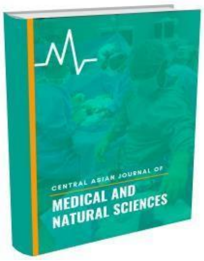

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Article

Real-time Smoke Detection with AI-Based Sensor Fusion

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Abstract: A Fire Alarm System is sensitive to smoke, fire, carbon monoxide (CO2), or general notification emergencies. This research paper, previous experimental data were collected to develop artificial intelligence (AI) models as an indicator of fire that detects smoke. Binary Classification 1 means Positive (fire), and zero means Not Positive (no fire). It was evaluated based on twelve input parameters related to indoor and outdoor environments. This task evaluated three different classifiers: Decision Tree Classifier (DTC), Random Forest Classifier (RFC), and Gradient Boosting Classifier (GBC). The results indicated that every model was giving 99.99% accuracy. A smoke detection device can be designed according to the highaccuracy AI models validated in the current study.

Keywords: Artificial Intelligence (AI); Sensor Fusion; Smoke Detection; Fire Alarm System; Binary Classification

1. Introduction

According to the Fire Protection Association (FPA), intelligent smoke detectors have higher accuracy than traditional optical and ionization detectors. However, the application of these innovative technologies in fire and evacuation practices is still limited. Despite the mandatory detector installation requirement, false alarm percentages remain high, accounting for 41% of the 555,795 cases in 2019. Only 28% of the cases had fires. Many resources were lost due to 67% of false alarms being "due to apparatus" at fault [1].

Studies show that smoke detectors only offer a minimal amount of protection because of their flaws, such as their inability to identify fires that are not smoke-related and being sensitive to false alarms brought on by smoke from cigarettes, steam, and dust. Conversely, multi-sensors measure multiple fire indicators, including air temperature, smoke concentration, carbon monoxide (CO), carbon dioxide (CO2), and other gases [2]. Even though they might be more costly, modifications to multi-sensors would be a more effective strategy to stop invalid alert activations than alternatives, like raising the system's maintenance level or correctly using certified detectors. When a fire starts, the smoke is typically heavy, dense, and highly absorbing. Additionally, burning fire tends to release more CO than CO2 into the environment. Flaming fire, on the other hand, produces more CO2 than CO. The gas sensors, which sense these flames and release gas in reaction, give rise to the prospect of early fire detection [3].

To classify different variables, machine learning (ML) algorithms have the advantage of recognizing their correlations. Adaptive neuro-fuzzy inference (ANFIS), support vector

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machines (SVM), multi-stage pattern recognition video image analysis, and unsupervised modified K-means clustering models have been developed for early fire detection [4], [5], [6], [7]. Also, deep learning (DL) methodologies, such as convolutional neural networks (CNN) [8] and deep neural networks [9], were implemented for the same purpose. Even with adequate training and modeling, performance may still be affected by DL methods' more flexible categorization capabilities and more expensive hardware requirements. Another disadvantage of such detection systems regarding delayed response time is the complexity of handling imagery data and the difficulty of obtaining high-quality photographs of smoke or flame in the early phases of fire ignition [10]. Fire systems depend on physical and chemical sensor-based fire detectors, which detect signals like hot temperature and CO_2 concentration.

Related Work

Limited previous studies discussed the topic of multi-sensor fusion-based approaches for early fire detection applications. To identify the occurrence of fires, data consisting of smoke, air temperature, and relative humidity sensors were collected [4]. The ANFIS algorithm was integrated with the Global System for Mobile Communication (GSM) to detect the place of the flames and then issue a red alert. Also, ANFIS was integrated with multi-sensors and was implemented as an early alert [11], showing high precision. In another study of [12], a technique for fire detection was installed in an electric vehicle (EV) by integrating ANFIS with the Arduino microcontroller using data readings consisting of air temperature, flame, and smoke sensors.

Chou and his team [13] installed a multi-sensor smart system for home applications integrated with AI capabilities. The Probabilistic Neural Network (PNN) classifier managed CO% and air temperature readings. Also, [14] presented the Trend Predictive Neural Network (TPNN) based system classifier to handle six sensors' measurements. The study predicted the false positive (FP) with high accuracy and the false negative (FN) with lower accuracy, respectively. Metal oxide gas sensors were tested by Lee and his group [15] in order to detect fires. Multigas sensor readings were collected from a smart building and integrated with several ML techniques [16] to detect gas leakages and fire risks.

Moreover, another [17] found that traditional smoke detectors were inadequate for protecting building residents from fires. To develop a smart system that can detect heat, fire, and smoke in green buildings, we have built three different classifiers in this work: a Decision Tree Classifier (DTC), a Random Forest Classifier (RFC), and a Gradient Boosting Classifier (GBC). The intelligent detecting system was developed using various input features, including temperature, air pressure, humidity, and the levels of several gases, including CO_2, H_2, and ethanol. Multiple metrics were used to verify and validate the proposed system's accuracy and precision.

2. Materials and Methods

Exploration Data Analysis

To perform the current classification task, previous experimental data were collected from different environments and fire sources. The dataset is 60.000 readings long and includes the following input parameters: Temperature (°C) and air Temperature. Humidity (%): Relative humidity. TVOC (ppb): Total Volatile Organic Compounds. eCO_2 (ppm): Concentration of CO_2. Raw H_2: Raw Hydrogen. Raw Ethanol: Raw Ethanol. Pressure (hPa): Air pressure. PM1.0: Particulate matter < 1.0 microns. PM2.5: Particulate matter < 2.5 microns. NC0.5: Concentration of particulate matter of diameter < 0.5 microns. NC1.0: Concentration of particulate matter < 1.0 microns. NC2.5: Concentration of particulate matter of < 2.5 microns. Meanwhile, the target was Fire Alarm: one means Positive, and zero means Not Positive. The data was cleaned, and no missing values or duplicates were found. Fig.1 shows the Intelligent system development and configuration. Also, Fig. 2 presents the distribution of features with the target (fire alarm). Meanwhile,

Fig. 3 displays the Pearson correlation coefficient (PCC), which reflects the features' correlations with the target variable. The Fire Alarm is highly correlated with humidity, TVOC, Raw Ethanol, and pressure. Moreover, the target moderately correlates to Temperature, Raw H2, PM1.0, and NC0.5. Meanwhile, low correlations were observed with eCO2, PM2.5, NC1.0 and NC2.5.

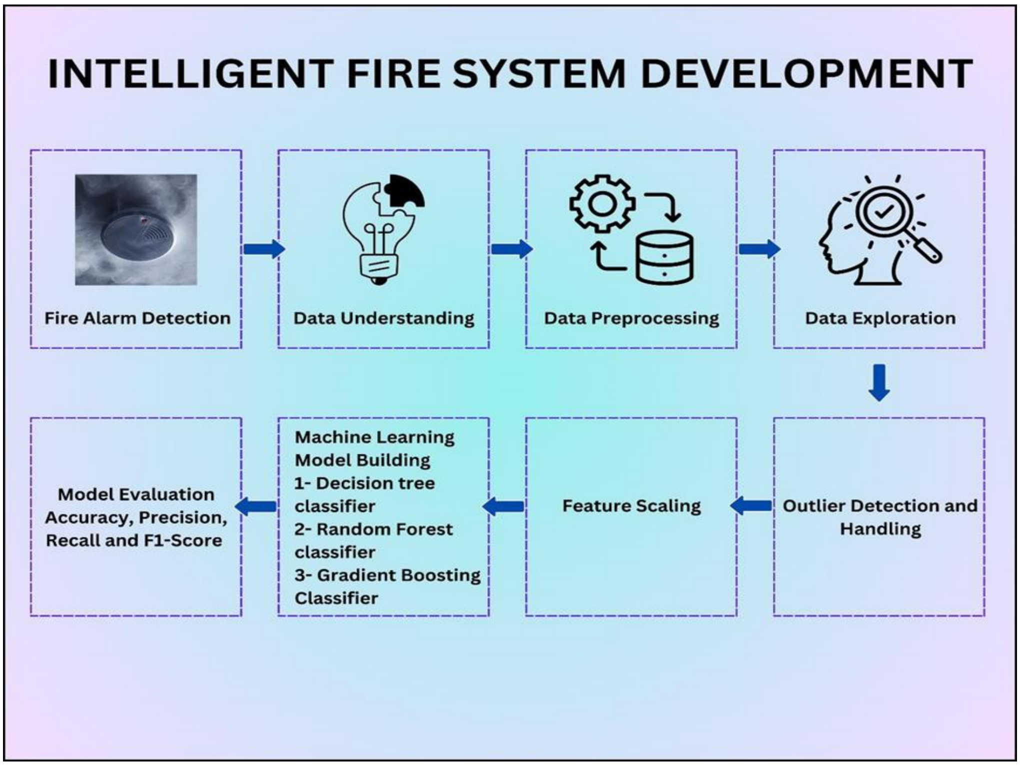
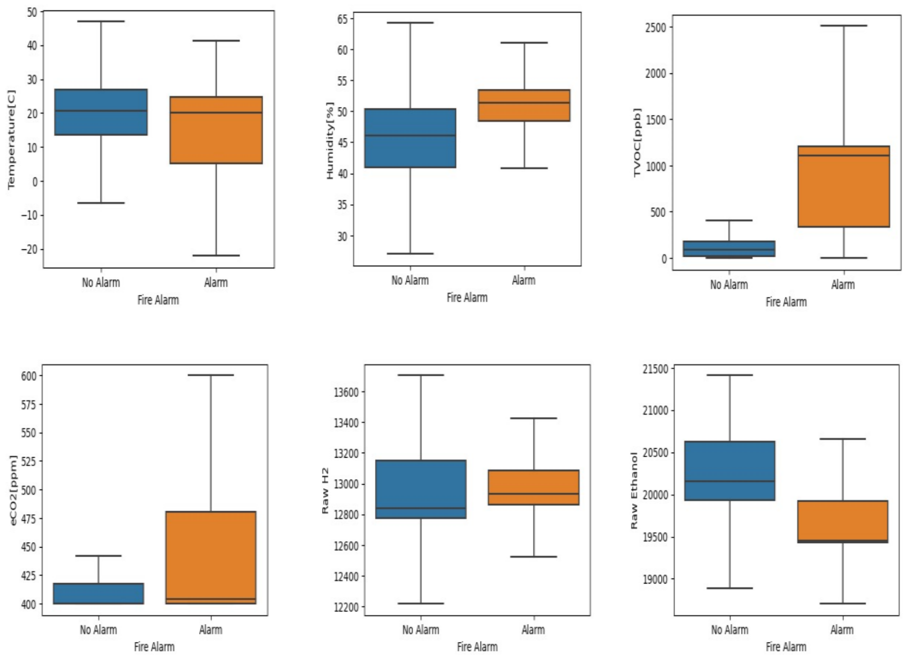


Fig. 1. Intelligent fire system development and configuration.



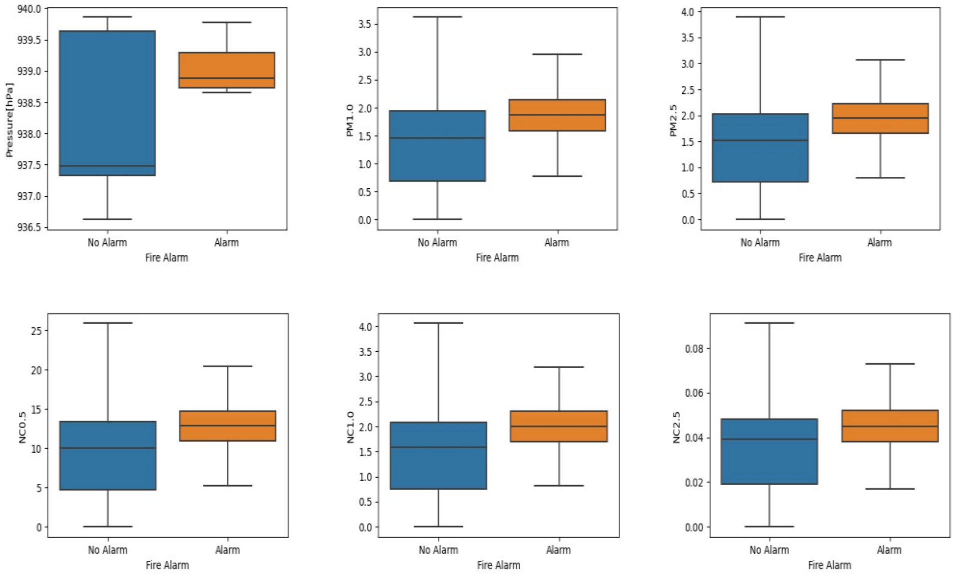


Fig. 2. Features correlations with target variable (Fire Alarm).

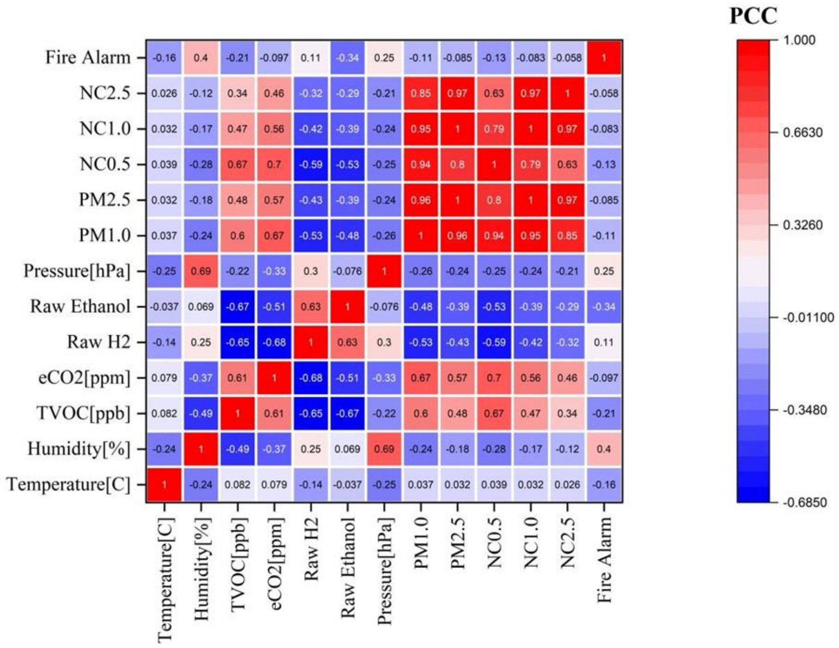


Fig. 3. Heatmap visualization correlation between features.

Machine Learning Algorithms

Decision tree classifier (DTC)

The decision tree classifier (DTC) [18, 19] is a supervised learning model that can be applied to different domains and applications. It can be used for both tasks, such as classification and regression, due to its advantages, such as being easy to implement and elaborate, requiring little data re-processing (can be done with easy normalization or standardization), and easy to manage data in numbers or categories. On the other hand, some disadvantages could have appeared, especially when the trees are deep learning, and specific instances can perform less accurately than ensemble methods (e.g., Random Forests or Gradient Boosting). The main architecture of the Decision tree classifier could be like (1) structure of trees, (2) decision rules, (3) leaf nodes, and (4) criteria of splitting Criteria.

Random Forest classifier (RFC)

Random forest classifier (RFC) [20] was 1st developed in 2001. It is a powerful model belonging to ensemble machine learning algorithms that can manage classification and regression tasks due to its multiple decision trees. Random forest classifier is developed due to its advantages like high accuracy in predictive targets, no overfitting observed, the solving regression and classification tasks with the same precision and can be used for feature selection. To avoid its disadvantages, it is preferable to apply it on exceedingly small datasets. The main architecture of this model can be included: (1) decision trees ensemble, (2) bootstrapped sampling, (3) random feature selection, and (4) average/voting.

Gradient Boosting Classifier (GBC)

A Gradient Boosting Classifier (GBC) [21-23] is another ML model belonging to the ensemble learning family. It is an excellent selection to be implemented for classification tasks due to its predictive capabilities. The advantages of this classifier are that it can be implemented in many cases, solving overly complex data, using feature selections, and handling outliers in data. Also, to avoid its disadvantages, it is recommended not to apply sensitive hyperparameters and consume more computational time than random forest. The key characteristics and components of this classifier could be (1) weak learners' ensemble, (2) sequential training, (3) learning rate, and (4) combining predictions. The weak learner was trained using an objective (loss function and regularization) function at iteration t as the following:

$$\mathbb{L}(t)\,(xi, yi) = \sum_{i=1}^{N} \mathscr{L}(yi, yi(t-1) + ft(xi)) + \Omega(ft) \qquad (1)$$

Classification Metrics

The performance evaluation of each classifier was performed using different metrics such as Accuracy, Precision, Recall, and F1-Score [24-26]. The equation of each metric is written below:

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \qquad (2)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \qquad (3)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \qquad (4)$$

$$\mathrm{F1-Score} = \frac{2 * (Precision * Recall)}{Precision + Recall} \qquad (5)$$

3. Results and Discussion

The classification reports of three models, a decision tree classifier, random forest classifier, and gradient boosting classifier, are presented in this part. Tables (1-3) suggest that the classification models have achieved excellent performance, with perfect precision, recall, and F1-Scores for both classes (0= alarm and 1= no alarm) and an accuracy of 1.00. This indicates that the model is providing accurate predictions for both classes. According to this high accuracy, the suggested three models can be used as intelligent fire detection systems by providing some information about the trained input features to decide the class (0 or 1). The three developed models were tested by giving the following input: (Temperature = 20.960, Humidity = 57.25, TVOC = 100, eCO2 = 548, H2 = 12835, Raw Ethanol = 19474, Pressure = 238.972, PM1.0 = 1.89, PM2.5 = 1.96, NC0.5 = 13.01, NC1.0 = 2.028, NC2.5 = 0.046) and the result was (No Alarm).

Table 1. Classification report of Decision tree classifier (DTC).

	Precision	Recall	F1-Score	Support
Alarm	1	1	1	3605
No Alarm	1	1	1	8921
Accuracy			1	12526
Macro Average	1	1	1	12526
Weighted Average	1	1	1	12526

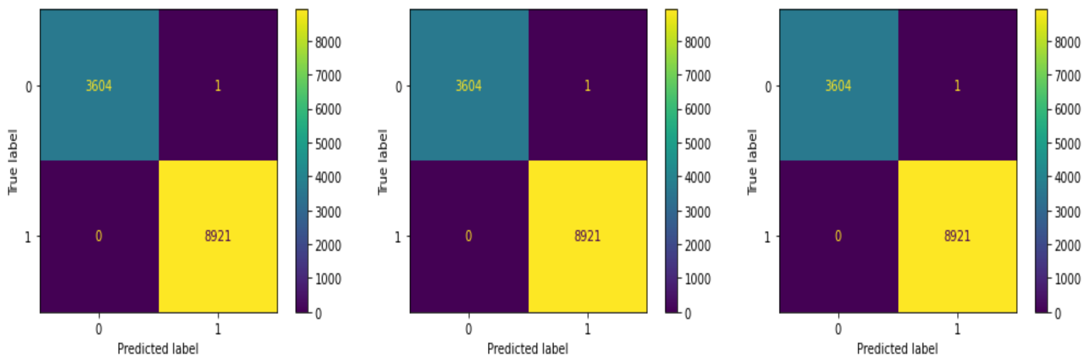
Table 2. Classification report of Random Forest classifier (RFC).

	Precision	Recall	F1-Score	Support
Alarm	1	1	1	3605
No Alarm	1	1	1	8921
Accuracy			1	12526
Macro Average	1	1	1	12526
Weighted Average	1	1	1	12526

Table 3. Classification report of Gradient Boosting Classifier (GBC).

	Precision	Recall	F1-Score	Support
Alarm	1	1	1	3605
No Alarm	1	1	1	8921
Accuracy			1	12526
Macro Average	1	1	1	12526
Weighted Average	1	1	1	12526

Moreover, the confusion Matrix for testing data using a decision tree classifier (DTC), random forest classifier (RFC), and gradient boosting classifiers (GBC) is presented in Fig. 4. The three matrices show that only one entry is misled from the accurate result (falls in True Negative (TN)).



Decision tree classifier *Random Forest classifier* *Gradient Boosting Classifier*

Fig. 4. Confusion Matrix for testing data using three different classifiers.

4. Conclusion

This study used experimental data to create artificial intelligence (AI) models that detect smoke, which is often a fire signal. Based on twelve input factors linked to interior and outdoor surroundings, binary classification—where one denotes positive (fire), and zero denotes not positive (no fire)—was assessed. Three distinct classifiers—Decision Tree Classifier (DTC), Random Forest Classifier (RFC), and Gradient Boosting Classifiers (GBC)—were developed for this assignment. The correlation between the fire alarm and TVOC, pressure, raw ethanol, and humidity is strong. Target also weakly correlates with temperature, raw H2, PM1.0, and NC0.5. Low associations with eCO2, PM2.5, NC1.0, and NC2.5 were also noted. Moreover, all three of the models provide 99.99% accuracy.

REFERENCES

[1] S. Chen, J. Ren, Y. Yan, M. Sun, F. Hu, and H. Zhao, "Multi-sourced sensing and support vector machine classification for effective detection of fire hazard in early stages," Computers and Electrical Engineering, vol. 101, p. 108046, 2022.

[2] S. L. Rose-Pehrsson et al., "Multi-criteria fire detection systems using a probabilistic neural network," Sensors and Actuators B: Chemical, vol. 69, no. 3, pp. 325-335, 2000. [3] D. Gutmacher, U. Hoefer, and J. Wöllenstein, "Gas sensor technologies for fire detection," Sensors and Actuators B: Chemical, vol. 175, pp. 40-45, 2012.

[3] B. Sarwar, I. S. Bajwa, N. Jamil, S. Ramzan, and N. Sarwar, "An intelligent fire warning application using IoT and an adaptive neuro-fuzzy inference system," Sensors, vol. 19, no. 14, p. 3150, 2019.

[4] C.-C. Ho, "Nighttime fire/smoke detection system based on a support vector machine," Mathematical Problems in Engineering, vol. 2013, 2013.

[5] T. X. Truong and J.-M. Kim, "Fire flame detection in video sequences using multi-stage pattern recognition techniques," Engineering Applications of Artificial Intelligence, vol. 25, no. 7, pp. 1365-1372, 2012.

[6] Chakraborty and T. K. Paul, "A hybrid clustering algorithm for fire detection in video and analysis with color-based thresholding method," in 2010 International Conference on Advances in Computer Engineering, 2010: IEEE, pp. 277-280.

[7] K. Muhammad, J. Ahmad, and S. W. Baik, "Early fire detection using convolutional neural networks during surveillance for effective disaster management," Neurocomputing, vol. 288, pp. 30-42, 2018.

[8] J. Gotthans, T. Gotthans, and R. Marsalek, "Deep convolutional neural network for fire detection," in 2020 30th international conference radioelektronika (RADIOELEKTRONIKA), 2020: IEEE, pp. 1-6.

[9] Gaur et al., "Fire sensing technologies: A review," IEEE Sensors Journal, vol. 19, no. 9, pp. 3191-3202, 2019.

[10] F. Rachman et al., "Design of the early fire detection based fuzzy logic using multisensor," in IOP Conference Series: Materials Science and Engineering, 2020, vol. 732, no. 1: IOP Publishing, p. 012039.

[11] R. Sowah, K. O. Ampadu, A. Ofoli, K. Koumadi, G. A. Mills, and J. Nortey, "Design and Implementation of a Fire Detection and Control System for Automobiles using fuzzy logic," in 2016 IEEE industry applications society annual meeting, 2016: IEEE, pp. 1-8.
[12] P.-H. Chou et al., "Development of a smart home system based on multi-sensor data fusion technology," in 2017 International Conference on Applied System Innovation (ICASI), 2017: IEEE, pp. 690-693.
[13] M. Nakıp and C. Güzeliş, "Multi-sensor fire detector based on trend predictive neural network," in 2019 11th International Conference on Electrical and Electronics Engineering (ELECO), 2019: IEEE, pp. 600-604.
[14] K. Lee, Y.-S. Shim, Y. G. Song, S. D. Han, Y.-S. Lee, and C.-Y. Kang, "Highly sensitive sensors based on metal-oxide nanocolumns for fire detection," Sensors, vol. 17, no. 2, p. 303, 2017.
[15] L. Salhi, T. Silverston, T. Yamazaki, and T. Miyoshi, "Early detection system for gas leakage and fire in a smart home using machine learning," in 2019 IEEE International Conference on Consumer Electronics (ICCE), 2019: IEEE, pp. 1-6.
[16] J. Fonollosa, A. Solórzano, and S. Marco, "Chemical sensor systems and associated algorithms for fire detection: A review," Sensors, vol. 18, no. 2, p. 553, 2018.
[17] E. Toulabinejad, M. Mirsafaei, and A. Basiri, "Supervised discretization of continuous-valued attributes for classification using RACER algorithm," Expert Systems with Applications, p. 121203, 2023.
[18] R. Romano, A. Barbul, and R. Korenstein, "From modeling dose-response relationships to improved performance of decision-tree classifiers for predictive toxicology of nanomaterials," Computational Toxicology, p. 100277, 2023.
[19] C.-Y. Chen, W.-C. Lin, and H.-Y. Yang, "Diagnosis of ventilator-associated pneumonia using electronic nose sensor array signals: solutions to improve the application of machine learning in respiratory research," Respiratory Research, vol. 21, no. 1, pp. 1-12, 2020.
[20] Kumar, S. Upadhyayula, and H. Kodamana, "A Convolutional Neural Network-based gradient boosting framework for prediction of the band gap of photo-active catalysts," Digital Chemical Engineering, p. 100109, 2023.
[21] Y. Liu, S. Jin, L. Song, Y. Han, and B. Yu, "Prediction of protein ubiquitination sites via multi-view features based on eXtreme gradient boosting classifier," Journal of Molecular Graphics and Modelling, vol. 107, p. 107962, 2021.
[22] V. Kniazev, A. Erofeev, A. Demidov, D. Orlov, and D. Koroteev, "Advanced well stimulation selection with gradient boosting," Geoenergy Science and Engineering, p. 212026, 2023.
[23] M. H. Daneshvari, E. Nourmohammadi, M. Ameri, and B. Mojaradi, "Efficient LBPGLCM texture analysis for asphalt pavement raveling detection using eXtreme Gradient Boost," Construction and Building Materials, vol. 401, p. 132731, 2023.
[24] G. Ajayi and J. Ashi, "Effect of varying training epochs of a Faster Region-Based Convolutional Neural Network on the Accuracy of an Automatic Weed Classification Scheme," Smart Agricultural Technology, vol. 3, p. 100128, 2023.
[25] R. G. Poola and L. Pl, "COVID-19 diagnosis: A comprehensive review of pre-trained deep learning models based on feature extraction algorithm," Results in Engineering, p. 101020, 2023.