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Original Paper

Method for Identifying Combustibles in Fires Based on Flame Spectroscopy Information

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Abstract

Fires are one of the common disasters. If a fire occurs in a place with dense personnel and concentrated property, it will cause a large number of casualties and significant economic losses. Different types of objects can cause different fires, each requiring different extinguishing methods. This article aims to investigate the possibility of using flame spectroscopy to classify combustibles. Firstly, flame spectroscopy data of different combustibles are collected through experiments, with SG smoothing and Principal Component Analysis (PCA) selected as preprocessing methods. Subsequently, five machine learning algorithms are used for in-depth analysis and modeling, comparing the classification results of these five models to identify the model with the best classification performance. This study achieves the goal of classifying combustibles in fires using flame spectroscopy information.

Keywords

Flame spectrum, Optical fiber spectrometer, Classification of combustibles

1. Introduction

Fires, as a type of sudden disaster, come in various forms and are typically classified based on the nature of the burning material. According to current national standards (GB/T 4968-2008, Fire Classification), fires are categorized into six classes: A, B, C, D, E, and F, each of which requires different response measures and extinguishing agents. Rapid and accurate identification of fire types during the initial stages is crucial for devising effective firefighting strategies. Presently, fire detection technologies mainly include optical remote sensing techniques (Chen, Zhang, Xin, et al., 2018; Jia, Duan, & Wang, 2024), multi-sensor information fusion technologies (Wang, Li, Yu, et al., 2014; Su, Hu, & Liu, 2024; Liu, Liu, Zeng, et al., 2024), and image and video technologies (Zheng, Luo, Hui, et al.,

2024; Li, 2023; Shenyuan, Guozhong, Xiaolong, et al., 2024), offering features such as broad monitoring ranges and fast response times.

Current fire detection methods primarily focus on determining the occurrence of fires rather than identifying the types of burning materials. For instance, Zhang Zhiyi (2011) proposed a fire combustible recognition method based on image processing, utilizing infrared images to extract temperature and shape features of flames for identifying combustible types. However, smoke generated during combustion interferes with the extraction of flame features. Jiang Jingxue (2012) used combustion sound as a criterion for fire detection; different materials produce combustion sounds with varying frequencies and amplitudes, enabling the differentiation of fire combustible categories. Nevertheless, this method was tested in a combustion chamber, where real-life noise could hinder combustion sound recognition. Liu Kai et al. (2019) utilized the distinct characteristics of fire smoke particles from different combustibles as a basis for identifying various burning materials, achieving a high accuracy rate in combustible identification. However, this method may face sensor recognition challenges in more complex scenarios such as windy conditions. Li Peng et al. (2021) established a spectral curve database for burning sulfur (nitrogen) substances, comparing collected fire flame spectral curves with the database to identify the presence of sulfur (nitrogen) substances in fire combustibles. This method offers advantages such as quick response, non-destructive testing, and high accuracy. Flames from different combustibles emit unique radiation spectra, containing abundant information. Hence, the author used an optical fiber spectrometer to measure the radiation spectra of flames under different conditions in the laboratory to investigate the potential use of flame spectroscopy in classifying fire combustible types.

2. Experimental Materials and Instruments

2.1 Experimental Materials

The experiment is divided into two groups of combustible materials. The first group consists of solid combustibles including wood and paper, while the second group comprises liquid combustibles such as candles, butter, alcohol, and olive oil. For each type of combustible material, there are 40 sets of flame spectral data. In total, there are 6 sets of spectral data, amounting to 240 sets. Using the SPXY method, the different types of combustible materials are divided into training and prediction sets in a 3:1 ratio.

2.2 Experimental Instruments

The working principle of the spectral acquisition system is illustrated in Figure 1. The primary instrument used in this experiment is the Aurora 4000 spectrometer. This spectrometer operates within a wavelength range of 200-1100nm. In this experiment, the optical imaging principle is employed. The flame of combustion is passed through a convex lens, creating an inverted real image on a screen on the other side of the lens. By placing the probe of the fiber optic outside the screen and aligning it with the flame through a small hole, flame spectra from different parts of the flame can be collected. A total of 40 data points are collected by the spectrometer at different positions within the flame of each

combustible material.

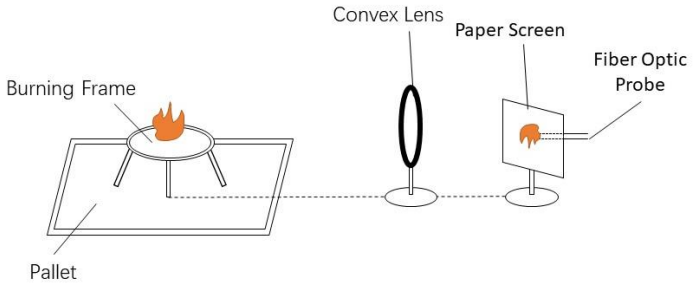


Figure 1. Experimental Principle Diagram

3. Data Processing and Analysis Methods

3.1 Spectral Data Preprocessing

The obtained spectral data contains additional irrelevant information, such as interference from natural light, noise possibly generated by the camera or instrument, or spectral variations. Therefore, preprocessing is essential before conducting classification modeling to eliminate this extraneous information, reduce model complexity, and enhance the robustness and accuracy of both the spectral data and the classification model. In essence, preprocessing of spectral data is an indispensable step in establishing a combustible material classification model. Different preprocessing methods are needed for varying analysis systems and issues at hand; thus, a single preprocessing method is insufficient. In this experiment, SG smoothing and Principal Component Analysis (PCA) preprocessing methods are employed to preprocess the flame spectra with the aim of reducing noise interference and improving the signal-to-noise ratio.

3.2 Data Processing and Analysis Methods

In this study, the sample set is divided into training and prediction sets in a 3:1 ratio using the SPXY splitting method. Based on the training set, combustible material classification models are established using five algorithms: AdaBoost, Random Forest, Gradient Boosting, Decision Tree, and SVM. Subsequently, these models are used to classify the prediction set, and the model performance is evaluated and compared based on model reports to identify the optimal data modeling approach.

3.3 Model Evaluation Methods

Accuracy: Measures the proportion of correct predictions out of the total predictions made.

Precision: Indicates the proportion of true positive predictions out of all positive predictions made.

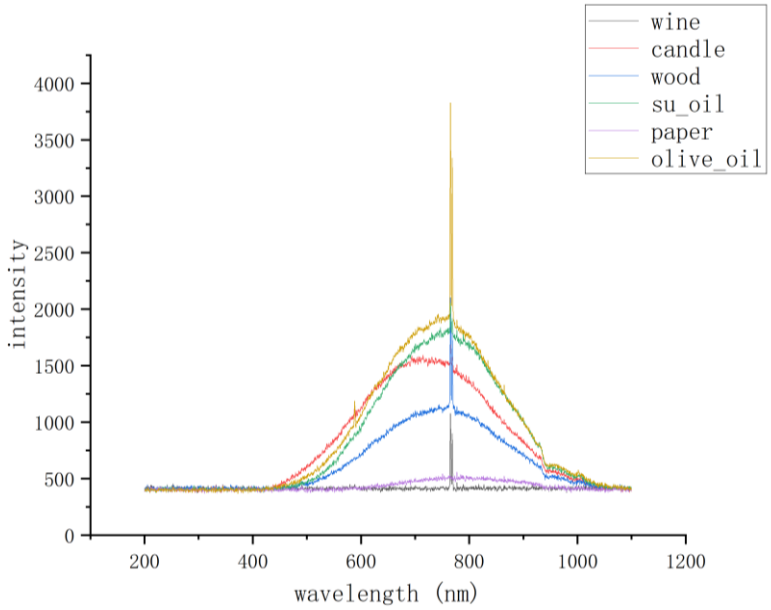
Recall (Sensitivity): Calculates the proportion of true positives identified correctly out of all actual positives.

F1 Score: Harmonic mean of precision and recall, providing a balance between the two metrics.

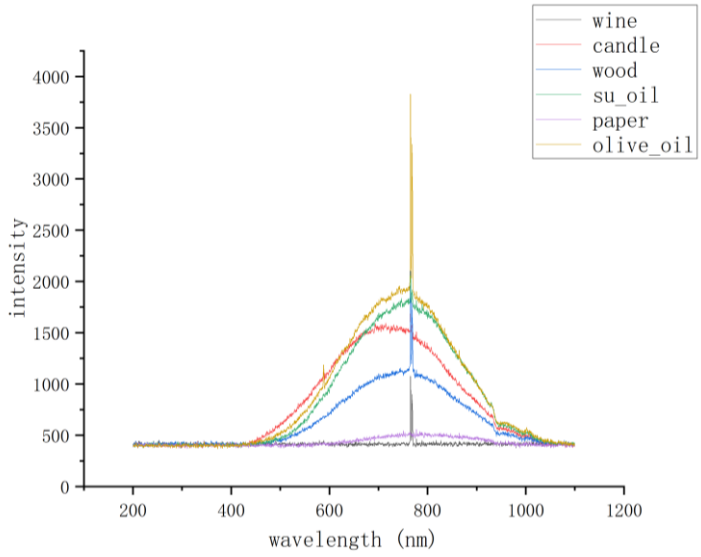
4. Experimental Results

4.1 Savitzky-Golay Smoothing

During the spectral data collection process, the probe occasionally moves slightly to capture data from different positions within the flame. The average value of these data points is taken as the spectral value for that sample. By averaging the spectral data for each sample, the original spectral curves for wood, paper, candle, butter, alcohol, and olive oil are obtained, as shown in Figure 2(a). The spectral curves after Savitzky-Golay smoothing are depicted in Figure 2(b).From the figures, it can be observed that within the wavelength range of 400-1100nm, the spectral curves of various combustible samples exhibit similar shapes, making it challenging to directly classify the different combustible materials. Therefore, modeling and classification are necessary to distinguish between them.



(a) Original Spectra

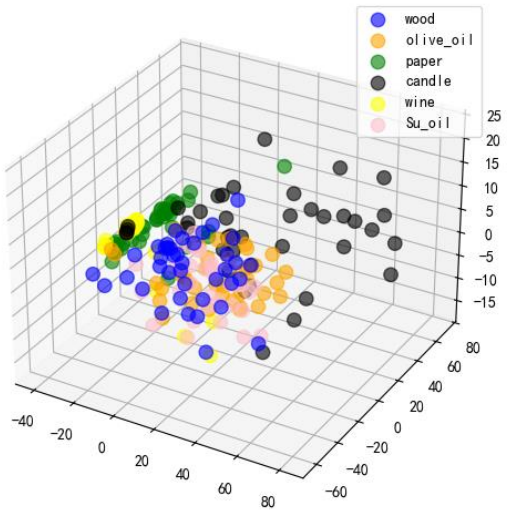


(b) Spectra After SG Smoothing

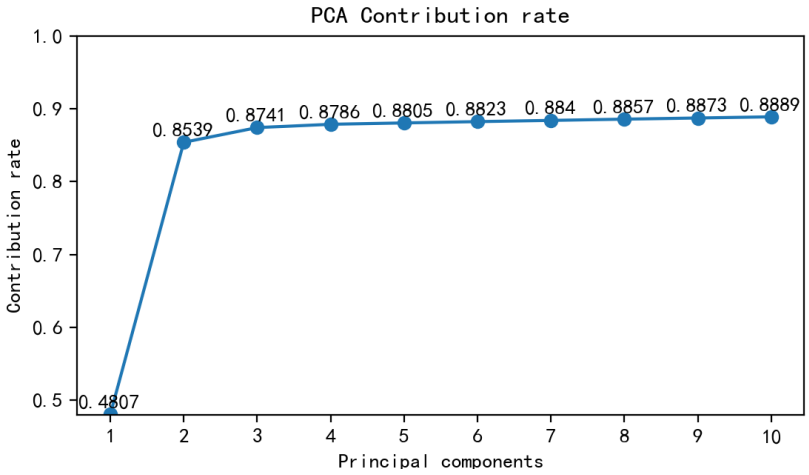
Figure 2. Combustible Material Spectra

4.2 PCA Feature Band Extraction

Using PCA for principal component analysis, the spatial distribution scatter plot of the first three principal components (PC1-PC3) for the six combustible material samples—wood, paper, candle, butter, alcohol, and olive oil—is shown in Figure 3(a). It can be observed that there is a certain degree of overlap in the spatial distribution of samples from adjacent classes, making direct classification of combustible materials very challenging. Figure 3(b) displays the cumulative variance contribution rate of the first 10 principal components. It is evident that the first principal component contributes to over 85% of the variance, summarizing the main characteristic information of the original spectra to a significant extent. To minimize the loss of effective spectral information and ensure computational efficiency, the study ultimately selects the first 10 principal components as feature variables for the subsequent combustible material classification task.



(a) Score Plot of the First Three Principal Components



(b) Cumulative Contribution Rate of the First 10 Principal Components

Figure 3. Feature Band Extraction Using PCA

4.3 Classification Results

After standardizing the data processed through PCA, the classification is performed. Utilizing the selected principal components as inputs, the classification results report the outputs. Following the training steps with five different classifiers, the classification results of each classifier are as follows.

Table 1. Classification Results of AdaBoost

	Classification Report for AdaBoost Classifier			
	precision	recall	f1-score	support
Wood	0.73	0.67	0.70	12
Olive oil	0.69	0.92	0.79	12
Paper	1.00	0.92	0.96	12
Candle	1.00	0.83	0.91	12
Wine	0.92	1.00	0.96	12
Su Oil	0.64	0.58	0.61	12
accuracy			0.61	72
macro avg	0.60	0.61	0.59	72
weighted avg	0.60	0.61	0.59	72

Table 2. Classification Results of Random Forest

	Classification Report for Random Forest Classifier			
	precision	recall	f1-score	support
Wood	1.00	0.75	0.86	12
Olive oil	0.73	0.67	0.70	12
Paper	1.00	0.75	0.86	12
Candle	0.69	0.75	0.72	12
Wine	0.80	1.00	0.89	12
Su Oil	0.60	0.75	0.67	12
accuracy			0.78	72
macro avg	0.80	0.78	0.78	72
weighted avg	0.80	0.78	0.78	72

Table 3. Classification Results of Gradient Boosting

	Classification Report for Gradient Boosting Classifier			
	precision	recall	f1-score	support
Wood	1.00	0.75	0.86	12
Olive oil	0.67	0.50	0.57	12
Paper	1.00	0.83	0.91	12
Candle	0.71	0.83	0.77	12
Wine	0.86	1.00	0.92	12
Su Oil	0.56	0.75	0.64	12
accuracy			0.78	72
macro avg	0.80	0.78	0.78	72
weighted avg	0.80	0.78	0.78	72

Table 4. Classification Results of Decision Tree

	Classification Report for Decision Tree Classifier			
	precision	recall	f1-score	support
Wood	0.54	0.58	0.56	12
Olive oil	0.46	0.50	0.48	12
Paper	1.00	0.83	0.91	12
Candle	0.57	0.67	0.62	12
Wine	0.86	1.00	0.92	12
Su Oil	0.50	0.33	0.40	12
accuracy			0.65	72
macro avg	0.65	0.65	0.65	72
weighted avg	0.65	0.65	0.65	72

Table 5. Classification Results of SVM

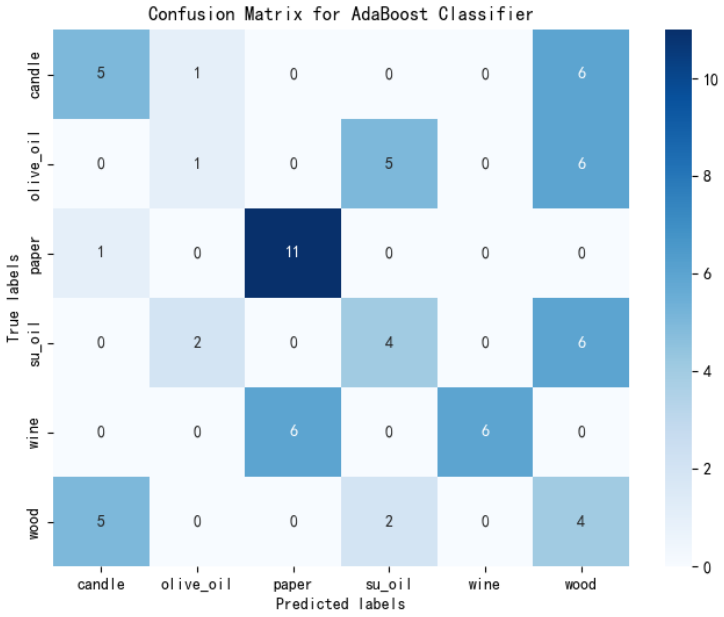
	Classification Report for SVM Classifier			
	precision	recall	f1-score	support
Wood	0.73	0.67	0.70	12
Olive oil	0.69	0.92	0.79	12
Paper	1.00	0.92	0.96	12
Candle	1.00	0.83	0.91	12
Wine	0.92	1.00	0.96	12
Su Oil	0.64	0.58	0.61	12
accuracy			0.82	72

macro avg	0.83	0.82	0.82	72
weighted avg	0.83	0.82	0.82	72

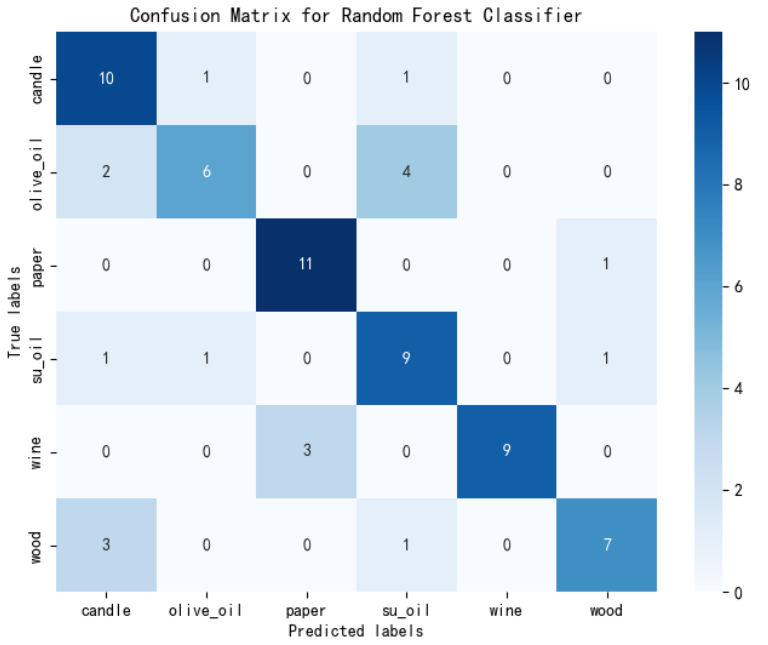
As shown in the table, among these five classifiers, SVM exhibits the highest classification accuracy. The lowest classification accuracy is observed for oils, specifically olive oil and butter, representing substances with similar properties.

4.4 Confusion Matrix Heatmap

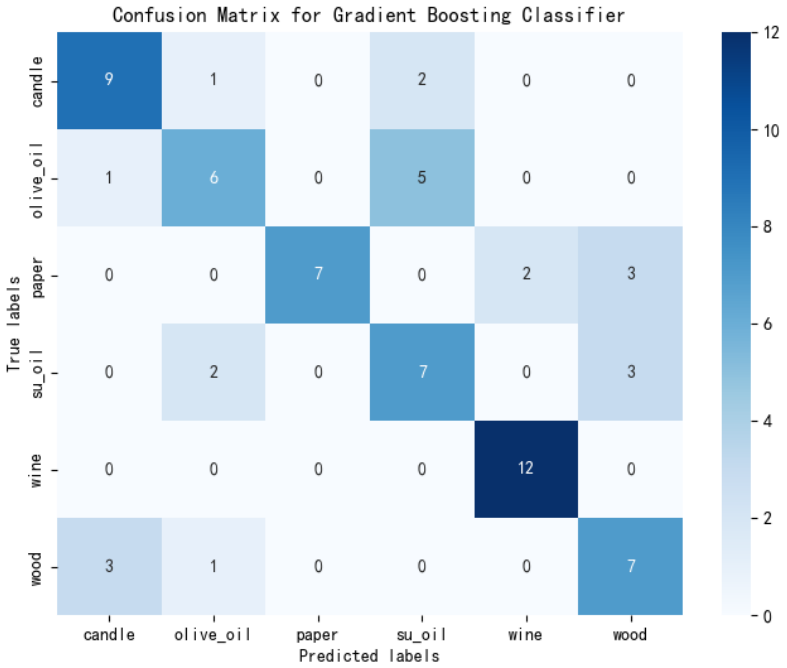
A confusion matrix is a matrix representation method used to evaluate the performance of a classification model, comparing the differences between the model's predicted results and the actual class labels. A heatmap is a data visualization technique that represents data using colored squares or matrices to display data distribution and relationships. Combining the confusion matrix and heatmap allows for a more comprehensive evaluation of the classification model's performance.



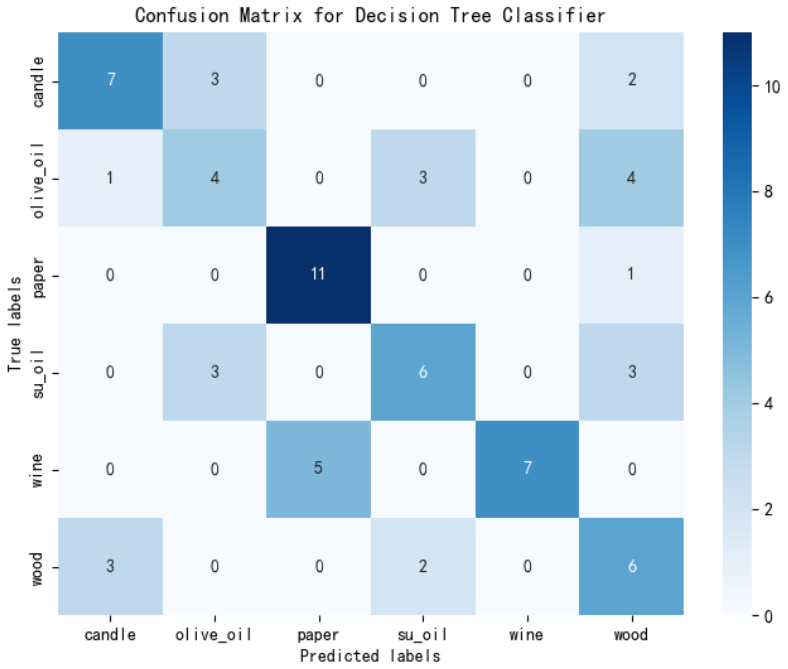
(a) AdaBoost



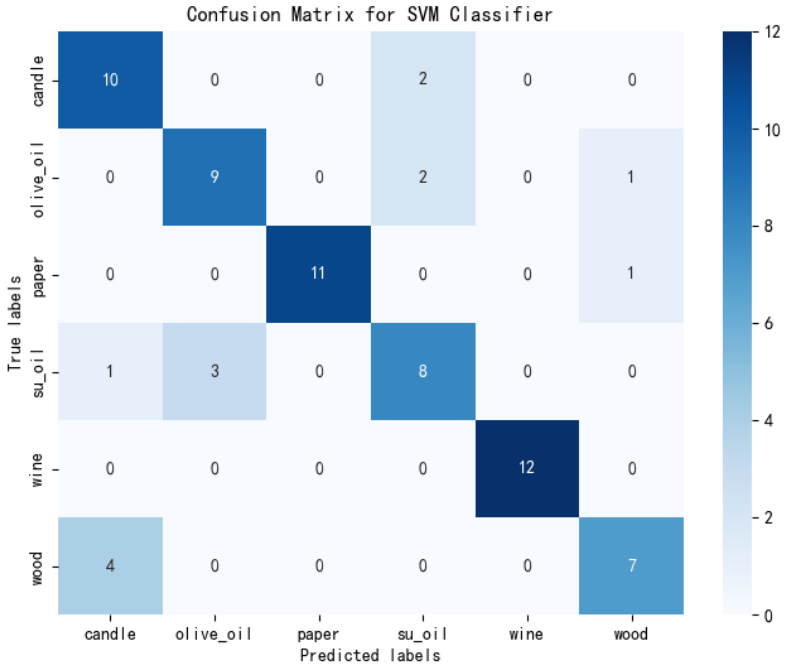
(b) Random Forest



(c) Gradient Boosting



(d) Decision Tree



(e) SVM

Figure 4. Feature Band Extraction Using PCA

5. Conclusion

The study focuses on combustible materials, utilizing a fiber optic spectrometer system to acquire flame spectral data from six combustible material samples. The data is preprocessed with SG smoothing and subjected to Principal Component Analysis (PCA). Five classification

algorithms—AdaBoost, Random Forest, Gradient Boosting, Decision Tree, and SVM—are employed to build combustible material classification models for training and classification. The final output includes the classification results and their corresponding confusion matrix heatmaps. Results indicate that among the five classification algorithms, SVM achieves the highest classification accuracy and demonstrates the best performance.

The research findings suggest that based on fiber optic spectrometer technology and appropriate machine learning algorithms, it is possible to effectively classify different types of combustible materials. These six combustible materials can be categorized into two groups: solid combustibles (wood chips, paper) and liquid combustibles (olive oil, candle, alcohol, butter). The confusion matrix heatmap reveals a higher probability of misidentification among combustible materials of the same type. Different types of combustible materials possess distinct combustion properties, while combustibles of the same type exhibit similar combustion attributes. The study demonstrates that flame spectra can serve as a basis for combustible material classification, and the results can further contribute to combustible material classification and flame spectral analysis.

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