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LSTM-based Early Fire Detection System using Small Amount Data

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ABSTRACT

Despite the continuous advancement of science and technology, fire accidents continue to occur without decreasing over time, so there is a constant need for a system that can accurately detect fires at an early stage. However, because most existing fire detection systems detect fire in the early stage of combustion when smoke is generated, rapid fire prevention actions may be delayed. Therefore we propose an early fire detection system that can perform early fire detection at a reasonable cost using LSTM, a deep learning model based on multi-gas sensors with high selectivity in the early stage of decomposition rather than the smoke generation stage. This system combines multiple gas sensors to achieve faster detection speeds than traditional sensors. In addition, through window sliding techniques and model light-weighting, the false alarm rate is low while maintaining the same high accuracy as existing deep learning. This shows that the proposed fire early detection system is a meaningful research in the disaster and engineering fields.

Key Words : Fire early detection, Multi-gas sensor, Deep-learning, LSTM

1. Introduction

According to the McGill Pain Index, one of the greatest pains a person can feel is burning pain[1]. Fire accidents that cause such the burning pain threaten people around the world every year. According to statistics provided by International Technical Committee for the Prevention and Extinction of Fire (CTIF) from 2015 to 2019, fire casualties continue to increase worldwide. This report states that about 4,000 people die and about 15,000 are injured due to fires in the United States every year[2]. Fire occurrence consists of four stages. At the beginning of a fire, an initial decomposition stage occurs, which is the stage of ultra-fine particle decomposition products that have not yet caused damage to the facility. And then, the initial combustion stage occurs in which damage to the facility occurs due to the smoke generated thereafter. After that, the combustion expansion stage in which smoke and heat are generated by the flame, and then the flashover stage in which the fire spreads completely. Most of the conventional fire detection systems often detect fire in the initial stage of combustion, which is the second stage when smoke is generated among the four stages described above. Because conventional fire alarms operate based on smoke detection, they are very effective in the initial combustion stage where smoke and heat are generated[3]. There is also a fire alarm that is judged by the quality of air, but the effect is not so good due to the low selectivity of the sensor mounted on the alarm and the high false detection rate[4]. Therefore, the ability to detect a fire in the initial decomposition stage, which is the stage before smoke occurs, is the most important.

Most fire alarm systems used in real life were developed with smoke detection sensors due to cost. Smoke detection sensors detect fire using an infrared-based transmission and reception system. However, this method does not have high fire detection performance, so

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vision-based fire detection technology is being researched. First, research that developed an efficient Convolutional Neural Networks (CNN) framework for fire detection in camera images resulted in improved smoke and flame detection accuracy than before[5]. Other imaging artificial intelligence researches have used Fast Regions with CNN features (Fast-RCNN), Region-based Fully Convolutional Networks (R-FCN), Single Shot Multi-Box Detector (SSD), and You Only Look Once (YOLO) to increase detection speed and precision[6-10]. However, these researches still failed to reduce false alarms. Additionally, these vision-based fire detections were unable to detect the invisible initial combustion, resulting in delayed fire response.

Accordingly, research on fire detection based on chemical gas sensors was proposed[11,12]. These researches proposed a fire detection method that measures various volatile substances with gas sensors, obtains patterns from the measured sensors, and distinguished them using a pattern recognition algorithm. However, the limitation that the false detection rate may increase as the drift and low selectivity problems of the sensor that acquires the pattern were not resolved was also mentioned. In addition, another research was proposed to estimate fire occurrence rate using temperature, smoke concentration, and carbon monoxide concentration collected through multiple sensors. This research used a backpropagation network utilizing non-uniform sampling and trend extraction to clearly distinguish fire signals from other diverse environments. As a result, detection time was reduced by 32% compared to before. However, the data set does not include combustible materials commonly found in homes, which can lead to false alarms.

There are also studies using both the vision-based sensors mentioned above and chemical gas sensors[13,14]. These researches built a hybrid model using Adaboost and various multilayer perceptrons, and used the Adaboost Local Binary Pattern (Adaboost-LBP) model and CNN to detect early fires. As a result, detection accuracy reached 99% and the false alarm rate was significantly reduced. However, there are concerns that data collection costs will increase due to the large amount of data used, and there are concerns that computational complexity will increase due to training using complex models.

In this paper, eight chemical gas sensors are used to increase the selectivity of the sensors, and the sensor data sets obtained at various temperatures are applied to a Long Short-Term Memory (LSTM) model to overcome the existing fire alarm system. As a result, we succeeded in detecting fires more accurately and earlier. The proposed early fire detection system uses a machine learning-based classification method using a total of eight oxide semiconductor gas sensors to increase the insufficient selectivity of a single sensor. In addition, the time interval was determined and the fire was determined using the LSTM algorithm. This algorithm reflects historical patterns and current critical information, resulting in fewer false alarms and faster detection. The experiment was conducted in a total of three scenarios, and the results using eight sensors showed an accuracy of 98.47%, and the results using two sensors that appeared to be main component sensors showed a high accuracy of 99.76%. Through these results, we were able to achieve higher accuracy and higher selectivity even with two sensors.

2. Materials and Methods

The proposed fire early detection system consists of the order shown in Fig. 1. The system is divided into a sensor module part for fire detection and an artificial intelligence model application part for early detection that learns the data obtained from the sensor module in the LSTM model after preprocessing. A multi-sensor module consisting of two modules obtains measured data at each temperature, processes outliers and missing values, and performs preprocessing in the order of averaging normalization to match the range of each data. The preprocessed data is divided into window sliding algorithms and the amount is increased to designate a class as one of 0 and 1 in each row within a window, and when the class is designated, the class is designated as one of 0 and 1 in one window. Once this two time class designation is completed, learning is performed with the LSTM model, and the new data is predicted with the completed model to determine the fire.

The sensor module that performs fire detection consists of a total of eight multi-sensors, and consists of semiconductor chemical gas sensors to sensitively measure toxic gases as well as heat and smoke among various elements generated in the fire. The semiconductor gas sensor has a lower manufacturing unit price and a smaller size than the electrochemical gas sensor, a relatively simple operating principle, and high compatibility with a semiconductor production processes[15]. However, due to the nature of the operating principle, there is a disadvantage that it can react to gases other than selected gases due to cross sensitivity problems, but using nanomaterials can reduce the particle size of sensor materials in semiconductor gas sensors, which can greatly increase sensor sensitivity[16,17]. In addition, the semiconductor gas sensor can increase gas sensitivity selectivity by manufacturing various gas-sensitive materials in the form of an array[18].

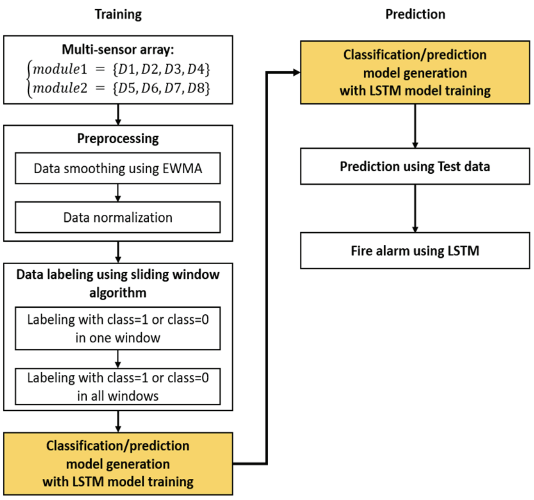


Fig. 1. The proposed early fire detection system.

Generally, when performing numerical variable preprocessing, the data is scaled and normalized to fit or adjust the range of each data, and after ranging, outliers or missing values are eliminated in various ways. If this process is not performed, when data is obtained by the sensor array, the results may vary significantly depending on the measurement environment, and thus, the preprocessing is performed with this process in this paper. To obtain applicable data in various environments, not only in specific environments similar to experimental environments, the measurements are averaged and normalized when a fire situation is sensitively detected by the sensor array. Among the moving average calculation methods, we apply averaging using Exponentially Weighted Moving Average (EWMA), which is the most flexible to apply time series data, and at important times, we apply normalization using Min-Max Normalization, a method to convert all sensor values to values between 0 and 1. In this way, the averaged data reduces the sensor's abnormal value, lowering the false detection rate in fire detection, quickly capturing changes in fire situation, enabling real-time operation, and normalized data makes clear comparison of each sensor data. Afterwards, for faster outlier detection, the data is separated around the point at which the outlier is detected, reducing the overall data range and processing the time axis more precisely.

The finely processed data goes into labeling for training the deep learning model. The deep learning model has the advantage that the model can perform feature engineering work that analyzes the characteristics of the data by itself and can obtain high precision. However, in general, there is a disadvantage that the amount of data required for learning is large. To overcome the shortcomings of deep learning and make full use of its advantages, the labeling step uses a sliding window algorithm, as shown in Fig. 2. The sliding window algorithm is monotonically changing[19]. Since it has a particular effect on the dataset, the sensor data is duplicated in chronological order based on k and s by setting a sliding interval s for a specific window size k and at what interval to slide. Because it slides in chronological order, it is possible to significantly increase the amount of learning data with redundant generation using sliding window techniques while taking the sequence of time series data as it is.

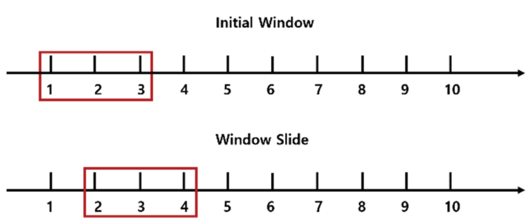


Fig. 2. A sliding window process.

Since the data is repeatedly generated by sliding at 1-second intervals based on window size k, this paper conducts precise labeling twice in total, with the first class designation considering the numbers inside the sliding window and the second class designation considering the whole windows. First, inside one window, labeling is performed with class 1 and 0 first. In this case, if the rate of fire in one window exceeds a specific rate, the class of the window is set to 1. In this way, each window is continuously generated according to the time sequence, and when the last window of the time sequence is reached, the second labeling is performed. Considering the number of windows set to class 1, the second labeling proceeds in such a way that a fire alarm sounds when the class 1 window exceeds a certain ratio in the entire time sequence. When determining the ratio in two labeling, the lower the ratio, the earlier the fire can be detected, so the ratio should be determined by considering both precision and fire detection speed. In addition, when the proposed method is used, a relatively lightweight model can be implemented when implementing the model required for subsequent learning, thereby reducing the amount of computation.

In this paper, the data that has been labeled twice in total enters training using the LSTM model. The LSTM algorithm is mainly used for sentence prediction or time series data because the prediction accuracy is high in the data in which the order exists. Thus, we use the LSTM model to shorten fire detection time and increase accuracy. At this time, because the label step is precisely performed, the model can be relatively light-weight, reducing the time complexity of the model, and at the same time, very low computing power can be used to derive high accuracy, efficiently. The learned model acts as a key core for predicting early detection of fire in real world situations.

3. Results and Discussion

3.1 Experimental Environment

The experiment used data from previous research[20]. The experiment tested rubberized PVC samples with eight oxide semiconductor gas sensors at four different temperatures. As shown in Table 1, the experimental environment was conducted by setting the rubber PVC samples to temperatures of 50°C, 100°C, 200°C, and 350°C. Typically, no heating was done initially to obtain non-fire state data, and specific heating points were set to obtain fire and non-fire state data at all temperatures. Since the measurement time was different for each temperature, the heating time was also different. It was commonly measured in the range of 1 second to 2000 seconds, and data was collected at 1 second intervals.

Table 1. Sample heating measurement environment

Temperature (° C)	Measurement time (sec)	Start time of heating (sec)
50	1 to 1852	1256
100	1 to 1923	1142
200	1 to 1881	747
350	1 to 1805	725

As illustrated in Table 2, the sensor array used to obtain data was configured by selecting NiO, In_2O_3, SnO_2, WO_3, and Fe_2O_3 from various oxides for high selectivity. Among them, NiO has particularly excellent performance in hydrogen sulfide gas detection, and module1-D4's TGS823 uses SnO_2 as an alcohol sensor, and module2-D8's TGS826 operates as an ammonia gas sensor. This sensor array sets voltage and resistance values according to the characteristics of each sensor.

Table 2. Sensor type for an experimental environment

Module 1				Module 2			
D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**
NiO	In_2O_3	SnO_2	TGS823	In_2O_3	WO_3	Fe_2O_3	TGS826

In the experiment, data was collected using a sensor array and resistance values for various temperature cases. And resistance values existing as log data were saved as csv files and preprocessed. Fig. 3 is a graph at 350 degrees among the normalized data. Since the value is a resistance value, most sensors draw a downward curve when a fire occurs, but only NiO was confirmed to draw an upward curve. NiO has the property of increasing resistance when it reacts with the target gas, so it reacts in the opposite way to other sensors. Therefore, in this paper, for easy data comparison, D1 corresponding to NiO was converted to be inverse and then machine learning was performed.

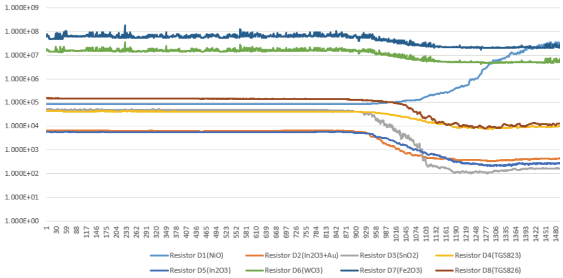


Fig. 3. Graph of sensor resistance values at 350 degrees experiment case.

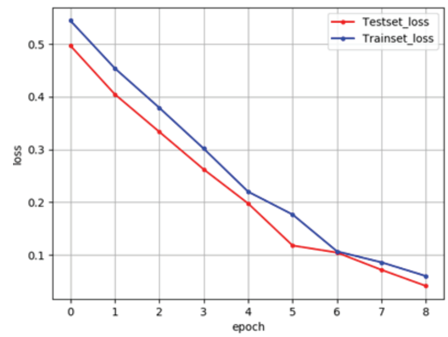
The EWMA was used for the normalized data and after several experiments, the window size was determined to be 12 that did not damage the original data too much and did not miss the real-time property. For efficient model learning, the averaged data was extracted for about 1000 seconds per temperature, focusing on the section where rapid changes occur among sensor data listed in chronological order, and the time axis was more detailed. LSTM learning was conducted by stacking layers using functions provided by TensorFlow. Learning data and test data were divided into 7:3 ratios and verification data were verified using test data. Since the class is divided only into 0 and 1, the output layer was constructed using sigmoid as an active function in the last layer, and Adam was used as an optimization function when compiling the model. When the model is driven, the batch size is designated as 32 and the epoch is designated as 9, and in order to prevent overfitting, an additional function that automatically stops when overfitting is used.

3.2 Experimental Scenarios and Results

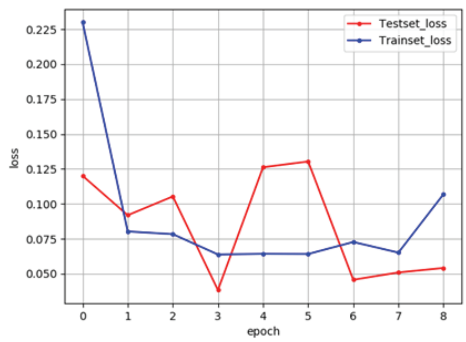
The experiment was conducted by dividing it into three scenarios as shown in Table 3. The experiment was conducted by varying the temperature and sensor range, respectively. As a result of the experiment, in scenario 1, which progressed as 350 degrees, which has the most obvious change, it was stopped in epoch 5, and high accuracy of 99.28% and error 0.04% was obtained as shown in Fig. 4(a). Scenario 2, where all temperatures and sensors were entered, showed 98.47% accuracy and an error of 0.05%, as shown in Fig. 4(b). In Scenario 3, among sensor data D1 to D8, D2 and D3, which showed the most distinct changes as a result of analysis, were selected as main component sensors and experiments were conducted with only main component sensors. As a result of the experiment, a high accuracy of 99.76% and an extremely low error of 0.009% were obtained as shown in Fig. 4(c).

Table 3. Experimental Scenario

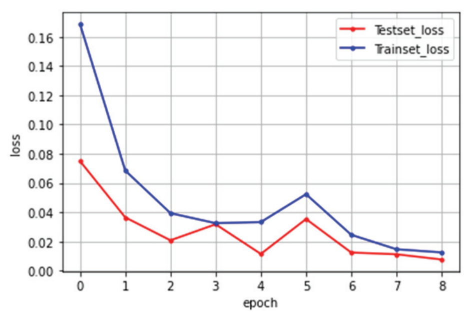
Scenario	Temperature	Sensor
1	350 degrees applied data to the PVC	Use of full sensor data
2	Use of full temperature data	Use of full sensor data
3	Use of full temperature data	Using D2, D3 sensor data



(a)



(b)



(c)

Fig. 4. Show the accuracy and error of scenarios 1(a), 2(b), and 3(c), respectively.

A confusion matrix was used to evaluate the performance of model predictions. The confusion matrix is possible to evaluate Precision, Recall, F1 Score, and Accuracy with a total of four figures[21,22]. Performance indicators evaluate the accuracy of model prediction resulting in 98.55% precision, 99.27% recall, 98.9% F1 score, and 99.76% accuracy based on Scenario 3. This result can also be confirmed by the Confusion matrix in Fig. 5.

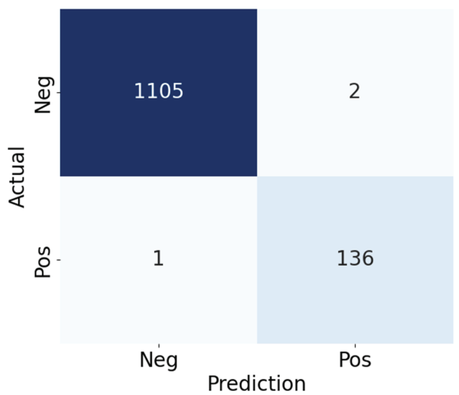


Fig. 5. Confusion matrix for scenario 3.

4. Conclusions

In this paper, we proposed a fire early detection system that can detect fire in the initial combustion stage using a multi-sensor module composed of a sensitive semiconductor-type chemical gas sensor and an LSTM model. Time series data were collected at 1-second intervals with a total of 8 multi-sensors, and in order to improve the performance of the LSTM model, normalization and averaging were performed to fit the range of data and refine outliers. After that, the amount of insufficient data was increased by dividing the data in 100-second increments with a window sliding algorithm, and then labeling was performed twice to increase the learning and prediction accuracy of the LSTM model. As a result of learning and prediction through three scenarios, it was confirmed that the accuracy of the model was high with an average of 99.17% and an average error of 0.03%. In future research, we plan to design a predictable system with only the main component sensor that can detect a normal fire by automatically removing the sensor with large outliers in the prediction stage, which can detect the fire earlier by advancing the class function.

References

1. Wong, Cynthia A., "Advances in labor analgesia." *International journal of women's health*, 2010, pp. 139-154.
2. The World Fire Statistics for 2019. https://www.ctif.org /sites/default/files/2021-06/CTIF_Report26_KOREA. pdf (07.06.2021).
3. Nazir, Amril, *et al.*, "Early fire detection: a new indoor laboratory dataset and data distribution analysis," *Fire*, vol. 5, no. 1, 2022.
4. GAUR, Anshul, *et al.*, "Fire sensing technologies: A review," *IEEE Sensors Journal*, vol. 19, no. 9, 2019, pp. 3191-3202.
5. Muhammad, Khan, *et al.*, "Convolutional neural networks based fire detection in surveillance videos," *IEEE Access*, vol. 6, 2018, pp. 18174-18183.
6. Li, Pu, and Wangda Zhao, "Image fire detection algorithms based on convolutional neural networks," *Case Studies in Thermal Engineering*, vol. 19, 2020, 100625.
7. T. H. Lee, C.-S. Park, "Real-Time Fire Detection Method Using YOLOv8," *Journal of the Semicond uctor & Display Technology*, vol. 22, no. 2, 2023.
8. I.-H. Park, *et al.*, "Deep-learning based In-situ Mon itoring and Prediction System for the Organic Light Emitting Diode," *Journal of the Semiconductor & Display Technology*, vol. 19, no. 4, 2020, pp. 126-129.
9. H. Ahn, Y.-H Lee, "A Research of CNN-based Object Detection for Multiple Object Tracking in Image : A Research of CNN-based Object Detection for Multiple Object Tracking in Image," *Journal of the Semiconductor & Display Technology*, vol. 18, no. 3, 2019, pp. 110-114.
10. Y.-H. Lee, Y. Kim, "Comparison of CNN and YOLO for Object Detection," *Journal of the Semiconductor & Display Technology*, vol. 19, no. 1, 2020, pp. 85-92.
11. Fonollosa, Jordi, Ana Solórzano, and Santiago Marco, "Chemical sensor systems and associated algorithms for fire detection: A review," *Sensors*, vol. 18, no. 2, 2018, 553.
12. Wu, Lesong, Lan Chen, and Xiaoran Hao, "Multi-sensor data fusion algorithm for indoor fire early warning based on BP neural network," *Information*, vol. 12, no. 2, 2021, 59.
13. Saeed, Faisal, *et al.*, "Convolutional neural network based early fire detection," *Multimedia Tools and Applications*, vol. 79, no. 13, 2020, pp. 9083-9099.
14. Vorwerk, Pascal, *et al.*, "Classification in Early Fire

Detection Using Multi-Sensor Nodes—A Transfer Learning Approach," *Sensors*, vol. 24, no. 5, 2024, 1428.
15. K. N. Kim, "Principles and applications of gas sensors," *Monthly Instrumentation Technology*, 2004.
16. D. Sarangi, *et al.*, "Characterization studies of diamond-like carbon films grown using a saddle-field fast-atom-beam source," *Journal of Vacuum Science & Technology A: Vacuum, Surfaces, and Films*, vol. 18, no. 5, 2000, pp. 2302-2311.
17. Batzill, Matthias, "Surface science studies of gas sensing materials: SnO_2," *Sensors*, vol. 6, no. 10, 2006, pp. 1345-1366.
18. H.-W. Jang, "Development trends of semiconductor gas sensors," *Electrical & Electronic Materials*, vol. 24, no. 1, 2011, pp. 34-42.
19. Y. B. Yahmed, *et al.*, "ADAPTIVE SLIDING WINDOW ALGORITHM FOR WEATHER DATA SEGMENTATION," *Journal of Theoretical & Applied Information Technology*, vol. 80, no. 2, 2015.
20. K. Lee, *et al.*, "Highly sensitive sensors based on metal-oxide nanocolumns for fire detection," *Sensors*, vol. 17, no. 2, 2017, 303.
21. B. J. Kang, H.-C. Cho, "Development of a Deep Learning Prediction Model to Recognize Dangerous Situations in a Gas-use Environment," *Journal of the Semiconductor & Display Technology*, vol. 21, no. 1, 2022, pp. 132-135.
22. M. J. Kim, et al., "Study on the Failure Diagnosis of Robot Joints Using Machine Learning," *Journal of the Semiconductor & Display Technology*, vol. 22, no. 4, 2023, pp. 113-118.

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