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Development of CNN-Transformer Hybrid Model for Odor Analysis

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Abstract

The study identified the various causes of odor problems, the discomfort they cause, and the importance of the public health and environmental issues associated with them. To solve the odor problem, you must identify the cause and perform an accurate analysis. Therefore, we proposed a CNN-Transformer hybrid model (CTHM) that combines CNN and Transformer and evaluated its performance. It was evaluated using a dataset consisting of 120,000 odor samples, and experimental results showed that CTHM achieved an accuracy of 93.000%, a precision of 92.553%, a recall of 94.167%, an F1 score of 92.880%, and an RMSE of 0.276. Our results showed that CTHM was suitable for odor analysis and had excellent prediction performance. Utilization of this model is expected to help address odor problems and alleviate public health and environmental concerns.

Keywords: *CNN-Transformer Hybrid Model, CNN+LSTM Hybrid Model, CNN model, LSTM Model, ELM Model, Odor.*

1. INTRODUCTION

In recent studies, machine learning (ML) and deep learning techniques have been applied to odor analysis, enabling accurate and efficient odor detection and classification. Previous research primarily utilized machine learning algorithms such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) for analyzing odor data and evaluating their performance [1-3]. CNN in particular, has been effectively employed for odor classification, allowing for rapid and accurate classification by simultaneously extracting data features and performing classification [4]. Additionally, CNN can effectively process data by learning spatial relationships. However, CNN requires large amounts of data and computational power, and its interpretability is limited as it is difficult to interpret which features it relies on for classification [5].

Random Forest (RF), on the other hand, evaluates the importance of various features and provides generalized results without overfitting the training data. RF demonstrates stable performance even with relatively small datasets. However, RF is relatively slower and requires more memory when dealing with large amounts of data, and its interpretability is limited. LSTM is specialized in processing sequential data and is useful for predicting current odor patterns by retaining previous information [6]. LSTM exhibits excellent performance in modeling sequential data and is suitable for handling odor data with temporal dependencies [7]. However, LSTM requires high computational costs and is most effective when trained on large-scale

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datasets.

Therefore, in this study, the goal is to propose a neural network structure that combines CNN and Transformer and evaluate its performance for odor analysis. Transformer provides efficient and parameter-effective modeling compared to traditional sequence modeling [8, 9]. By combining it with CNN, we aim to develop a more powerful odor analysis model. To achieve this, we utilize a publicly available dataset consisting of 120,000 odor samples and construct a *CTHM* to evaluate its performance.

2. DESIGN OF MODEL

The objective of this study is to propose *CTHM* structure by combining CNN and Transformer and evaluate its performance in odor analysis. To assess the performance of the proposed *CTHM*, accuracy, precision, recall, F1-score, and the model's predictive ability are measured by calculating the RMSE value.

2.1 Design of CNN-Transformer Hybrid Model

The *CTHM* structure, as shown in Figure 1, defines the input data format through the Input layer. The CNN layer extracts feature from the sequential data by performing convolution and pooling operations, and applies Layer Normalization. The Transformer layer takes the output of the CNN layer as input [7, 8]. It consists of an attention layer and a feed-forward neural network layer (FNN), followed by global average pooling. The output layer is a dense layer with two nodes, using the sigmoid activation function (SAF).

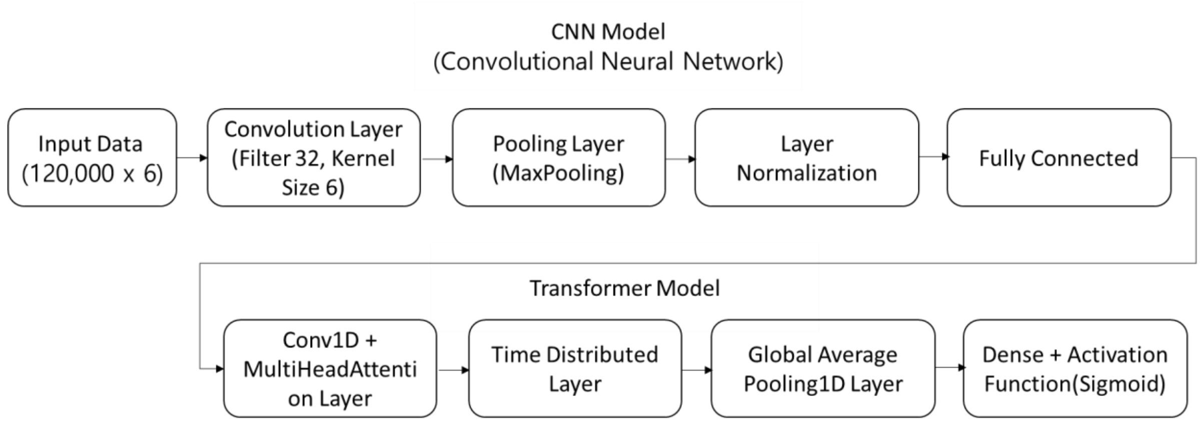

Figure 1. CNN-Transformer Hybrid Neural Network Architecture

2.2 Dataset

The dataset used in this study is presented shown in Table 1. Table 1 shows provides an overview of the types and quantities of data based on the given information. The total number of data samples is 120,000, and these data samples consist of 120 time series data. Each time series data is measured for 5 seconds and includes data on hydrogen sulfide, ammonia, benzene, toluene, and other variables. The total measurement time is 600 seconds (10 minutes), and there is a total of 1,000 samples in the dataset. Among them, 600 samples are normal data and 400 samples are abnormal data.

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).

Table 1. Composition for the dataset

Division	Total Data	Normal Data	Abnormal Data	Remarks
Time Series Data Composition	120 * 1,000			
Measurement Time (seconds)	600			
Number of Data	1,000	600	400	
Total Number of Data	120,000			

Table 2 represents the normal and abnormal ranges for the given odor substances. Each odor substance has an average and standard deviation for both the normal and abnormal ranges. For example, hydrogen sulfide has a normal range of 0.4 ppm with an average of 0.3 ppm and a deviation of 0.3 ppm, while the abnormal range is 40 ppm with an average of 20 ppm and a deviation of 20 ppm. The same information is provided in the table for ammonia, benzene, and toluene.

Table 2. Composition of Odor data

Division	Normal range (ppm)	Abnormal (ppm)	Range	Remarks
Hydrogen Sulfide	0.4 ± 0.3	40 ± 20		
Ammonia	9 ± 4	300 ± 100		
Benzene	0.05 ± 0.03	50 ± 20		
Toluene	12.36 ± 3	500 ± 200		

3. RESULTS OF MODEL PERFORMANCE EVALUATION

The *CTHM* achieved an accuracy of 93.000%, which represents the proportion of correctly classified instances among the entire dataset. The precision, which is the ratio of correctly predicted instances of odor existence to the total predicted instances of odor existence, is 92.553%. The recall, which is the ratio of correctly predicted instances of odor existence to the total actual instances of odor existence, is 94.167%. The F1-Score, which is the harmonic mean of precision and recall, is 92.880%. Additionally, the root means square error (RMSE), which measures the average distance between the predicted values and the actual values, is 0.276. Please note that these performance metrics indicate the effectiveness of the *CTHM* in odor analysis.

Table 3. Results of evaluating the performance of artificial intelligence models

Model	Accuracy	Precision	Recall	F1-Score	RMSE
CNN-Transformer	93.000	92.553	94.167	92.880	0.276

4. CONCLUSION

In this study, a neural network architecture called CNN-Transformer, which combines CNN and Transformer, was proposed. The performance evaluation was conducted using metrics such as accuracy, precision, recall, F1 score, and RMSE. The experiment utilized a publicly available odor dataset consisting of 120,000 data samples. The dataset was composed of 1,000 datasets, with each dataset containing 120 time series data. The dataset included 600 normal data samples and 400 abnormal data samples.

The *CTHM* achieved an accuracy of 93.000%, a precision of 92.553% (the ratio of correctly predicted odor presence among the predicted odor presence), a recall of 94.167% (the ratio of correctly predicted odor presence among the actual odor presence), and an F1 score of 92.880%. The RMSE, which represents the average squared difference between the predicted values and the actual values, was measured as 0.276. Among the four-performance metrics, the *CTHM* exhibited the best performance, indicating its suitability for odor analysis. Its low RMSE and superior prediction performance compared to other models support this evaluation. Therefore, the utilization of the *CTHM* is expected to be beneficial in addressing odor-related issues and mitigating public health and environmental problems.

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