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FULL LENGTH ARTICLE

Multisensory Fusion Approaches for Accurate Smoke Detection in Smart Environments

Ahmed Hatip[1,*] **Karla Zayood**[2]

[1] Gaziantep University, Turkey

[2] Online Islamic University, Department of Science and Information Technology, Doha, Qatar

Emails: Kollnaar5@gmail.com · zayyyoood134@gmail.com

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ABSTRACT

The reassessment of alarm systems' role 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 plots variable distribution graphs and bar charts, carries out correlation analyses, and makes comparisons with previous studies; these findings give insight into how effective sensor fusion methods can be for smoke detection. The research results indicate that incorporating multiple sensors can significantly enhance detection accuracy and reliability. Thus, the findings 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 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 and has caused extensive research on how to make it more reliable and efficient [1, 2, 3]. For instance, traditional smoke detectors normally use one sensor each and hence have limitations that include accuracy, reliability, and response time. As such, the integration of multiple sensors through sensor fusion techniques is considered a potential solution for improving smoke detection performance [4, 5, 6].

Sensor fusion is the process of combining data from various sensors in order to obtain a more complete picture of what is happening around us [7]. Specifically, this method works by merging information from different kinds of devices, such as optical, thermal, or chemical sensors, into a single entity that gives an indication of where potential fires may occur. By doing this, it becomes possible to compensate for weak points coming from individual components, thereby making their overall performance better than before [8, 9, 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, 12, 13, 14, 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].

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 evaluates their effectiveness in accurately identifying and categorizing smoke particles. The research also assesses 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. 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 was 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.

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

Table 1. Adaboost algorithm used for multisensor fusion.

Algorithm 1: Adaboost Algorithm
1: Input: Let D be the dataset that includes $\{(a_1,b_1),(a_2,b_2),\ldots,(a_m,b_m)\}$.
2: Let λ be the learning (base) algorithm.
3: Let T be the total number of learning rounds.
4: Initialize $D_1(i) = 1/m$.
5: For $t = 1,\ldots,T$.
6: $h_t = \lambda(D, D_t)$; weak learner is trained with distribution D_t.
7: $\varepsilon_t = \Pr_{i\sim D_t}\left[h_t(a_i) \neq b_i\right]$; error measure.
8: $\alpha_t = \frac{1}{2}\ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$; determine the weight of h_t.
9: $D_{t+1}(i) = \frac{D_t(i)}{Z_t}\begin{cases}\exp(-\alpha_t), & h_t(a_i) = b_i,\\ \exp(\alpha_t), & h_t(a_i) \neq b_i.\end{cases}$
10: Return $H(a) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(a)\right)$.

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.

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 overall accuracy and reliability of smoke detection.

3. RESULTS AND DISCUSSION

This study visualizes the collected and preprocessed data to understand the distribution, association, and classification performance of multisensor fusion for smoke detection. The graphical analyses include variable distributions, correlation analysis, classifier accuracy, execution-time comparison, and threshold-based performance curves.

Figure 1 shows the distribution of the sensor variables used in the smoke detection process. These distribution plots help reveal the range, spread, and relative behaviour of the collected measurements before classification. Variables with clear distributional differences between smoke and non-smoke cases provide useful discriminatory information for classifier training.

Figure 2 shows the correlation matrix for the sensor variables. Correlation analysis helps identify redundant or strongly associated sensor measurements and guides the selection of

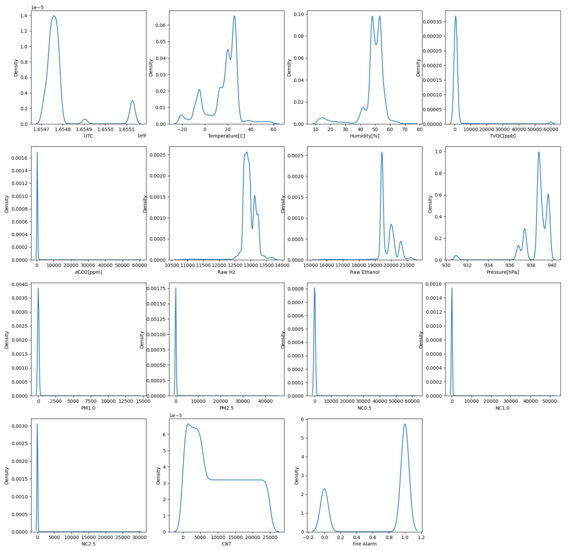

Figure 1. Variable distribution plots for the collected sensor readings.

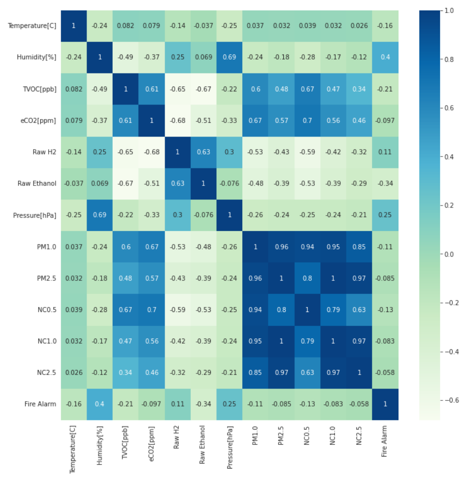

Figure 2. Correlation analysis among sensor variables.

informative features. In the fusion process, highly correlated variables may be combined or reduced, while complementary variables can strengthen the detection model by providing diverse information.

The comparative accuracy analysis assesses how effectively different machine learning classifiers detect and classify smoke across the dataset. By depicting accuracy scores or performance metrics such as precision, recall, and F1-score, 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.

The time comparison of machine learning algorithms 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.

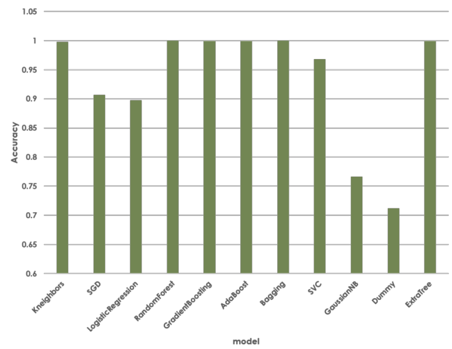

Figure 3. Comparison of machine learning classifier accuracy.

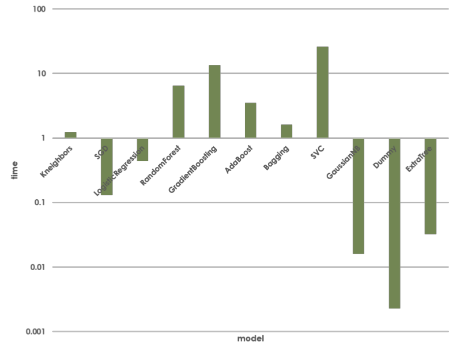

Figure 4. Time comparison of machine learning algorithms.

Table 2. Summary of comparative classifier evaluation for smoke detection.

Evaluation Aspect	Purpose	Expected Benefit
Accuracy comparison	Identify reliable classifiers	Improved detection reliability
Execution-time comparison	Assess computational cost	Real-time suitability
ROC analysis	Evaluate threshold behaviour	Better false-alarm control
Precision–recall analysis	Evaluate positive-class quality	Stronger imbalanced-data performance

In Figure 5 and Figure 6, the left and right performance-curve analyses respectively showcase the receiver operating characteristic (ROC) curve and precision–recall curve for the smoke detection system. The ROC curve 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 and assists in selecting an optimal threshold for classification. The precision–recall curve illustrates the trade-off between precision and recall, offering a comprehensive evaluation of classifier performance, particularly in scenarios with imbalanced class distributions.

Together, the visual comparisons and threshold-based curves support comprehensive assessment and optimization of the smoke detection system. They also provide guidance for selecting classifiers that balance accuracy, computational speed, and reliability in real-time smart-environment applications.

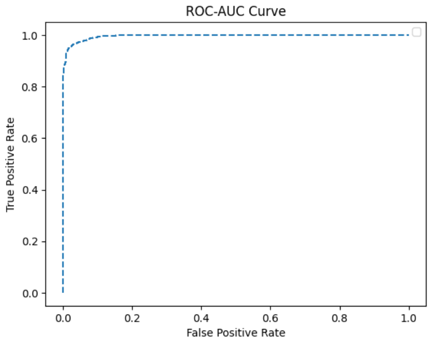

Figure 5. Receiver operating characteristic (ROC) curve for smoke detection.

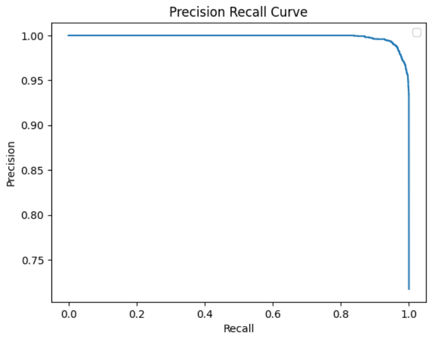

Figure 6. Precision–recall curve for smoke detection.

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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