odor occurrence, which is most required in manufacturing industry or real life, using odor complex sensors. In addition, the proposed learning model uses a complex odor sensor to receive four types of data such as hydrogen sulfide, ammonia, benzene, and toluene in real time, and applies this data to an inference model to detect and predict odor conditions. The proposed model evaluated the prediction accuracy of the learning model through performance indicators according to accuracy, and the evaluation result showed an average performance of 94% or more.

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

1. INTRODUCTION

Recently, various application services using artificial intelligence are being actively developed. In particular, in the field of IoT, research to provide real-time prediction services in industrial sites using artificial intelligence technology is actively underway [1, 2]. In particular, the demand for artificial intelligence services that can detect and predict anomalies in real time is very high in the manufacturing industry [3].

In industrial sites that handle chemical components or industrial sites that process and store waste, odors are generated and many civil complaints are generated, so management is necessary. An on-site monitoring system is being applied [4, 5]. However, in most cases, existing systems for detecting odors detect outliers after they have already occurred, rather than predicting the discovery of outliers. For this reason, it is because the existing system is not applied with AI-based prediction service technology. In addition, the development of an artificial intelligence learning model is actively under way to provide prediction services such as odor detection [6].

There is a research report that odors along with domestic fine dust that have recently occurred can have harmful effects on the human body, such as headaches, dizziness, and disgust. In Korea, various studies are being conducted through analysis of the cause of odor generation and machine learning [8-10]. In order to prevent damage from diseases caused by odors and improve national public health, it is very important to predict levels of odors that may occur in advance and inform them so that preventive measures can be taken.

In this paper, a 1-D CNN predicts multiple time series data by fusing a linear (1D) Convolutional Neural

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Network (CNN) [11] with a Long Short-Term Memory (LSTM) model used for time series data analysis. and LSTM mixed neural network architecture. For the experiment of the proposed architecture, 120,000 pieces of data were collected by directing a situation in which odors are artificially generated, such as an environment in which an odor complex sensor is installed, in a time series format. Using the obtained data set, we evaluated the accuracy of the proposed neural network and performance comparison model and compared the results.

2. RESEARCH CONTENT

The purpose of the study is to evaluate the accuracy of the model by measuring the level of odor using the odor composite sensor using a mixed neural network model of 1-D CNN and LSTM and to provide the results. In the case of odor for which data prediction is performed, various environmental data that may affect odor data, which is target data, should be considered. Data measurement using a deep learning model mainly uses time series data and a Recurrent Neural Network (RNN) structure, and can predict results that may occur after input data. However, existing RNN models receive time-series data such as text, voice, and video, and require a separate structure to receive different types of time-series data and check the relationship. The convolution operation used in the CNN structure can obtain feature values between data in the masking range.

Therefore, in this paper, instead of the commonly used matrix-type convolution operation, we use 1-D convolution operation that performs convolution operation by listing data in one column to obtain data results in a form suitable for RNN time series operation. expected to be obtained. A time-series data set using various data affecting odor was obtained and a mixed neural network model of 1-D CNN and LSTM suitable for data measurement was proposed.

3. DESIGN OF 1-D CNN AND LSTM MIXED NEURAL NETWORK MODEL USING TIME SERIES DATA

This chapter describes the data collection and preprocessing process to create an artificial intelligence learning model. In addition, time-series data such as hydrogen sulfide, ammonia, benzene, and toluene are used as training data for the data required to create a mixed neural network model of CNN and LSTM from the odor composite sensor. Since it was not possible to create real-time data in the field using the odor complex sensor, an odor model was developed by randomly creating a data set.

3.1 Design of Mixed Neural Network Model of CNN and LSTM

In this paper, the proposed method to improve the prediction accuracy of time series data obtained from the odor sensor is to design a neural network model with a structure that can consider various environmental data. It forms a mixed structure in the form of adding an LSTM layer to the CNN model.

The proposed hybrid model consists of an input layer, a CNN layer, an LSTM layer, and an output layer. Fig. 1. is a structure designed for a mixed neural network model of CNN and LSTM in which four time series data sets are input.

CNN models are divided into 1D, 2D, and 3D, and general CNNs collectively refer to 2D, which is usually used for image classification. Here, D is an abbreviation of dimension, which means 1D, 2D, and 3D CNN models are used depending on the type of input data.

The time series data used in Fig. 1 is odor data such as hydrogen sulfide, ammonia, benzene, and toluene collected from the target data, “Industrial Complex in Jangseong, Korea”. Assuming that the t th data of each data is a_t, b_t, c_t, and d_t, respectively, the sets A, B, C, and D for each data set can be expressed as the following equation (1) [12].

$$A=\{\ a_t\ \}_{t\in M}, \text{ A is target data} \tag{1}$$
$$B=\{\ b_t\ \}_{t\in M}, \text{ B is 1}^{st}\text{ environment data}$$
$$C=\{\ c_t\ \}_{t\in M}, \text{ C is 2}^{nd}\text{ environment data}$$
$$D=\{\ d_t\ \}_{t\in M}, \text{ D is 3}^{rd}\text{ environment data}$$

All the data obtained were measured on a daily basis, and the sequential length was set to 30 to obtain the time series characteristics for one month. Therefore, the set M consists of a total of 30 natural numbers, incremented by 1 from the starting value. Here, t depends on the bundle of input time series data, so $M=\{i, i+1, \ldots, i+29\}$. At this time, the value of i is determined according to the data set used, and is determined as a natural number within the range of 0<i<12000 according to the maximum number of data sets used in this paper. Also, as the label of the model, the next value a_i+30 of the last element (a_i+29) of the target data set A is input.

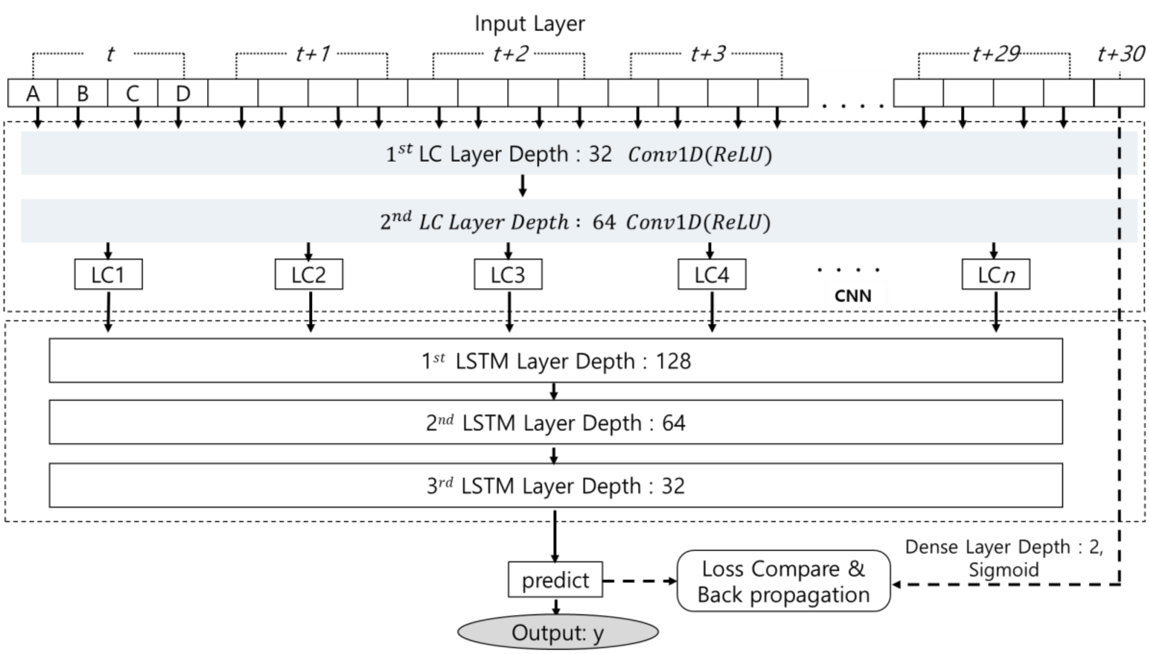

Figure 1. Structure of CNN+LSTM Mixed Model

Datasets A, B, C, and D are time-series data measured at the same time, and new time-series data can be reconstructed by grouping the t th element in each set. Let x_t be the element of the reconstructed input time series data set, and x_t can be expressed as $x_t = (a_t, b_t, c_t, d_t)$ at time t. The reconfigured input data set X can be expressed as Equation (2) below.

$$X=\{\ x_t \mid x_t=(a_t, b_t, c_t, d_t)\}_{t\in M} \tag{2}$$

In this case, Z is equal to the set M of t in Equations (1)-(4). Since sets A, B, C, and D each have 30 elements, X has 120 elements. The shape of X input to the model is (1×120). In the input layer, the data set X rearranged into a form suitable for the neural network model passes through a 1-D convolutional layer [13].

The convolution filter has a feature of receiving multiple inputs according to the size of the filter and returning one output through a convolution operation. Therefore, if a (1×4) size filter or a (1×2) filter is used in two layers for element $x_t=(a_t, b_t, c_t, d_t)$ at time t, a value cv_t of size (1×1) is returned. At this time, the filter stride should be adjusted to be the same as the filter size so that elements can be grouped into one value only at the same t. Fig. 1 the first 1-D convolutional layer is a layer with a filter size (1×2), a stride length of 2, and a depth of 32, and the output is $(1\times60\times32)$. The second 1-D convolutional layer uses the same filter size and stride, is a layer with a depth of 64, and has an output of $(1\times30\times64)$. t of cv_t is $t\in M$, where M is equal to the set M of t in Equations (1) to (4). The convolution layer output set CV can be expressed as Equation (3) below.

$$CV=\{cv_t\}_{t\in M} \tag{3}$$

At this time, CV is the output of the 1-D convolutional layer. cv_t still has time-series characteristics because x_t, a set of data measured at the same time, has become a single value through convolution calculation. Therefore, the set CV can be used as an input of a recurrent layer that can analyze time series characteristics. The cyclic layer prevents gradient vanishing by using Long Short Term Memory(LSTM) cells [14] that can resolve long-term dependencies and obtain time-series characteristics well. Fig. 1, three LSTM layers were used. The first and second layers are many-to-many LSTM cells that receive 30 elements equal to 1-D convolutional and output 30 elements. Each layer returns an output of (1×30×128). The third layer uses a many to one method to obtain the final output y. With a depth of 64, it returns an output of (1×1×64) as a fully connected layer. A fully connected layer (dense layer) can make a (1×1×64) size output obtained from the circular layer into one (1×1) size output through full connection. The output of the fully connected layer outputs the predicted value y of the value of a_t+1.

The proposed model uses the Mean Squared Error(MSE) [15] loss function to calculate the label a_i+30 and error, and model optimization is performed using the Adam optimizer [16].

3.2 Data Collection

For data collection, 120,000 data were collected as shown in Figure 2 by directing the situation in which odor is artificially generated, such as the environment where the odor complex sensor is installed, in a time series format.

Items that cause odor 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 Four data items were selected and collected: (normal range (0.05 ± 0.03) ppm, abnormal range (50 ± 20) ppm, toluene (normal range (12.36 ± 3) ppm, abnormal range (500 ± 200) ppm).

	A	B	C	D	E	F	G
1	No	Time	Hydrogen_sulfide	Ammonia	Benzene	Toluene	IsNormal
2	1	0:00	0.15	12	0.027	9.36	Normal
3	2	0:05	0.61	5	0.049	14.36	Normal
4	3	0:10	0.57	7	0.032	14.36	Normal
5	4	0:15	0.19	7	0.029	11.36	Normal
6	5	0:20	0.59	10	0.078	13.36	Normal
7	6	0:25	0.62	5	0.078	13.36	Normal
8	7	0:30	0.51	8	0.061	14.36	Normal
9	8	0:35	0.26	9	0.041	12.36	Normal
10	9	0:40	0.33	12	0.034	14.36	Normal
11	10	0:45	0.34	5	0.03	9.36	Normal
12	11	0:50	0.49	9	0.065	9.36	Normal
13	12	0:55	0.24	12	0.031	9.36	Normal

119985	104	8:35	22.84	147	16.695	149	AbNormal
119986	105	8:40	16	211	23.002	146	AbNormal
119987	106	8:45	22.48	209	15.977	210	AbNormal
119988	107	8:50	15.46	208	22.462	207	AbNormal
119989	108	8:55	22.12	206	15.254	204	AbNormal
119990	109	9:00	14.91	134	14.89	202	AbNormal
119991	110	9:05	14.64	202	14.525	128	AbNormal
119992	111	9:10	14.36	128	21.369	124	AbNormal
119993	112	9:15	14.09	198	13.791	193	AbNormal
119994	113	9:20	21.21	197	13.422	191	AbNormal
119995	114	9:25	21.02	120	20.538	113	AbNormal
119996	115	9:30	13.26	193	20.26	185	AbNormal
119997	116	9:35	20.65	114	12.307	182	AbNormal
119998	117	9:40	12.69	111	19.699	179	AbNormal
119999	118	9:45	12.41	109	11.557	177	AbNormal
120000	119	9:50	12.13	106	11.18	94	AbNormal
120001	120	9:55	19.9	103	18.851	91	AbNormal

Figure 2. 120,000 Samples of Data Collected

3.3 Data Preprocessing

For data collection, 120,000 data were collected as shown in Fig. 3 by directing the situation in which odor is artificially generated, such as the environment where the odor complex sensor is installed, in a time series format.

The 120,000 collected data were composed of 120 sets, and the normal data was composed of 600 sets and the abnormal data was composed of 400 sets, making a total of 1,000 data sets. Here, 120 pieces of raw data, 5 seconds each for each time-series data of hydrogen sulfide, ammonia, benzene, toluene, etc., were created through the odor composite sensor, and were collected for a total of 600 seconds (10 minutes). Fig. 3 shows a sample of the amount of change in the time series for one set of collected data items.

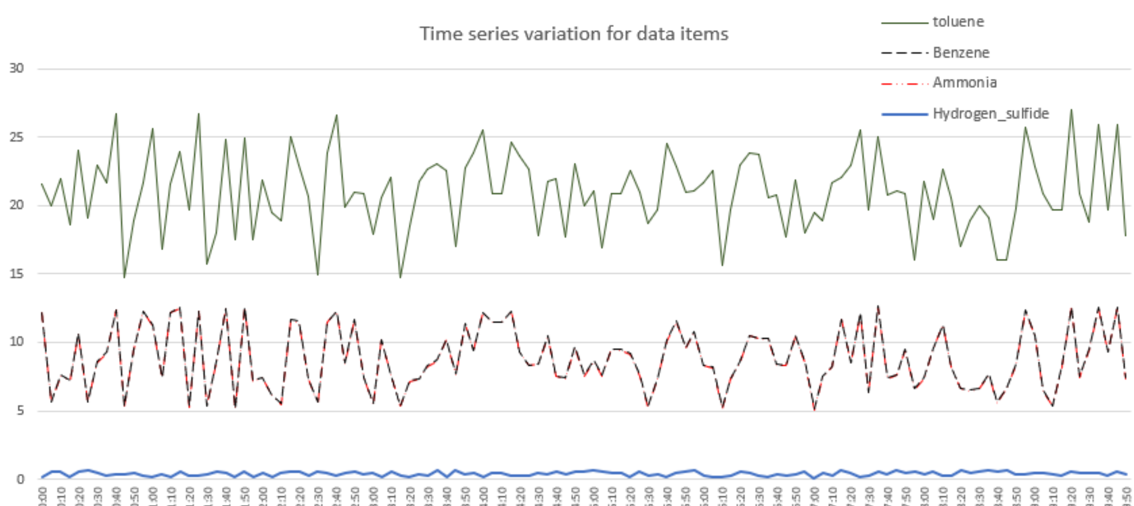

Figure 3. A sample of the amount of change in the time series for one set of collected data items

3.4 Implementation of the Model

In this paper, in order to prevent divergence of the weight of the time series data obtained from the odor composite sensor, the total number was normalized based on the domestic odor, and the time series data time step was set to 30, the number of days in a month. In addition, in order to designate a comparison model for the experimental results, a single RNN (RNN-1) structure using one recurrent layer and an LSTM-3 structure with increased neural network depth were designed using three LSTM layers. The comparison model performed data prediction using only target data, and confirmed the results when data prediction was performed considering environmental data.

Table 1. Learning loss result value according to the number of epochs

Epochs	Loss	Acc	Val_loss	Val_acc	Epochs	Loss	Acc	Val_loss	Val_acc
1 iters	0.3192	0.8737	0.2020	0.9300	6 iters	0.2648	0.8925	0.2016	0.9300
2 iters	0.2655	0.8925	0.2003	0.9300	7 iters	0.2639	0.8925	0.2021	0.9300
3 iters	0.2681	0.8925	0.2021	0.9300	8 iters	0.2626	0.8925	0.2082	0.9300
4 iters	0.2671	0.8925	0.2012	0.9300	9 iters	0.2627	0.8925	0.2001	0.9300
5 iters	0.2645	0.8925	0.2071	0.9300	10 iters	0.2629	0.8925	0.2154	0.9300

Table 1. shows the change of the loss function according to the learning of the designed model. Neural network training was performed with a mini batch size of 100 and a total of 50 epochs. Since the prediction result does not change significantly even if the number of epochs is increased, the difference in results for each model structure for the same epoch was compared.

In addition, the proposed model was implemented using Keras, a deep learning design API, in a Python environment. The neural network structure required for implementation uses the Keras neural network model function set. The mixed model design of 1-D CNN and LSTM was designed according to the data used for a total of 4 types of data.

Table 2 shows high performance with accuracy of 93%, precision of 92.553%, recall of 94.167%, and F1-score of 92.880%. Therefore, the CNN+LSTM mixed model will be used as an opportunity to prevent or prevent odors by predicting odors according to climate changes in Korea, as shown in the four performance indicators.

Table 2. Performance results of CNN+LSTM mixed model

Division	Accuracy	precision	Recall	F1-score
CNN+LSTM mixed model	93.000	92.553	94.167	92.880

4. CONCLUSION

In this paper, the proposed odor composite sensor was developed, odor time series data was collected, and a deep learning model was proposed to predict odor levels using a model combining CNN and LSTM. The proposed model consists of 120 data sets of 120,000, and through the odor complex sensor, 120 pieces of time-series data such as hydrogen sulfide, ammonia, benzene, and toluene are configured for 5 seconds each, for a total of 600 seconds (10 minutes). The prediction accuracy of the data collected in units was confirmed. The mixed neural network structure of CNN and LSTM proposed in this paper increases the system complexity by adding a 1D convolution layer in the existing RNN and LSTM stacked neural network structure, but the increase in learning and prediction time is not significant. Also, assuming that daily data prediction is performed, it can be seen that a more accurate numerical prediction improves the performance of the model rather than a fast prediction time.

In addition, even if the mixed model presented in this paper uses the same neural network structure, differences in prediction accuracy may occur depending on the data to be learned, and when designing a model, it is important to find the type and number of environmental data that are most effective for data prediction.

This model can then be fused with existing odor prediction technology to predict more accurate odor levels.

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