Data Labeling Method Combining Visual and Thermal Images for Effective AI-Based Chemical Recognition

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***Abstract*— This paper proposes a data labeling methodology that combines visual and thermal imagery to improve AI-based hazardous chemical recognition. Conventional visual analysis alone is often insufficient for detecting chemical accidents due to colorless or volatile properties of substances. To address this limitation, thermal imaging was utilized to capture pixel-level temperature variations, which were then processed and labeled into four representative classes: fire, reaction, leak, and vaporization. The labeled datasets were used to train a YOLOv8 model, achieving classification accuracies of 100% for reaction and vaporization, 73% for fire, and 50% for leak, with an overall average accuracy of 80.75%. These results demonstrate that the proposed visual–thermal data labeling method enhances detection reliability, providing a foundation for more effective AI-based chemical disaster response systems.**

Keywords— hazardous chemicals detection system, artificial intelligence, thermal Images data, data labeling

I. Introduction

With the rapid growth of Korea's chemical industry and the increasing volume of chemical production and distribution, the need for effective responses to chemical disasters has become more critical [1], [2]. Owing to their hazardous nature, chemical accidents require initial remote detection of the substances involved, followed by appropriate countermeasures tailored to their specific properties. For certain highly toxic or reactive substances, site access is impossible without protective suits until the effects subside; thus, remote assessment is indispensable in the early response stage [3].

Accurate chemical detection is essential for timely and effective disaster response. Recent studies on AI-based chemical detection have primarily focused on delineating and labeling affected regions, then building learning datasets to train recognition models [4], [5]. However, chemical incidents manifest in various forms—fires, leaks, reactions, and vaporization—and their diverse characteristics (e.g., colorlessness, invisibility, or volatile behavior) make it difficult to define accurate boundaries using visual imagery alone.

Thermal imaging offers a complementary modality, capturing infrared radiation and rendering temperature variations as color-coded images. Since chemicals often absorb or emit heat depending on the incident type, thermal signatures can reveal areas of fire, vaporization, or leaks otherwise invisible in the visual spectrum. In this study, we propose a visual–thermal data labeling method that improves chemical substance detection by combining visual video images with thermal imaging data. This fusion enables accurate delineation of spill or exposure regions and provides high-quality labeled data for AI model training.

II. Data Labeling Method Combining Visual and Thermal Images

A. Data Acquisition

Thermal data captured during chemical experiments were categorized into four representative classes: fire, reaction, leak, and vaporization. Each class was labeled accordingly to generate AI training datasets. A YOLOv8-based model was then trained and validated on this dataset. The thermal data were collected using a FLIR Duo Pro R 640 camera, capable of simultaneously capturing visual and thermal imagery at a resolution of 640×512 pixels, frame rate of 30 Hz, and wavelength range of 7.5–13.5 μm. Experiments were conducted under controlled conditions with strict safety protocols in both indoor and outdoor environments.

The dataset was designed to reflect four representative types of chemical incidents:

- **Fire experiments** used oil-based substances (e.g., kerosene, toluene) and alcohols due to their high combustibility.
- **Reaction tests** were performed with acids.
- **Vaporization tests** targeted substances that evaporate at room temperature.
- **Leak tests** involved various liquid spills.

B. Data Processing and Labeling

Thermal imagery was recorded in SEQ format, which stores pixel-level temperature values. Since SEQ files are not directly compatible with common image editing tools, the flirpy Python library was used for decoding, extracting, and filtering thermal data.

To improve interpretability, color maps were applied to highlight temperature gradients. The processed images revealed clear distinctions:

- **Fire**: high-temperature flames and smoke shown in bright yellow/red.
- **Reaction**: localized heating at the reaction site brighter than the container.
- **Leak**: spill areas cooler than surroundings, represented in darker tones.
- **Vaporization**: evaporating zones detected as subtle cooler regions in purple/blue.

As illustrated in Fig. 1, the differences across categories become evident after preprocessing.

For AI training, bounding box annotations were applied to all accident regions, as shown in Fig. 2. A total of 600 labeled images were used per class for training, while 100 images per class (collected under different conditions) were used for testing. The labeling was designed to reflect pixel-level accident boundaries, minimizing noise and ensuring high-quality ground-truth data.

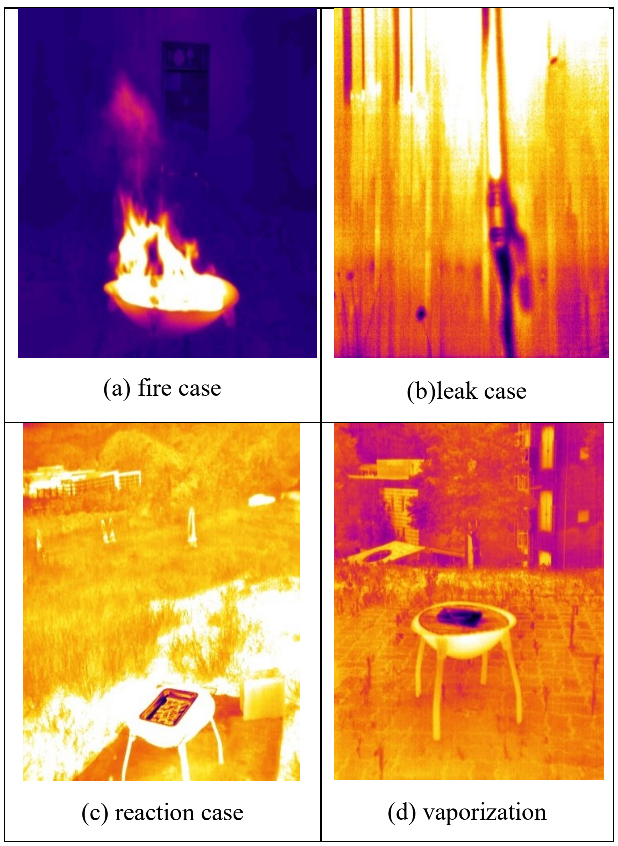

Fig. 1. Examples of thermal image data classification

C. Model Training and Evaluation

Fig. 2 illustrates the labeling process. Bounding boxes were applied to all detected chemical-incident areas to generate AI training data. Training was conducted with 600 labeled images per class, extracted from two separate videos. Testing employed 100 independent images per class. Predictions were accepted when the confidence level exceeded 80%. The YOLOv8 model achieved 100% accuracy for reaction and vaporization, 73% for fire, and 50% for leaks, yielding an overall average of 80.75% accuracy. The lower accuracy for fire and leak cases is attributed to data quality limitations and the inherent variability of those phenomena.

Fig. 2. An example of of thermal image data labeling

III. CONCLUSION

This paper proposed a thermal–visual data labeling methodology for hazardous chemical recognition. By leveraging SEQ-format thermal imagery, preprocessing with flirpy, and systematic annotation, the method successfully generated high-quality labeled datasets. Training with YOLOv8 achieved an average accuracy of 80.75%, demonstrating the feasibility of thermal–visual fusion in chemical accident classification.

Future work will focus on increasing dataset diversity, particularly for fire and leak scenarios, and incorporating additional sensor modalities to further improve recognition performance.

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