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# PREDICTING FIRE ALARMS USING MULTI-SENSOR DATA: A BINARY CLASSIFICATION APPROACH

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**ABSTRACT**

Fires pose significant threats to human life, property, and the environment. Early detection of fire incidents is crucial to prevent extensive damage and to ensure the safety of occupants. Traditional fire alarm systems typically rely on a single type of sensor, such as smoke detectors or heat sensors, to detect specific fire indicators. These systems operate based on predefined thresholds and triggers. However, they can be prone to false alarms triggered by non-fire-related events (e.g., cooking fumes or dust) and may not provide early warning signs in certain scenarios. To address these limitations, researchers and engineers have turned to advanced technologies, such as multi-sensor data analysis and machine learning algorithms, to develop more reliable and efficient fire alarm prediction systems. On the other hand, the need for a more robust and accurate fire alarm prediction system stems from the shortcomings of traditional methods. False alarms not only lead to wasted resources but also desensitize occupants, potentially leading them to ignore genuine alarms. Additionally, a delayed response to a fire incident can result in severe consequences, making it essential to develop an intelligent system that can effectively and timely predict fire events. Therefore, this work presents the utilization of multi-sensor data and binary classification to develop a more reliable fire alarm prediction system. The experiments are conducted using a dataset collected from various sensor inputs, including air temperature, humidity, $CO_2$ concentration, molecular hydrogen, ethanol gas, and air pressure etc. Then applied binary classification algorithm to learn patterns from the data and classify fire-related events accurately. The results showed promising improvements in prediction accuracy, reduced false alarm rates, and early detection of fire incidents.

**Keywords:** Internet of things, Fire alarm, Data analytics, Predictive analytics, Machine learning.

## 1. INTRODUCTION

The research topic, "Predicting Fire Alarms Using Multi-Sensor Data: A Binary Classification Approach," represents a significant advancement in fire safety and early warning systems. Fire emergencies pose a substantial threat to life, property, and the environment, making timely detection and response critical. This research stands at the intersection of sensor technology and machine learning, aiming to revolutionize our ability to predict fire incidents by leveraging multi-sensor data [1]. The motivation behind this research is rooted in the compelling need to enhance fire safety, reduce the devastating consequences of fires, and improve our ability to prevent them. Traditional fire detection systems often rely on single-sensor technologies, such as smoke detectors, which may have limitations in terms of accuracy and early detection. The primary objective of this research is to harness the power of multi-sensor data to develop robust binary classification models capable of predicting the occurrence of fire alarms with high accuracy [2]. To achieve this goal, the research delves into the integration of various sensors, including smoke detectors, heat sensors, gas sensors, and optical sensors, to create a comprehensive fire detection system. Machine learning algorithms play a pivotal role in analyzing the

2581-4575

International Journal For Recent Developments in Science & Technology

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data generated by these sensors, learning patterns and anomalies that precede fire incidents. The resulting models can provide valuable insights into the early stages of fires, enabling timely responses and evacuation procedures [3].

Furthermore, ethical considerations are central to this research. It emphasizes the importance of responsible data handling, privacy protection, and the ethical deployment of technology to ensure that the benefits of advanced fire prediction do not compromise individual rights or data security [4]. In this introductory overview, we will explore the key components and objectives of this research. We will discuss the limitations of traditional fire detection methods, introduce the role of multi-sensor data in early fire prediction, and underscore the transformative potential of machine learning in enhancing fire safety. Additionally, the ethical considerations and real-world applications of this research will be highlighted [5]. "Predicting Fire Alarms Using Multi-Sensor Data: A Binary Classification Approach" signifies a pioneering effort to leverage sensor technology and machine learning to transform fire safety [6]. By fusing multi-sensor data with advanced analytics, this research seeks to provide early warning capabilities, reduce the impact of fire emergencies, and ultimately save lives and protect property and the environment [7].

The motivation behind the research on "Predicting Fire Alarms Using Multi-Sensor Data: A Binary Classification Approach" is rooted in the urgent need to enhance fire safety, minimize property damage, and ultimately save lives [8]. Fires pose a significant and ever-present threat, and their rapid detection and response are crucial in preventing catastrophic outcomes [9]. Traditional fire detection systems, often reliant on single-sensor technologies, may have limitations in terms of accuracy and early warning capabilities. Therefore, this research is driven by the desire to harness the power of multi-sensor data, incorporating a diverse range of sensors, to create a comprehensive fire detection system [10]. The objective is to develop advanced machine-learning models capable of accurately predicting fire alarms well in advance of a full-blown fire. By doing so, this research has the potential to revolutionize fire safety practices, providing early warnings that enable timely evacuation, effective firefighting, and reduced property damage. Ultimately, the primary motivation is to protect lives, property, and the environment from the devastating consequences of fires while advancing the state of the art in fire detection technology.

## 2. LITERATURE SURVEY

Liu, et al. [11] proposed a new multi-sensor fire detection method based on long short-term memory (LSTM) networks, named EIF-LSTM. EIF-LSTM integrates environmental information fusion, which is divided into two steps. First, EIF-LSTM extracts the time series characteristics of the monitoring environment by processing multi-sensor time series readings, including environmental indicator variation information and environmental level information. The normalized multi-sensor time series readings, environmental indicator variation information and environmental level information are fused together for fire prediction. Jana, et al. [12] proposed Hybrid Ensemble Based Machine Learning for Smart Building Fire Detection Using Multi-Modal Sensor Data. The proposed model uses feature engineering pre-processing techniques followed by a synergistic integration of four classifiers namely, logistic regression, support vector machine (SVM), Decision tree and Naive Bayes classifier to yield better prediction and improved robustness. A database from NIST has been chosen to validate the research under different fire scenarios.

Wan, et al. [13] proposed Gaussian Process for the Machine Learning-based Smart fire Detection System. the multi-sensor detection system is combined with image recognition process. Image

International Journal For Recent Developments in Science & Technology
2581-4575
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recognition is utilized to help the fire detection, when the decision from the multi-sensor system is uncertain or the data is not available/faulty. Image features are extracted by using machine learning methods. Then, the Gaussian classification method is applied to detect the specific fire case. Li, at al. [14] proposed an indoor fire perception algorithm based on multi-sensor fusion. the sensor data features were fully extracted by improved temporal convolutional network (TCN). Then, the dimension of the extracted features was reduced by adaptive average pooling (AAP). Finally, the fire classification was realized by the support vector machine (SVM) classifier. Experimental results demonstrated that the proposed algorithm can improve accuracy of fire classification by more than 2.5% and detection speed by more than 15%, compared with TCN, back propagation (BP) neural network and long short-term memory (LSTM).

Lu, et al. [15] proposed a multi-task learning-based forest fire detection model (MTL-FFDet), which contains three tasks (the detection task, the segmentation task and the classification task) and shares the feature extraction module. In addition, to improve detection accuracy and decrease missed and false detections, we proposed the joint multi-task non-maximum suppression (NMS) processing algorithm that fully utilizes the advantages of each task. Furthermore, considering the objective fact that divided flame targets in an image are still flame targets, our proposed data augmentation strategy of a diagonal swap of random origin is a good remedy for the poor detection effect caused by small fire targets. An, et al. [16] proposed Indoor Fire Detection Algorithm Based on Second-Order Exponential Smoothing and Information Fusion. This work focuses on the temporal characteristics of sensor information, creatively introducing second-order exponential smoothing into the information fusion algorithm. The RNN structure is used to fit the formula and adaptively trained with various types of fire data. Experimental results show that the proposed algorithm achieves an accuracy of 98% in fire recognition, significantly improving the accuracy of fire recognition.

Martinsson, et al. [17] proposed A Novel Method for Smart Fire Detection Using Acoustic Measurements and Machine Learning. The acoustic data collected in this study is used to define an acoustic sound event detection task, and the proposed machine learning method is trained to detect the presence of a fire event based on the emitted acoustic signal. The method is able to detect the presence of fire events from the examined material types with an overall F-score of 98.4%. Guo, et al. [18] proposed a novel method with improved cyclic spectral covariance matrix (ICSCM) and motor current signal analysis, which achieves multi-sensor data fusion for rotating machinery fault detection. Firstly, an improved cyclic spectral is proposed to process multi-sensor signals collected from rotating machinery, which adaptively acquires multi-sensor mode components. Finally, ICSCM is incorporated into extreme learning machine classifier to identify different fault types for rotating machinery. The merits of the proposed method are validated using two datasets.

## 3. PROPOSED METHODOLOGY

### 3.1 Overview

The binary classification task to predict fire alarms using multi-sensor data. It begins by importing necessary libraries like Pandas, NumPy, and scikit-learn components. The dataset is read from the file 'smoke_detection_iot.csv' and undergoes basic exploratory data analysis, including shape, info, and correlations. Feature scaling is applied, and class imbalance is checked. The data is then split into training and testing sets, considering the class distribution. Two models, logistic regression and random forest classifier, are trained and evaluated using various metrics like accuracy, classification report, and

2581-4575
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confusion matrix. Figure 4.1 shows the proposed system model. The detailed operation illustrated as follows:

**step 1: Importing Libraries**:

- The project begins by importing essential Python libraries and components, including Pandas for data manipulation, NumPy for numerical operations, Matplotlib and Seaborn for data visualization, and scikit-learn for machine learning tasks. These libraries provide the necessary tools for data analysis and modeling.

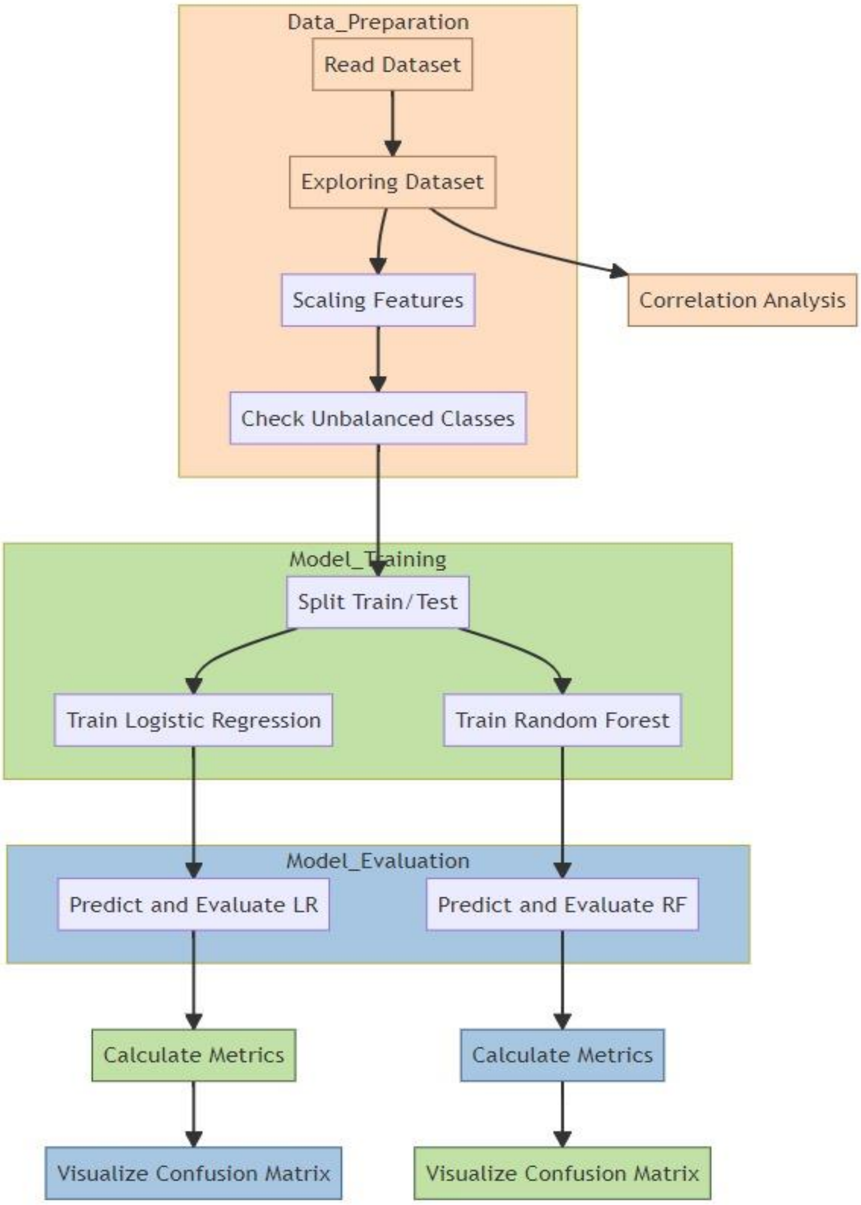


Figure 1. Proposed System model.

**step 2: Reading the Dataset**:

- The dataset containing information related to smoke detection in an IoT environment is loaded from the file 'smoke_detection_iot.csv.' Basic information about the dataset is displayed to ensure it has been successfully imported, including the first few rows to gain an initial understanding of the data.

**step 3: Exploring the Dataset**:

- Dataset exploration begins with examining its shape, providing the number of rows and columns. This step establishes the dataset's dimensions.
- Information about the dataset, including data types and non-null counts, is checked to understand its structure.
- Correlations between features are visualized using a heatmap, which provides insights into how different variables are related to each other.
- Duplicate rows are checked and potentially removed to ensure data quality and prevent redundancy.

**step 4: Scaling the Feature Columns**:

- To ensure that features are on the same scale and do not dominate the modeling process, feature scaling is applied. The MinMaxScaler is used to normalize feature values within a specific range (e.g., [0, 1]).

**step 5: Checking for Unbalanced Classes**:

- The distribution of classes in the target variable, which likely represents smoke detection outcomes (e.g., 'Smoke Detected' and 'No Smoke Detected'), is assessed. An imbalance in class distribution can affect model performance.

**step 6: Splitting Data into Train and Test Splits**:

To facilitate model training and evaluation, the dataset is split into training and testing sets. It's important to ensure that the split maintains the original class distribution, addressing any class imbalance. Stratified splitting may be used for this purpose.

**step 7: Random Forest Classifier**:

- A Random Forest classifier, a machine learning model known for its ensemble learning capabilities, is chosen as the primary model for smoke detection.
- The model is trained on the training data using the scaled features.
- Model evaluation is performed by assessing its accuracy, which indicates how well it predicts smoke detection outcomes.
- Additionally, the model's performance is evaluated using a classification report, which provides metrics such as precision, recall, F1-score, and support, offering a comprehensive understanding of its predictive capabilities.
- A confusion matrix is generated to visualize the model's performance in classifying 'Smoke Detected' and 'No Smoke Detected' instance.

### 3.2 Data Preprocessing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while

2581-4575
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doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task. A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data pre-processing is required tasks for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

- Getting the dataset
- Importing libraries
- Importing datasets
- Finding Missing Data
- Encoding Categorical Data
- Splitting dataset into training and test set
- Feature scaling

## 4. SIMULATION RESULTS

```
LogisticRegression classification_report:

              precision    recall  f1-score   support

           0       0.91      0.97      0.94      3575
           1       0.99      0.96      0.97      8951

    accuracy                           0.96     12526
   macro avg       0.95      0.97      0.96     12526
weighted avg       0.97      0.96      0.96     12526
```

Figure 2: Classification report for Logistic Regression

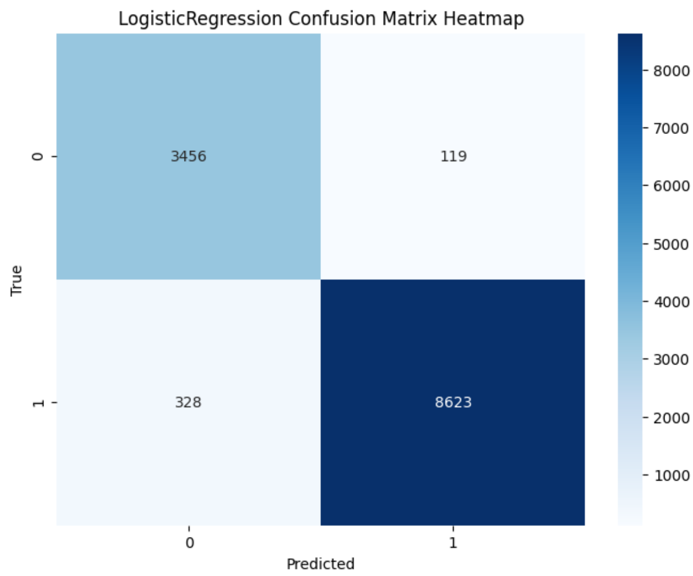


Figure 3: Confusion matrix for Logistic Regression

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2581-4575
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```
Random Forest Classifier Confusion matrix:

              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3575
           1       1.00      1.00      1.00      8951

    accuracy                           1.00     12526
   macro avg       1.00      1.00      1.00     12526
weighted avg       1.00      1.00      1.00     12526
```

Figure 4: Classification report for Random Forest Classifier

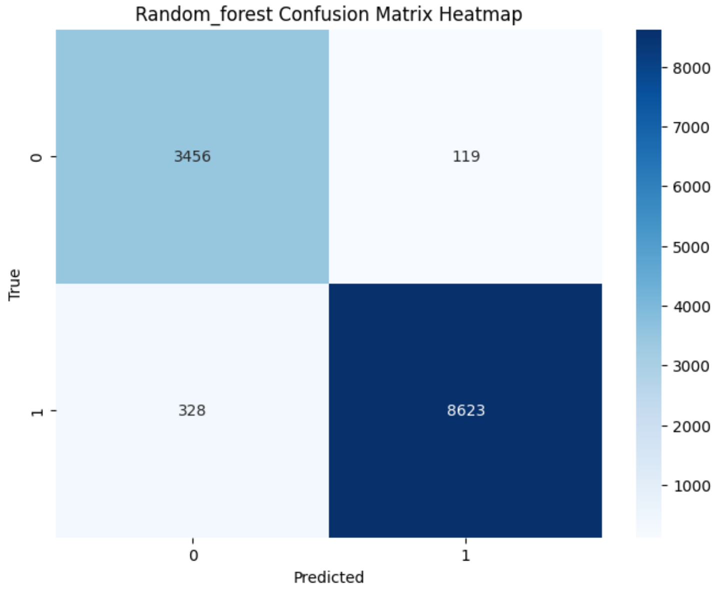


Figure 5: Confusion matrix for Random Forest classifier

## 5. Conclusion

The project focused on smoke detection in an IoT environment has demonstrated a comprehensive workflow for data analysis and predictive modeling. Beginning with the importation of essential libraries and the loading of the 'smoke_detection_iot.csv' dataset, the project underwent a thorough exploration of the data's characteristics, including its shape, structure, and feature correlations. Feature scaling was applied for normalization, and class imbalance was assessed in the target variable, providing insights into the data's class distribution. The dataset was efficiently split into training and testing sets, ensuring representative subsets for model training and evaluation. The Random Forest classifier, known for its ensemble learning capabilities, was selected and trained to predict smoke detection outcomes. Model evaluation using accuracy, classification reports, and a confusion matrix provided a holistic understanding of the model's predictive performance. This project signifies a significant step towards implementing automated smoke detection in IoT environments, enhancing safety and security.

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2581-4575
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