Multisensory Fusion Approaches for Accurate Smoke Detection in Smart Environments

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Abstract

The reassessment of alarm systems' role in this regard has led to the search for improved ways of detecting fire. In this study, sensor fusion is explored to improve the accuracy and reliability of smoke detection. Since individual sensors are limited in their capabilities, this research seeks to merge different sensor data using complex fusion techniques. This paper gives a detailed analysis of several types of sensors that are used indoors and outdoors as well as firefighter training grounds that have multiple fire sources. To work around this problem, the Adaboost algorithm was used as an ensemble learning technique where sensor data were combined iteratively to form a strong classification model. The study then goes on to meticulously plot variable distribution graphs/bar charts, carry out correlation analyses, and make comparisons with other studies done previously; these findings give insight into how effective sensor fusion methods could be when it comes to smoke detection. The research results indicate that incorporating multiple sensors can significantly enhance detection accuracy and reliability. Thus, the findings obtained from this study identify a promising path for creating more efficient smoke detection systems.

Keywords: Information fusion; Smoke detection; Machine Learning; Sensor Timeseries; Data Analytics.

1. Introduction

Smart technology evolution has brought about a total change in terms of security systems, especially in the area of fire detection and eradication. Among many threats, smoke detection is one of the important measures to reduce risks related to fire that has caused extensive research on how to make it more reliable and efficient [1-3]. For instance, traditional smoke detectors normally use one sensor each and hence have some limitations which include; accuracy, reliability, and response time. As such, the integration of multiple sensors through sensor fusion techniques is considered as a potential solution for improving smoke detection performance [4-6].

Sensor fusion is the process of combining data from various sensors in order to get a more complete picture of what is happening around us [7]. Specifically, this method works by merging information from different kinds of devices like optical, thermal, or chemical ones into a single entity thus giving us an idea about where potential fires may occur in general. By doing this, it becomes possible to create a stronger point while talking about any particular matter related to smoke detectors because they compensate for weak points coming from individual components thereby making their overall performance better than before [8-10].

Despite advancements, the field of smoke detection encounters several challenges. Smoke particles can vary significantly in composition and density, presenting difficulties for singular sensors to consistently detect and classify these particles accurately. Additionally, environmental factors, such as humidity or dust, might interfere with sensor readings, leading to false alarms or missed detections [11-15]. Addressing these challenges necessitates innovative approaches that go beyond single-sensor solutions, emphasizing the integration and synergy of diverse sensor data through sensor fusion techniques [16].

DOI: https://doi.org/10.54216/IJWAC.080202
Received: September 01, 2023 Revised: December 12, 2023 Accepted: March 08, 2024

This paper aims to explore the potential of sensor fusion methodologies in enhancing smoke detection and classification. By examining various sensor fusion strategies and classification algorithms, this study seeks to evaluate their effectiveness in accurately identifying and categorizing smoke particles. The research also endeavors to assess the practical applicability of these techniques in real-world scenarios, considering factors such as scalability, cost-effectiveness, and adaptability to different environments. Through this exploration, the ultimate goal is to contribute insights that advance the development of more reliable and efficient smoke detection systems.

2. Methodology

In this section, we outline the experimental design, data acquisition processes, sensor configurations, and the methodology for data integration and analysis.

The preprocessing phase was an integral component of this study's methodology, aimed at refining and harmonizing the collected data to facilitate the subsequent fusion process. Initially, the raw data obtained from diverse sensors across multiple scenarios underwent a series of preprocessing steps to ensure uniformity, consistency, and compatibility for effective fusion analysis.

The first step in the preprocessing pipeline involved data cleaning to address missing values, outliers, and inconsistencies across sensor readings. Specifically, missing data points were handled through imputation techniques such as mean substitution or interpolation to maintain dataset integrity. Outliers, identified using statistical methods or domain-specific thresholds, were either corrected or removed to prevent distortion of the fusion process by anomalous readings. Subsequently, standardization and normalization procedures were implemented to bring uniformity to the dataset. This involved scaling sensor readings to a common range or standard deviation to mitigate the impact of varying measurement scales across sensors [17-18]. Z-score normalization is employed to ensure that all sensor data are on a comparable scale, thus facilitating a more effective fusion process. Moreover, feature engineering techniques were applied to extract relevant features from the sensor data, enhancing the dataset's representational capabilities while reducing dimensionality. Feature selection methods, including correlation analysis and principal component analysis (PCA), were utilized to identify and retain informative sensor features essential for the fusion process while reducing computational complexity. Additionally, temporal alignment was crucial to synchronize sensor readings accurately. A consistent temporal reference using Universal Coordinated Time (UTC) timestamps was maintained throughout the dataset, ensuring precise alignment of sensor data across different scenarios and sensors.

Algorithm 1: Adaboost Algorithm

1: Input: Let D be the dataset that includes $\{(a_1, b_1), (a_2, b_2), \dots .(a_m, b_m)\}$;

2: Let λ be the learning (base) algorithm

3: Let T be the total No. of learning rounds.

4: $D_1(i) = 1/m$

5: for time $= 1, \dots, T$;

6: $h_t = \lambda(D, D_t)$; weak learner is trained with Distribution D_t

7: $\epsilon_t = \mathrm{PrPr}_{t\sim D_t}\,[h_t(a_i \neq b_i)]$; Error measure (entropy)

8: $\propto_t = \frac{1}{2}\ln\left(\frac{1-Et}{Et}\right)$; % determine the weigth of h_t

9: $D_{t+1}(i) = \frac{D_t(t)}{Z_t} * \begin{cases} \exp(-\propto_t) \text{ if } h_t(a_i) = b_t \\ \exp(\alpha_t) \text{ if } h_t(a_i) \neq b_t \end{cases} = \frac{D_t(t)\exp(-\alpha_t y_t\, h_t(a_1)}{Z_t}$

10: Return $H(a) = \text{sign}\,(\sum_{t=1}^{T} \propto_t h_t(b)$

Adaboost, a prominent ensemble learning technique, was employed in this study to harness the collective intelligence of diverse sensors and enhance the smoke detection process through effective data fusion. Adaboost operates as an ensemble learning method that sequentially combines multiple weak learners, typically decision trees or other base classifiers, into a robust and accurate classification model. The iterative nature of Adaboost involves assigning higher

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weights to misclassified instances in successive iterations, enabling the model to focus on learning from the previously misclassified samples, thus refining its predictive capabilities.

In the context of this study, Adaboost was leveraged as a fusion framework to amalgamate sensor data from various sources, effectively integrating the information captured by different sensors. The individual sensor readings, having undergone preprocessing to ensure uniformity and relevance, were utilized as input features for the Adaboost classifier. Through an iterative process, Adaboost incrementally learned from the diverse sensor data, iteratively adjusting the weights of the weak learners to prioritize the accurate classification of smoke instances while mitigating the influence of noise or irrelevant sensor readings (refer to algorithm 1).

The key strength of Adaboost lies in its ability to adaptively combine multiple weak classifiers, thereby creating a robust ensemble model that capitalizes on the diverse information provided by the sensors. By iteratively improving its predictive accuracy and emphasizing the importance of misclassified instances, Adaboost facilitated the fusion of sensor data, enhancing the smoke detection process's accuracy and reliability. The ensemble model constructed by Adaboost effectively exploited the complementary information offered by different sensors, leading to a more comprehensive and informed decision-making process in detecting smoke occurrences.

3. Results and Discussion

Herein, we present the empirical results obtained from the implemented sensor fusion techniques, detailing their performance in detecting and categorizing smoke particles.

The dataset utilized for this case study comprises readings obtained from a variety of scenarios to train the smoke detection system. These readings were collected using different types of smoke detectors, namely the Photoelectric Smoke Detector and Ionization Smoke Detector. The devices used for sensing smoke are typically housed in plastic enclosures, commonly resembling a disk around 150 millimeters (6 inches) in diameter and 25 millimeters (1 inch) in thickness, although variations in size and shape exist. To ensure a comprehensive dataset for training purposes, diverse environmental settings and fire sources were sampled [19]. These scenarios encompassed normal indoor and outdoor settings, including instances such as indoor wood fires within firefighter training areas, indoor gas fires within similar training contexts, outdoor scenarios involving wood, coal, and gas grills, as well as environments with high humidity levels, among others. The dataset consists of nearly 60,000 readings, each recorded at a sample rate of 1Hz across all sensors. Additionally, to maintain accurate data tracking, a Universal Coordinated Time (UTC) timestamp is affixed to every sensor reading, enabling precise temporal referencing and alignment within the dataset.

Table 1 encapsulates a comprehensive descriptive summary of the dataset utilized in this study. The dataset comprises approximately 60,000 individual readings collected from diverse scenarios and environmental settings. It encompasses a wide array of fire sources, including normal indoor and outdoor scenarios, firefighter training areas with wood and gas fires, as well as outdoor settings involving wood, coal, and gas grills, among various others. The dataset is richly varied to ensure a robust training sample for the smoke detection system. Each reading, sampled at a frequency of 1Hz across all sensors, is accompanied by a precise Universal Coordinated Time (UTC) timestamp, facilitating accurate temporal alignment and tracking. The summary in Table 1 provides essential statistical measures, including mean, median, standard deviation, minimum, and maximum values across different sensor readings, offering a comprehensive insight into the dataset's characteristics and variability across the sampled scenarios.

Table 1: Descriptive Summary of Dataset for Smoke Detection

	count	**mean**	**std**	**min**	**0.25**	**0.5**	**0.75**	**max**
UTC	62630	1654792066	110002	1654712187	1654743244	1654761920	1654777577	1655130051
Temperature[C]	62630.0	16.0	14.4	-22.0	11.0	20.1	25.4	59.9
Humidity[%]	62630.0	48.5	8.9	10.7	47.5	50.2	53.2	75.2
TVOC[ppb]	62630.0	1942.1	7811.6	0.0	130.0	981.0	1189.0	60000.0

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Received: September 01, 2023 Revised: December 12, 2023 Accepted: March 08, 2024

eCO2[ppm]	62630.0	670.0	1905.9	400.0	400.0	400.0	438.0	60000.0
Raw H2	62630.0	12942.5	272.5	10668.0	12830.0	12924.0	13109.0	13803.0
Raw Ethanol	62630.0	19754.3	609.5	15317.0	19435.0	19501.0	20078.0	21410.0
Pressure[hPa]	62630.0	938.6	1.3	930.9	938.7	938.8	939.4	939.9
PM1.0	62630.0	100.6	922.5	0.0	1.3	1.8	2.1	14333.7
PM2.5	62630.0	184.5	1976.3	0.0	1.3	1.9	2.2	45432.3
NC0.5	62630.0	491.5	4265.7	0.0	8.8	12.5	14.4	61482.0
NC1.0	62630.0	203.6	2214.7	0.0	1.4	1.9	2.2	51914.7
NC2.5	62630.0	80.0	1083.4	0.0	0.0	0.0	0.1	30026.4
CNT	62630.0	10511.4	7597.9	0.0	3625.3	9336.0	17164.8	24993.0
Fire Alarm	62630.0	0.7	0.5	0.0	0.0	1.0	1.0	1.0

Figure 1 presents a graphical representation illustrating the distribution of key variables within the dataset utilized for smoke detection analysis. This visualization aims to offer a comprehensive overview of the distribution patterns exhibited by crucial sensor readings across various scenarios. Through this graphical depiction, distinct patterns and variations in the dataset become apparent, providing insights into the range and spread of sensor readings in different environmental settings and fire sources. The visualization facilitates a clearer understanding of the variability and tendencies within the dataset, aiding in identifying potential trends or outliers that may significantly impact smoke detection performance. Analyzing the variable distribution visually in Figure 1 serves as a foundational step in comprehending the dataset's inherent characteristics and informs subsequent analysis and modeling strategies.

Figure 2 presents a correlation matrix that visually depicts the interrelationships and associations between various sensor readings within the smoke detection dataset. This graphical representation offers a comprehensive overview of the strength and direction of correlations among different variables. By employing color gradients or correlation coefficients, this visualization illustrates the degree of linear correlation between pairs of sensors. Understanding these correlations is pivotal in identifying potential redundancies or dependencies among sensors and can inform feature selection or dimensionality reduction strategies for modeling. The visualization in Figure 2 aids in uncovering underlying patterns and relationships, guiding the subsequent modeling process and contributing to the refinement of the smoke detection system by highlighting influential sensor relationships.

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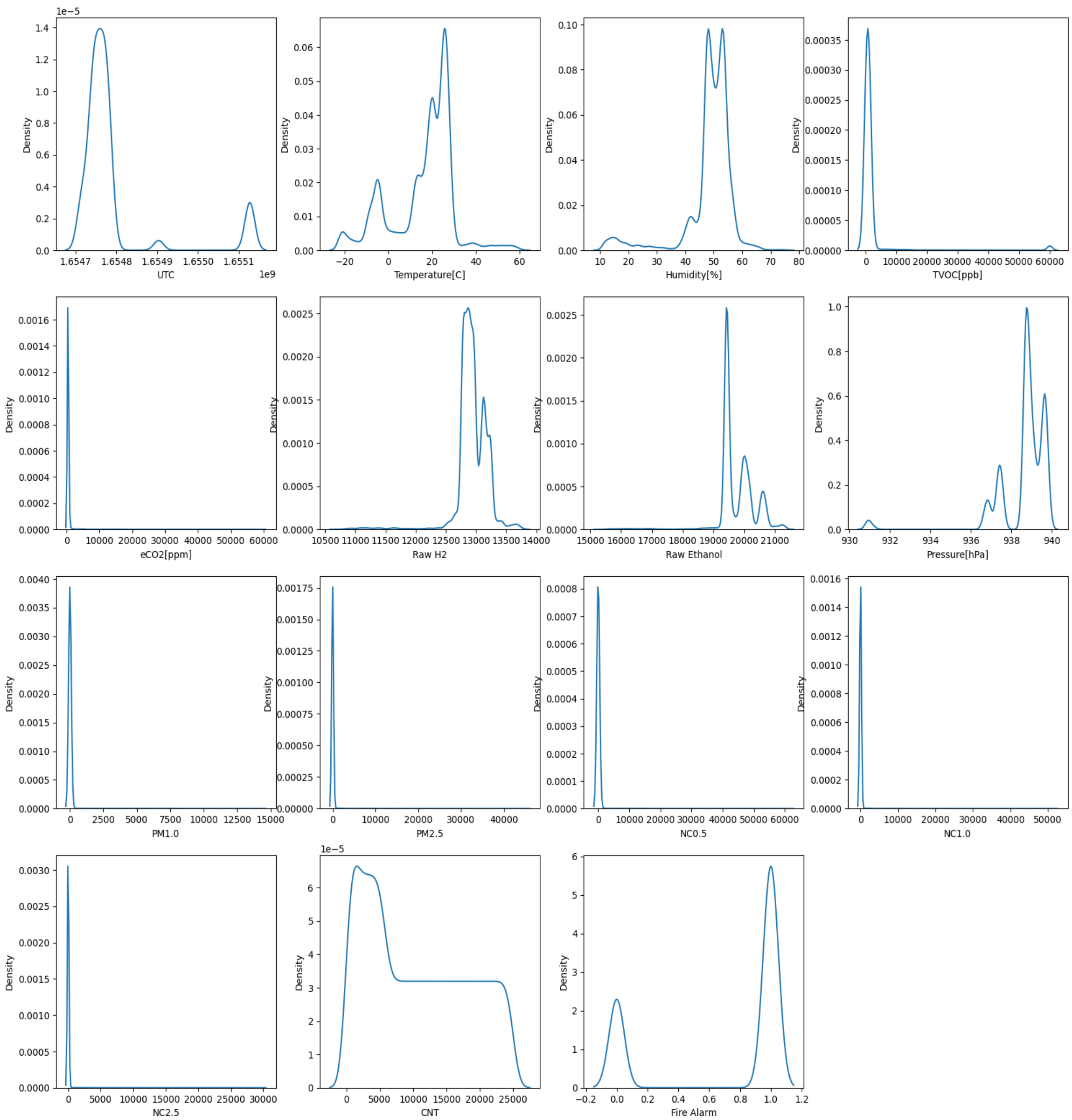

Figure 1: Distribution of Key Variables in the Smoke Detection Dataset

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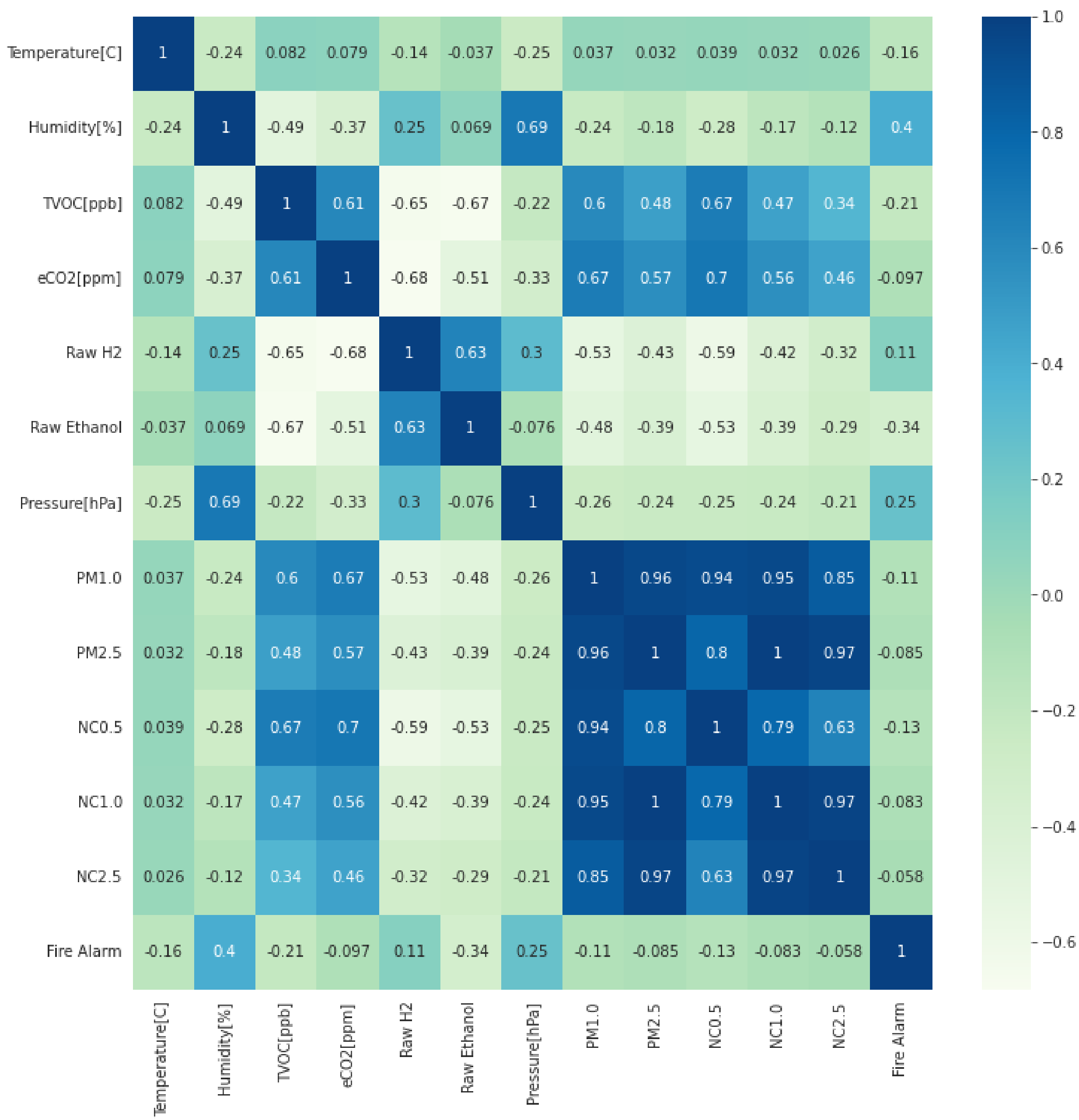

Figure 2: Correlation Matrix of Sensor Readings in the Smoke Detection Dataset

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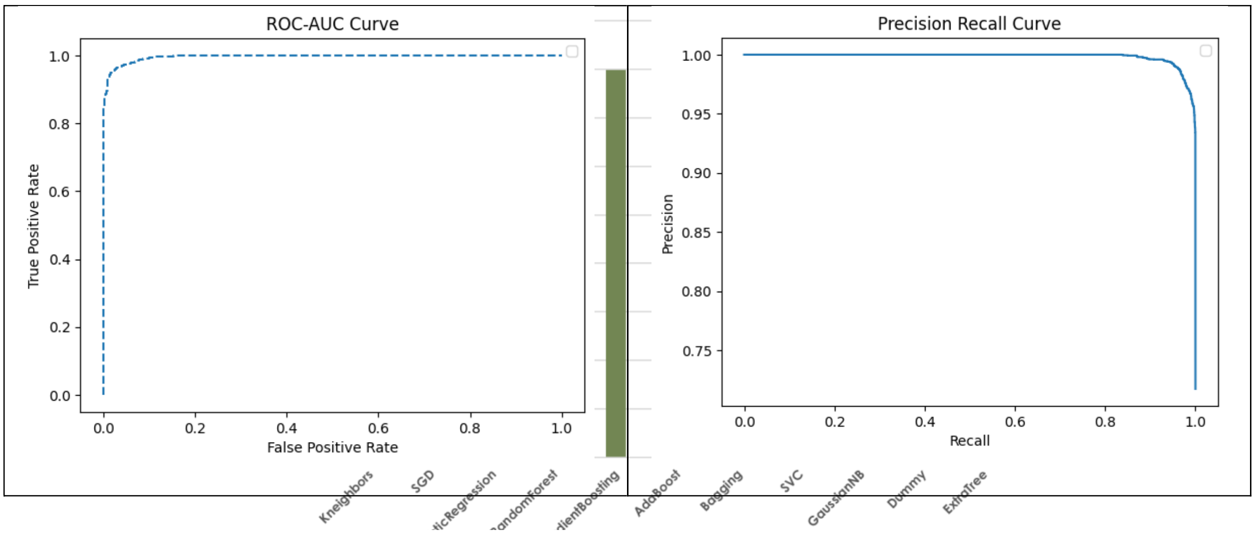

Figure 3: Comparison of ML Classifier Accuracy

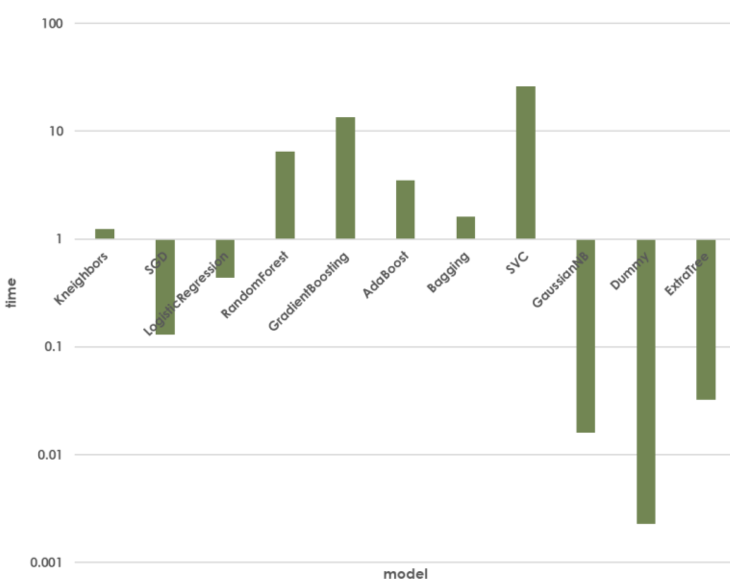

Figure 4: Time Comparison of ML Algorithms

In Figure 3, a comparative analysis of the accuracy metrics of various Machine Learning (ML) classifiers employed in the smoke detection system is presented. This visualization provides a detailed overview of the performance of distinct classifiers in accurately detecting and classifying smoke across the dataset. By depicting the accuracy scores or performance metrics such as precision, recall, and F1-score of each classifier, this comparative analysis aids in assessing their effectiveness in handling the complexities and variations present in smoke detection scenarios. Understanding the varying accuracies of these classifiers is instrumental in identifying the most suitable algorithm for real-time smoke detection applications, contributing to the refinement and optimization of the detection system.

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Figure 4 illustrates a comparative analysis of the time taken by different Machine Learning algorithms for smoke detection tasks. This visualization presents a clear overview of the computational efficiency and speed of various algorithms in processing and analyzing the dataset. By showcasing the time taken by each algorithm to execute smoke detection tasks, this comparison aids in identifying computational bottlenecks or performance differences among the classifiers. Understanding the time efficiency of these algorithms is crucial, especially in real-time applications, where rapid and efficient smoke detection is imperative. Figure 4 assists in making informed decisions regarding algorithm selection, considering both accuracy and computational speed for an optimized smoke detection system.

In Figure 5, the left and right sections respectively showcase the Receiver Operating Characteristic (ROC) curve and Precision-Recall curve analyses for the smoke detection system. The ROC curve, displayed in the left part, delineates the trade-off between true positive rate and false positive rate across varying classification thresholds. This curve provides insights into the classifiers' ability to distinguish between smoke and non-smoke instances, assisting in the selection of an optimal threshold for classification. Meanwhile, the Precision-Recall curve, depicted in the right section, illustrates the trade-off between precision and recall, offering a comprehensive evaluation of the classifiers' performance, particularly in scenarios with imbalanced class distributions. Analyzing these curves aids in comprehensively assessing the classifiers' performance, guiding decision-making processes, and optimizing the smoke detection system for enhanced accuracy and reliability.

4. Conclusion

this study delved into the realm of sensor fusion for smoke detection, addressing the imperative need for enhanced detection systems in fire safety. Through an exploration of diverse sensor types and scenarios, the research underscored the significance of sensor fusion methodologies in amalgamating heterogeneous data sources for improved detection accuracy. The preprocessing steps meticulously applied to harmonize and refine the dataset paved the way for effective fusion, ensuring uniformity and relevance of sensor readings. Leveraging Adaboost as an ensemble learning technique showcased the power of iterative fusion, capitalizing on diverse sensor information to create a robust classification model. The visualizations of variable distribution, correlation analyses, and comparative evaluations elucidated the effectiveness of the fusion process, enhancing understanding and guiding decision-making. This study contributes insights into the efficacy of sensor fusion techniques, offering a promising trajectory for the development of more reliable and efficient smoke detection systems. Moving forward, the integration of sensor fusion methodologies holds significant potential in advancing fire safety technology, emphasizing the importance of continued exploration and implementation in real-world applications.

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Received: September 01, 2023 Revised: December 12, 2023 Accepted: March 08, 2024

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DOI: https://doi.org/10.54216/IJWAC.080202
Received: September 01, 2023 Revised: December 12, 2023 Accepted: March 08, 2024