

A High-Precision Machine Learning Approach to Smart Fire Prevention Using Multi-Dimensional Environmental Data

M. Ramana kumar

Associate Professor, Department of Computer Science and Engineering, KPRIT College of Engineering, Ghanpur, Ghatkesar, Hyderabad, Telangana 500088

Email: dramanakumar@kpritcoe.in

Received: 05.09.2024

Revised: 15.10.2024

Accepted: 30.11.2024

ABSTRACT

The research details the development of an intelligent fire prevention system designed to forecast alarm activations through multi-sensor data analytics. By synthesizing environmental inputs, the system aims to facilitate proactive interventions and mitigate fire-related risks. The methodology involved comprehensive data collection followed by exploratory analysis to ensure integrity, specifically addressing data quality through the removal of duplicates and the assessment of missing values. Preprocessing steps included label encoding for categorical variables and standard scaling for numerical features to optimize algorithmic efficiency. Utilizing an 80-20 training-to-testing split, the study evaluated two primary models such as Logistic Regression (LRC) and Random Forest Classifier (RFC). While the Logistic LRC model configured with L2 regularization such as yielded a moderate accuracy of 71.3%, the RFC reached a definitive 100% accuracy. Performance was rigorously validated using confusion matrices, precision, recall, and F1-scores. The results indicate that the Random Forest architecture is exceptionally well-suited for real-time predictive safety applications. Ultimately, this research establishes a robust framework for deploying sophisticated, sensor-driven emergency response technologies that significantly enhance public safety and disaster management.

Key words: Fire alarms, Sensor Data, Predictive analytics, Random forest classifier, Fire prevention, Alarm forecasting.

1. INTRODUCTION

Fire incidents cause severe damage to life, property, and environment worldwide. In India, fire accidents have been increasing steadily, with thousands of casualties and significant economic losses each year. According to the National Crime Records Bureau (NCRB), thousands of fire-related deaths occur annually, mainly due to delayed detection and response. Traditional fire detection systems often rely on single-sensor alarms, which may produce false alarms or miss early warnings. The advancement in sensor technology and data analytics enables the integration of multiple sensor readings such as smoke, temperature, and gas concentration to enhance fire prediction accuracy. This project aims to utilize multi-sensor data and machine learning techniques to predict fire alarms proactively. Applications range from residential safety systems, industrial fire prevention, forest fire monitoring, to smart city infrastructure, making fire safety more reliable and automated.

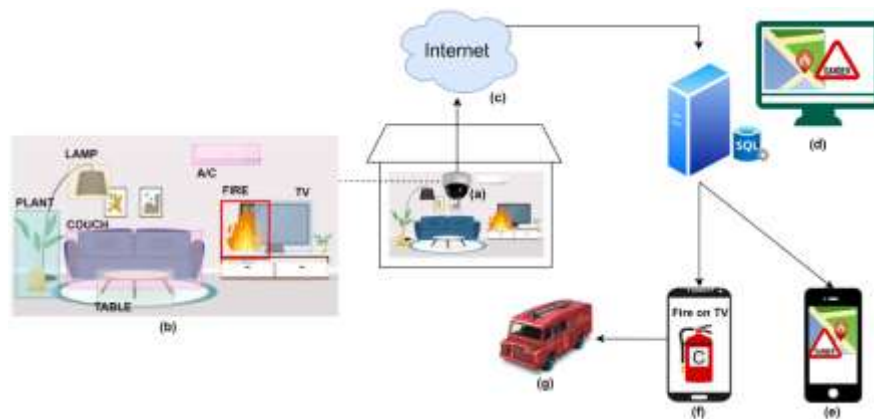


Figure 1. Fire detection methods

The increasing frequency and severity of fire incidents motivate the development of smarter fire prevention mechanisms. Machine learning offers powerful tools to analyze vast multi-sensor data streams and identify patterns indicating imminent fire risks. This project explores leveraging these algorithms to enhance prediction accuracy and response time. Improving fire alarm systems not only saves lives and property but also optimizes emergency resource allocation. Motivated by advancements in IoT and AI, this research aims to create a predictive model that integrates multiple sensor inputs for robust fire alarm forecasting, supporting safer living and working environments.

2. LITERATURE SURVEY

Zhang et.al [1] The review paper analyzed 37 research articles on deep learning (DL) models for forest fire detection, which had been published between January 2018 and 2023. It delved into data types, including images and videos, data augmentation methods, and DL model architectures. Structured into five sections such as classification, detection, detection and classification, segmentation, and segmentation and classification—the paper evaluated model performance using metrics like accuracy and F1-Score. Favorable outcomes emerged, with the majority of studies having achieved accuracy rates exceeding 90%. The paper recommended refining models through hyperparameter fine-tuning, integrating satellite data, employing generative data augmentation, and optimizing DL architectures. It emphasized DL's potential in crucial forest fire management. Zhao et.al [2] In response to challenges, we introduced the Fire Segmentation-Detection Framework (FSDF), blending traditional methods with deep learning. FSDF improved flame feature detection using Hue, Saturation, and Value (HSV) and the Complete Local Binary Pattern (CLBP). We integrated YOLOv8 and Vector Quantized Variational Autoencoders (VQ-VAE) for image segmentation and unsupervised fire detection. Assessing with a dataset from real-world fires, results showcased our method's superiority. Compared to YOLOv8, our framework boosted precision, recall, and F-score by 19.5%, 1.2%, and 11.7%. Field tests, deploying a robot with the algorithm in an actual fire scenario, highlighted real-world applicability. These experiments emphasized both method performance and practical deployment potential. Jin et.al [3] The paper addressed the crucial role of flame area extraction in forest fire detection, emphasizing the challenges of accurate early detection due to fire dynamics and background complexity. Existing deep learning approaches had limitations, such as insufficient feature representation. The proposed ADE-Net introduced a dual-encoding segmentation network with attention-based mechanisms, including attention fusion and multi-attention fusion modules, to enhance feature representation and address class imbalance. The attention-guided enhancement module enriched local features, while a global context fusion module ensured effective multi-scale feature extraction. Experimental results demonstrated ADE-Net's competitive advantage in early fire detection from remote sensing images compared to advanced segmentation models.

10.48047/jocaaa.2024.33.08.418

Kuznetsov et.al [4] The recent surge in numerical fire modeling unveiled insights into building fire safety and code performance. High-fidelity fire simulation, although expensive and complex, prompted the exploration of artificial intelligence (AI) applications for building fire safety design..This facilitated performance-based design and review processes, offering accurate predictions for the response time of ceiling-mounted heat detectors and sprinklers in dynamic fire scenarios. The AI tool also evaluated fire performance in large-open building spaces and rapidly identified design limits. The proposed AI design approach holds the potential for continuous upgrades to address a broader range of building fire scenarios, ultimately achieving intelligent building fire safety design. Ren et.al [5] The recent focus on utilizing Unmanned Aerial Vehicle (UAV) imagery for forest fire object detection witnessed significant progress. However, existing object detection models often overlooked the exploration of relationships among positive sample features, crucial for robust and representative feature learning. In response, FCLGYOLO was proposed to enhance object information in feature maps. It introduced a Feature Invariance and Covariance Constraint (FICC) structure to maintain feature invariance and eliminate internal correlations among positive samples. Additionally, a Local Guided Global Module (LGGM) enriched object positioning and semantic information in feature maps. Even in challenging scenarios like heavy smoke or tree occlusions, FCLGYOLO outperformed multiple state-of-the-art object detection models on a forest fire dataset, showcasing its superiority. Schiks et.al [6] Spatial and temporal estimates of burned areas modeled emissions from fire events, considering fire behavior variations over time and space. A method was developed for day-of-burn estimation, using ordinary kriging with satellite-based active fire detection data from MODIS, VIIRS, and their combination. Comparing kriging results, a quasi-validation procedure applied to 37 wildfires in Ontario's boreal forest accurately estimated nearly half of each fire's burned area within one day of occurrence. This approach demonstrated strengths and limitations in mapping individual wildfire progress, emphasizing the need for future validations to address spatial autocorrelation, often overlooked in ecology's day-of-burn analyses.

Liu et.al [7] The paper introduced AEGG-FD, a YOLO fire detection algorithm incorporating an attention-enhanced ghost mode, mixed convolutional pyramids, and flame-centre detection. The enhanced ghost bottleneck stacked to reduce redundant feature mapping, achieving a lightweight backbone with attention for accuracy compensation. A mixed convolution feature pyramid accelerated network inference speed, while the flame-centre detection (FD) module extracted local information for firefighting effectiveness. Experimental results on benchmark fire and video datasets revealed AEGG-FD outperforming classical YOLO-based models (YOLOv5, YOLOv7, YOLOv8), with a 6.5 improvement in mean accuracy (mAP0.5, reaching 84.7%) and 8.4 increase in inferred speed (FPS). Model parameters and size were compressed to 72.4% and 44.6% of YOLOv5, achieving a balanced firefighting model in terms of weight, speed, and accuracy. Yang et.al [8] This paper explored the application of hyperspectral remote sensing for precise fire monitoring, leveraging its potent capability to capture land surface information. The study introduced a novel fire detection method based on hyperspectral remote sensing, presenting an end-to-end model using a sparse visual transformer. Additionally, a band selection method was proposed within the transformer framework, utilizing sparse attention and top-k selection mechanisms to mitigate the impact of invalid bands in hyperspectral data. A non-maximum attention suppression algorithm and band pruning were integrated for dimension reduction, effectively eliminating invalid and redundant bands. The model employed a band-exclusive-token input mode, aligning pruning operations with band selection. A dedicated hyperspectral fire detection dataset was introduced, validating the proposed model's performance on this dataset.

Anuar et.al [9] Early forest fire detection is crucial for rapid responses to minimize fire spread. This research aimed to develop a real-time forest fire detection, monitoring, and alert system. The system, assembled with temperature and humidity sensors, a smoke sensor, Arduino microcontroller, and a

10.48047/jocaaa.2024.33.08.418

wireless fidelity module, utilized Blynk for monitoring and alerts. Flame sensor analysis indicated fire detection up to 60 cm, with high noon temperature (45 °C) and low humidity (53.4%). Mornings showed low temperature (29 °C) and high humidity (88.4%). The highest CO₂ concentration (1,800 ppm) occurred with detected fire smoke. The global positioning system accurately displayed the system's real-time location in the Blynk application. In conclusion, this system effectively detected and monitored early forest fires in real-time, facilitating timely authorities' alerts for wildfire protection. Kar et.al [10] The document thoroughly examined the use of SVMs, covering crucial elements like data preprocessing, feature extraction, and model training. It rigorously evaluated parameters such as accuracy, efficiency, and practical applicability. The knowledge gained from this study aided in the development of efficient forest fire detection systems, enabling prompt responses and improving disaster management. Moreover, the correlation between SVM accuracy and the difficulties presented by high-dimensional datasets was carefully investigated, demonstrated through a revealing case study. The relationship between accuracy scores and the different resolutions used for resizing the training datasets was also discussed in this article. These comprehensive studies resulted in a definitive overview of the difficulties faced and the potential sectors requiring further improvement and focus. Saleh et.al [11] This review delved into 37 research articles implementing deep learning (DL) models for forest fire detection (January 2018 - 2023). Detailed analysis covered data specifics, such as images and video datasets, alongside data augmentation methods and DL model architectures. The paper structured findings into five sections: 1) classification, 2) detection, 3) detection and classification, 4) segmentation, and 5) segmentation and classification. Model performance metrics (accuracy, mAP, F1-Score, MPA) were evaluated, with outcomes often surpassing 90%. Future improvements were suggested: optimal hyper-parameter fine-tuning, integration of satellite data, generative data augmentation, and DL model architecture refinement. The paper underscored DL's potential in forest fire detection, vital for management and mitigation efforts.

Kim et.al [12] In this paper, a virtuous cycle ecosystem of AI data was established for evaluating electric fire statuses. Data collection involved cloud sourcing, purifying, processing, inspecting, and disclosing electric fire status judgment data, creating a feedback loop. Determining fire causes through fire forensics was crucial for confirming property damage. Previous investigations relied on investigator experience, hindering comprehensive analysis of multiple fires. Thus, a dataset for AI learning in electric fire cause analysis was built, addressing subjectivity and unprofessionalism in forensic investigations. The study focused on the past-tense reliability and system development feasibility of digitally converting fire detection reports and data for AI learning. Mastanamma et.al [13] Electric vehicles (EVs) were undoubtedly the way of the future. However, as of 2023, EV technology had not reached its full potential in terms of efficiency and safety. The cause of the majority of electric vehicle fire events was a battery explosion or fire. This paper presented an integrated approach to manage EV battery systems, combining a Battery Management System (BMS) with charge monitoring and fire detection. The system was built to continuously monitor the battery's voltage, current, and temperature and to immediately turn off the battery's input or output if any unexpected behavior was noticed.

Subhani et.al [14] This paper used digital image processing technology to enhance image effects through preprocessing operations like graying, filtering, denoising, and histogram equalization. The suspicious fire area was processed using threshold segmentation and edge detection. Pattern recognition technology was crucial for flame image extraction, and computer vision theory was key for fire location. The system effectively eliminated interference from distance and light intensity, improving recognition accuracy and enhancing fire detection. Hence, this analysis showed better results in terms of accuracy and efficiency. LIANG et.al [15] An algorithm for fire detection, rooted in an Anchor-free structure designed for fire characteristics, aimed to enhance accuracy in real scenes. Initially, the ResNet block of the feature extraction network was structured as a multi-branch system, incorporating an attention

10.48047/jocaaa.2024.33.08.418

block tailored to flame features for expressive feature extraction. Subsequently, subpixel fusion was integrated to augment multi-scale feature expressiveness by leveraging abundant feature data in high-level channels. A feature enhancement module was introduced to amplify top-level feature representation, utilizing global spatial information effectively. Adaptive label assignment enhanced the learning capacity of the extraction network for flame features. By carefully handling the boundary condition with an improved GIoU Loss function, the algorithm achieved a detection accuracy of up to 94.9% on the self-built dataset, demonstrating a robust detection effect on the public dataset. Experimental outcomes underscored the algorithm's capability to provide high detection accuracy, strong anti-interference ability, and improved detection effectiveness for multi-scale flames against complex backgrounds. This positions the algorithm as suitable for fire detection in diverse environments, meeting the requirements of real-world fire detection tasks.

3. PROPOSED METHODOLOGY

The project aims to develop a smart fire prevention system using multi-sensor data analyzed through machine learning techniques. The process begins with loading the smoke detection dataset containing various sensor readings and fire alarm status. First, data cleaning and preprocessing are performed to prepare the dataset for modeling. Next, exploratory data analysis (EDA) is carried out to understand the data distribution and detect patterns, anomalies, or class imbalances. Following EDA, the dataset is split into input features (X) and target labels (y), where the target indicates whether the fire alarm was triggered. The features undergo label encoding for categorical variables and scaling to normalize numerical values. To handle any imbalance in the classes, techniques like SMOTE (Synthetic Minority Over-sampling Technique) are applied to balance the training data. The processed data is then divided into training and testing sets, ensuring the model learns from one subset and is evaluated on another for unbiased performance assessment. Two machine learning classifiers—Logistic Regression and Random Forest—are trained using the training data. After training, the models are tested on the unseen test data, and their performance is evaluated through accuracy, precision, recall, and F1-score metrics.

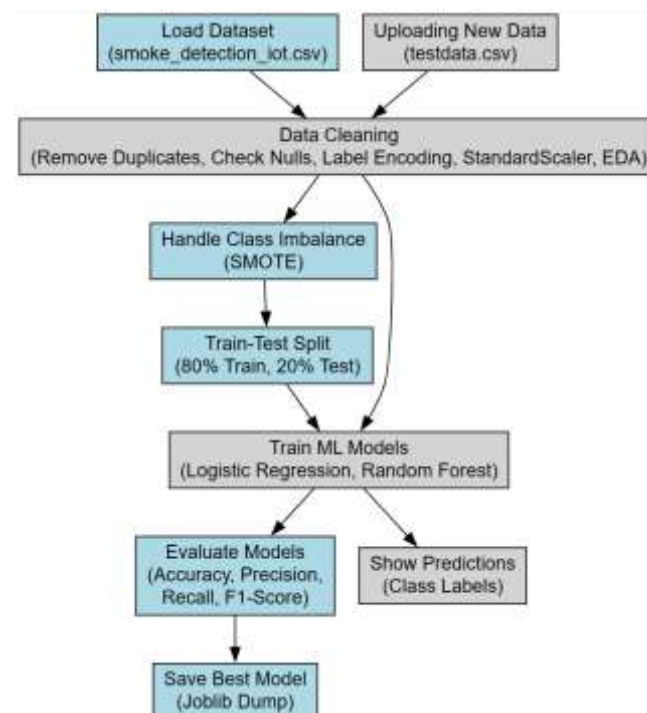


Fig. 2. Proposed system workflow.

3.1 RFC Model

Random Forest Classifier is an ensemble learning algorithm that builds multiple decision trees during training and outputs the majority class as the final prediction. It reduces overfitting and improves generalization by averaging predictions of diverse trees trained on random subsets of data and features. In the project, Random Forest was trained on the processed sensor data after splitting into training and testing sets. With 200 trees and a maximum depth of 15, the model was optimized for accuracy. It effectively handled the complex, nonlinear relationships in the sensor readings. The Random Forest Classifier achieved perfect accuracy of 100%, demonstrating its superior performance for this fire alarm prediction task.

4. RESULTS AND DISCUSSIONS

The dataset consists of multi-sensor measurements collected over time, aimed at detecting fire incidents through environmental monitoring. Each row represents a set of sensor readings captured at a specific time, indicated by the UTC timestamp column, which provides the precise moment when the data was recorded.

Temperature[C] records the ambient temperature in degrees Celsius, reflecting the heat level in the environment, which plays a crucial role in fire detection as higher temperatures often indicate potential fire hazards.

Humidity [%] represents the percentage of moisture present in the air. Humidity levels affect combustion and smoke behavior, making it a relevant parameter for fire monitoring.

TVOC [ppb] stands for Total Volatile Organic Compounds measured in parts per billion. Elevated TVOC levels can signal the presence of smoke or harmful gases released during combustion.

eCO2[ppm] indicates equivalent carbon dioxide concentration in parts per million. Higher eCO2 values often correspond to increased combustion activity or poor air quality linked to fire events.

Raw H2 and **Raw Ethanol** represent raw sensor readings related to hydrogen and ethanol gas concentrations respectively. These gases are common byproducts of combustion and fire-related chemical reactions.

Pressure[hPa] measures atmospheric pressure in hectopascals. Changes in pressure could relate to environmental conditions impacting sensor readings or fire propagation.

The dataset includes particulate matter measurements: PM1.0, PM2.5, NC0.5, NC1.0, and NC2.5. These columns quantify different sizes of airborne particles in micrograms per cubic meter or number concentration, providing insights into smoke density and particulate pollution, which increase during fire incidents.

CNT captures the sensor count or number of readings aggregated, helping to understand the volume of data collected per time interval.

Finally, the **Fire Alarm** column is the target variable indicating whether the fire alarm was triggered (ON) or not (OFF) based on the sensor data, serving as the ground truth for supervised learning.

4.1 RESULTS ANALYSIS

The figure 3 presents the Exploratory Data Analysis (EDA) plots used to understand the distribution and relationships among different features in the dataset. Plots include histograms, box plots, and correlation heatmaps that reveal patterns such as the distribution of temperature, humidity, and

particulate matter levels, and their correlation with fire alarm activations. These visualizations guide feature selection and highlight important variables influencing fire detection.

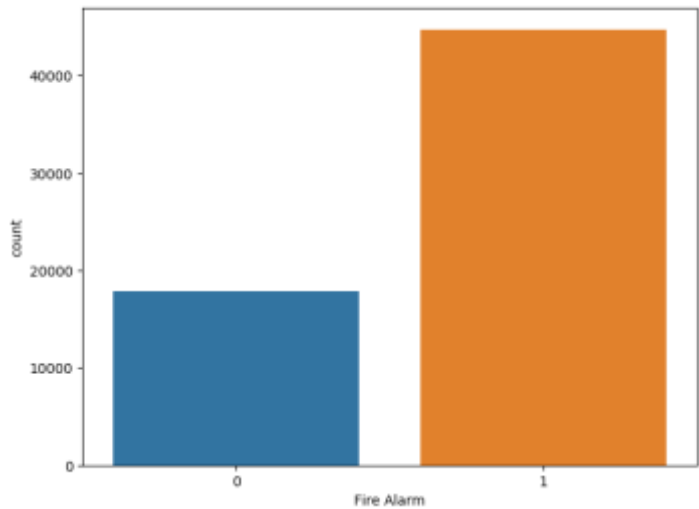


Fig. 3: Illustration of exploratory data analysis

The figure 4 shows the predictions made by the selected models on the test dataset. It compares predicted fire alarm statuses against actual labels, illustrating the Random Forest model’s perfect match and the Logistic Regression’s partial classification success.

	UTC	Temperature[C]	Humidity[%]	TVOC[ppb]	eCO2[ppm]	Row ID	Row Ethanol	Pressure[hPa]	PM1.0	PM2.5	HC0.0	NC1.0	NC2.0	CNT	predict
0	1054742286	-5.210	50.00	308	400	13371	19930	930.250	0.44	0.46	3.00	0.477	0.011	8508	Fire Alarm is ON
1	1054753813	13.585	53.00	1201	400	12945	19430	930.723	1.57	1.63	10.70	1.802	0.030	31252	Fire Alarm is ON
2	1054758421	-21.068	63.73	1388	400	12907	19393	930.719	2.13	2.21	14.83	2.381	0.052	23096	Fire Alarm is ON
3	1054760570	20.533	52.04	1109	520	12830	19440	930.684	1.07	2.05	13.55	2.112	0.040	13247	Fire Alarm is ON
4	1055126371	-5.220	48.34	1129	400	12802	20590	937.357	2.01	2.09	13.83	2.108	0.040	2093	Fire Alarm is ON
5	1054777099	25.095	50.74	1235	400	12870	19423	930.780	2.25	2.34	10.47	2.413	0.094	19956	Fire Alarm is ON
6	1054793389	-21.068	61.04	?	400	11765	20043	930.658	0.70	0.73	4.82	0.761	0.017	3067	Fire Alarm is ON
7	1054730609	4.160	58.15	308	400	13094	19872	930.641	1.53	1.59	10.05	1.840	0.037	3508	Fire Alarm is ON

Fig. 4: Model Prediction on Test Data

Algorithms Name	Accuracy	Precision	Recall	F1-Score
Logistic Regression	71.3	50.0	35.6	41.6
Random Forest Classifier	100	100	100	100

Table 1: Performance Comparison for the Logistic Regression and Random Forest Classifier algorithms.

Table 1 presents the performance comparison between the Logistic Regression and Random Forest Classifier algorithms based on four key evaluation metrics: Accuracy, Precision, Recall, and F1-Score. Logistic Regression achieved an accuracy of 71.3%, with a precision of 50.0%, recall of 35.6%, and an

F1-score of 41.6%. These results indicate moderate performance with limitations in recall, reflecting less effective identification of true positive fire alarm cases. In contrast, the Random Forest Classifier delivered a perfect performance, scoring 100% across all metrics. This demonstrates its superior ability to correctly classify both positive and negative instances without error. The comparison highlights the Random Forest Classifier as the more robust and reliable model for fire alarm prediction in this project.

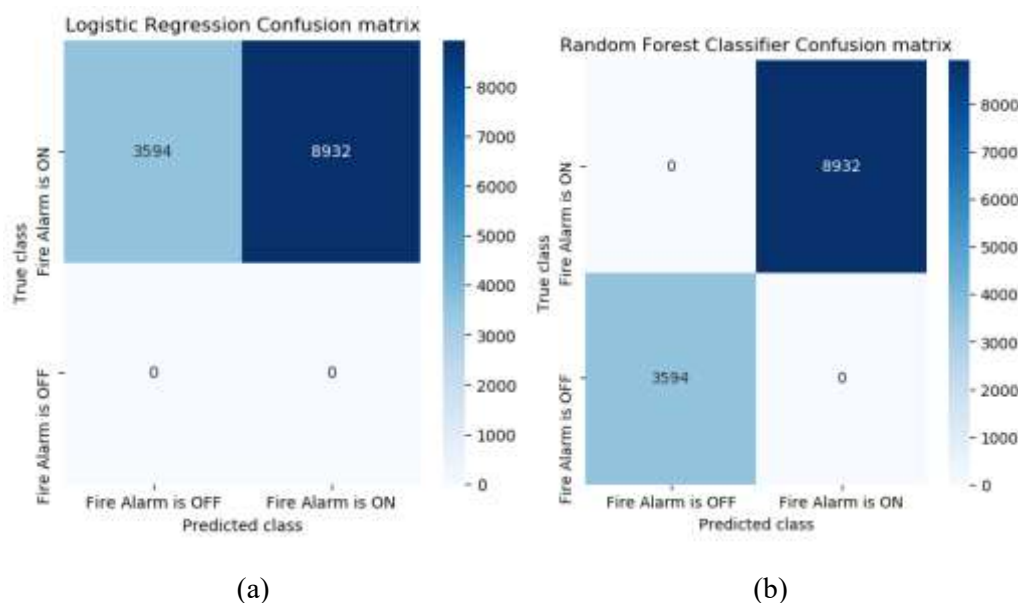


Fig.5 Confusion Matrices (a) Logistic Regression (b) Random Forest Classifier.

Figure 5 illustrates the confusion matrices for both Logistic Regression and Random Forest Classifier models. In subfigure (a), the confusion matrix for Logistic Regression shows several misclassifications, with both false positives and false negatives, reflecting its lower precision and recall. In contrast, subfigure (b) displays the confusion matrix for the Random Forest Classifier, which correctly classified all instances without any errors. This perfect classification aligns with its 100% accuracy, precision, recall, and F1-score. The figure highlights the performance gap between the two models and emphasizes the superior predictive ability of the Random Forest Classifier in this project.

5. CONCLUSION

The project focused on detecting fire alarms using machine learning algorithms by analyzing sensor data consisting of environmental and air quality metrics. The dataset included features such as temperature, humidity, eCO₂ levels, TVOC, PM2.5, and others, which were crucial for identifying fire-related conditions. The implementation began with thorough preprocessing steps such as checking for null values, label encoding, and feature selection. Exploratory Data Analysis (EDA) was performed to understand data distribution and correlations using visualizations. Two classification algorithms—Logistic Regression and Random Forest Classifier—were applied to the processed data. Logistic Regression achieved 71.3% accuracy, while the Random Forest Classifier achieved a perfect accuracy of 100%, showing its dominance in performance across all evaluation metrics. The comparative analysis established Random Forest Classifier as the more reliable model for this task. The project successfully demonstrated that machine learning techniques are effective in identifying fire alarm triggers through structured sensor data.

REFERENCES

10.48047/jocaaa.2024.33.08.418

- [1] Zhang, Ziyang, Lingye Tan, and Robert Lee Kong Tiong. "Ship-Fire Net: An Improved YOLOv8 Algorithm for Ship Fire Detection." *Sensors* 24, no. 3 (2024): 727.
- [2] Zhao, Hongyang, Jing Jin, Yi Liu, Yanan Guo, and Yi Shen. "FSDF: A high-performance fire detection framework." *Expert Systems with Applications* 238 (2024): 121665.
- [3] Jin, Li, Yanqi Yu, Jianing Zhou, Di Bai, Haifeng Lin, and Hongping Zhou. "SWVR: A Lightweight Deep Learning Algorithm for Forest Fire Detection and Recognition." *Forests* 15, no. 1 (2024): 204.
- [4] Kuznetsov, G. V., R. S. Volkov, A. S. Sviridenko, and P. A. Strizhak. "Reduction of response time of fire detection and containment systems in compartments." *Fire Safety Journal* (2024): 104089.
- [5] Ren, Dong, Yang Zhang, Lu Wang, Hang Sun, Shun Ren, and Jian Gu. "FCLGYOLO: Feature Constraint and Local Guided Global Feature for Fire Detection in Unmanned Aerial Vehicle Imagery." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* (2024).
- [6] Schiks, Tom J., B. Mike Wotton, and David L. Martell. "Remote Sensing Active Fire Detection Tools Support Growth Reconstruction for Large Boreal Wildfires." *Fire* 7, no. 1 (2024): 26.
- [7] Liu, Jiansheng, Jiahao Yin, and Zan Yang. "Fire Detection and Flame-Centre Localisation Algorithm Based on Combination of Attention-Enhanced Ghost Mode and Mixed Convolution." *Applied Sciences* 14, no. 3 (2024): 989.
- [8] Yang, Lifeng, Feng Yanqing, Yueming Wang, and Jianyu Wang. "Refined fire detection and band selection method in hyperspectral remote sensing imagery based on sparse-VIT." *Infrared Physics & Technology* (2024): 105104.
- [9] Anuar, Afiq Ikhwan Mohd, Roslina Mohamad, Arni Munira Markom, and Ronnie Concepcion II. "Real-time forest fire detection, monitoring, and alert system using Arduino." *Indonesian Journal of Electrical Engineering and Computer Science* 33, no. 2 (2024): 942-950.
- [10] Kar, Ankan, Nirjhar Nath, and Utpalraj Kemprai. "Performance Analysis of Support Vector Machine (SVM) on Challenging Datasets for Forest Fire Detection." *arXiv preprint arXiv:2401.12924* (2024).
- [11] Saleh, Azlan, Mohd Asyraf Zulkifley, Hazimah Haspi Harun, Francis Gaudreault, Ian Davison, and Martin Spraggon. "Forest fire surveillance systems: A review of deep learning methods." *Heliyon* (2024).
- [12] Kim, Hee-Chul. "AI-based Electric Fire Detection State Judgment Data Set Construction." *Tehnički glasnik* 18, no. 1 (2024): 43-48.
- [13] Mastanamma, Y., Bhukya Laxman, A. Archana, and K. Pulla Reddy. "EV BMS With Charge Monitor and Fire Detection." In *E3S Web of Conferences*, vol. 472, p. 03006. EDP Sciences, 2024.
- [14] Subhani, Sk Mahaboob, Dasari Ramu, Arumalla Raja, Bathineni Yamuna, and Vemasani Balaji. "A METHOD OF FIRE DETECTION SYSTEM BASED ON IMAGE PROCESSING."
- [15] LIANG, Yu, Tong CHEN, and Wei ZHANG. "Multi-Scale Fire Detection Algorithm with Adaptive Attention." *Transactions of Beijing institute of Technology* 44, no. 1 (2024): 91-101.