Journal of Educational Technology and Learning Creativity
Vol. 4, No. 1, June 2026, pp. 194~204
ISSN: 3021-7865, DOI: 10.37251/jetlc.v4i1.2614

Machine Learning-Based Multi-Sensor IoT System for Intelligent Indoor Fire Detection

Anggy Pradifta Junfithranaa[1], Hadi Almohab[2], Deshinta Arrova Dewi[3]
[1]Department of Electrical Engineering, Faculty of Engineering, Computer, and Design, Nusa Putra University, Sukabumi, Indonesia
[2]Department of Informatics, Faculty of Engineering, Computer, and Design, Nusa Putra University, Sukabumi, Indonesia
[3]Department of Computer Science and Technology, Faculty of Data Science and Information Technology, INTI International University, Nilai, Malaysia

Article Info

Article history:

Received Jan 5, 2026
Revised Mar 13, 2026
Accepted Apr 2, 2026
Online First Jun 15, 2026

Keywords:

Fire Detection
Public Safety
Smart Buildings
Machine Learning
Internet of Things (IoT)
Disaster Risk Reduction (DRR)

ABSTRACT

Purpose of the study: This study aims to develop an intelligent indoor fire detection system by integrating low-cost Internet of Things (IoT) sensors with machine learning-based multi-sensor data fusion to improve early fire hazard detection accuracy while reducing false alarms compared to conventional single-sensor fire detection systems.

Methodology: The system is implemented using an ESP32 microcontroller connected to temperature, humidity, flame, and sound sensors for real-time data acquisition. A dataset of 1,500 sensor samples is collected and labeled into Normal, Fire-Risk, and Fire classes. Decision Tree, Support Vector Machine, and Random Forest classifiers are trained and evaluated using Python-based machine learning libraries.

Main Findings: Experimental results indicate that the Random Forest model outperforms the other classifiers, achieving 95% overall accuracy, perfect recall for fire events, and a Macro ROC-AUC score of 0.993. Feature importance analysis reveals that humidity and temperature are the most influential parameters for early fire detection in indoor environments.

Novelty/Originality of this study: This study proposes a lightweight intelligent fire detection framework that integrates multi-sensor Internet of Things data including temperature, humidity, flame, and sound signals with machine learning–based classification for indoor environments. Unlike conventional systems that rely on single-sensor or threshold-based detection, the proposed approach utilizes multi-sensor data fusion and ensemble learning to improve early fire-risk identification while remaining computationally efficient for low-cost platforms such as the ESP32 microcontroller.

This is an open access article under the CC BY license

Corresponding Author:
Hadi Almohab,
Department of Informatics Engineering, Faculty of Engineering, Computer and Design, Nusa Putra University,
Jl. Raya Cibolang No.21, Cisaat, Sukabumi 43152, Jawa Barat, Indonesia
Email: hadi.almohab@nusaputra.ac.id

1. INTRODUCTION

Fire incidents represent a major threat to human life and property, particularly in indoor environments where early detection is critical. A substantial proportion of global fire accidents occur inside buildings, leading to significant human casualties and economic losses [1]-[3]. Indoor fires can escalate rapidly, reaching temperatures exceeding 400 °C and generating toxic gases within minutes [4]. These risks are further exacerbated by modern building designs, the increasing number of electrical and electronic devices, and human negligence, which remains one of the leading causes of fire outbreaks [5]-[7]. Despite the availability of existing fire detection technologies, achieving reliable and timely fire detection in indoor environments remains a challenging task due to the rapid development of hazardous conditions and the limitations of conventional detection systems.

Traditional fire detection systems typically rely on single-sensor mechanisms, such as smoke or temperature thresholds, to trigger alarms. Although widely deployed, these systems often produce false alarms due to environmental factors such as cooking fumes, steam, dust, or fluctuations in ambient conditions [8], [9]. Frequent false alarms reduce system reliability and may lead to decreased user trust and delayed responses in real emergency situations. To improve detection reliability, several studies have explored multi-sensor approaches that combine environmental parameters such as carbon monoxide concentration, smoke density, temperature, and humidity [10]-[14]. These multimodal systems provide a more comprehensive representation of environmental conditions and have demonstrated improved performance compared to single-sensor methods. Furthermore, artificial intelligence-based approaches, including fuzzy logic systems integrated with multi-sensor inputs, have been proposed to enhance decision-making capabilities and reduce false alarm rates [15], [16]. However, many of these approaches still rely on predefined rules and exhibit limited adaptability.

Recent developments in the Internet of Things (IoT) have enabled the deployment of distributed and real-time environmental monitoring systems. IoT-based fire detection frameworks integrate multiple sensors with embedded platforms to continuously monitor environmental parameters and transmit data for remote analysis and alert generation [17]-[21]. These systems offer advantages such as real-time monitoring, remote accessibility, and integration with smart building infrastructures. Nevertheless, many existing IoT-based solutions rely on static threshold-based decision mechanisms, limiting their ability to adapt to dynamic indoor conditions and complex environmental patterns [22], [23]. Previous studies have demonstrated the feasibility of such systems for monitoring and automated notification [24]-[26]; however, they often lack intelligent data analysis mechanisms capable of accurately distinguishing between normal conditions and early fire-risk scenarios.

To address these limitations, machine learning techniques have increasingly been applied to fire classification and prediction tasks. Supervised learning models, including Decision Trees, Support Vector Machines, k-Nearest Neighbors, and Random Forest classifiers, have shown promising performance in distinguishing fire and non-fire conditions based on sensor data [27]-[29]. Previous studies reported accuracies of up to 84 % using Support Vector Machines and Random Forest models, while multilayer perceptron networks achieved accuracies as high as 99.7 % [30], [31]. Among these approaches, Random Forest classifiers have demonstrated strong robustness and generalization capability due to their ensemble learning structure, with reported accuracies exceeding 99 % in several applications [32]-[34]. In addition, optimization techniques such as dynamic ensemble reduction and hierarchical ensemble learning have been proposed to reduce computational complexity and improve suitability for IoT deployment [35], [36].

In parallel, deep learning approaches, particularly convolutional neural networks (CNNs), have been widely applied for vision-based fire detection using image and video data. These models achieve high detection accuracy by extracting visual features associated with flames and smoke patterns [37]-[43]. However, such approaches typically require high-resolution cameras, stable lighting conditions, and significant computational resources, limiting their practicality for low-cost indoor deployments [44]-[47]. Although lightweight CNN architectures have been proposed to improve efficiency [48]-[50], they still rely on imaging hardware and complex processing pipelines, increasing implementation costs and limiting scalability.

Despite these advancements, a significant research gap remains in the development of an intelligent, adaptive, and resource-efficient indoor fire detection system capable of operating effectively in real-world environments. Existing IoT-based systems often lack intelligent classification mechanisms, while deep learning-based approaches are computationally expensive and hardware-dependent. Moreover, current multi-sensor systems are rarely optimized for edge deployment, and many rely on static thresholding rather than data-driven decision-making, limiting their adaptability to dynamic indoor conditions.

To address these challenges, this study proposes a machine learning-based multi-sensor IoT system for intelligent indoor fire detection. This study makes three main contributions. First, it integrates multi-sensor data fusion with supervised machine learning to enable multi-class classification of environmental conditions into Normal, Fire-Risk, and Fire, improving early detection capability. Second, it develops a lightweight and computationally efficient model optimized for edge deployment on an ESP32-based platform, ensuring real-time performance with minimal resource consumption. Third, it introduces a data-driven adaptive classification approach that replaces conventional threshold-based methods, significantly reducing false alarms in dynamic indoor environments. Overall, the proposed system provides a cost-effective, scalable, and accurate solution for indoor fire detection, achieving a practical balance between performance and computational efficiency suitable for real-world IoT applications.

2. RESEARCH METHOD

2.1. System Architecture

The proposed fire detection system integrates Internet of Things sensing with machine learning–based classification to enable early identification of fire and fire-risk conditions. The overall system architecture, illustrated in Figure 1, consists of four main layers: the sensor layer, the edge processing layer, the cloud storage layer, and the machine learning analysis layer. At the sensor layer, environmental parameters are continuously monitored using multiple low-cost sensors designed to capture key indicators associated with fire incidents. These parameters include temperature, humidity, flame intensity, and acoustic signals. The use of multiple sensors enables a more comprehensive representation of environmental conditions and helps reduce the limitations associated with single-sensor fire detection systems.

The edge processing layer is implemented using an ESP32 microcontroller, which performs data acquisition and preliminary signal processing. The ESP32 was selected due to its integrated Wi-Fi capability, low power consumption, and suitability for Internet of Things applications. Sensor readings are collected through the microcontroller's analog-to-digital converter and transmitted wirelessly through Wi-Fi communication. The collected sensor data are then transmitted to a cloud-based database, which forms the cloud storage layer of the system. This layer stores environmental measurements and provides a centralized dataset for preprocessing, machine learning model training, and performance evaluation. Finally, the machine learning analysis layer performs classification tasks to identify environmental conditions as Normal, Fire-Risk, or Fire states. This layered architecture allows real-time environmental monitoring while enabling intelligent data-driven fire detection.

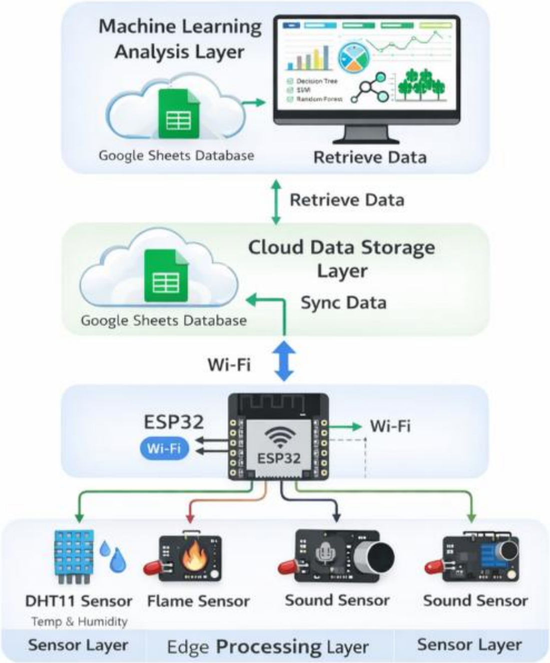


Figure 1. Overall system architecture of the proposed IoT-based fire detection framework.

2.2. IoT Hardware Setup and Data Acquisition

2.2.1. Sensors and Microcontroller

The hardware component of the proposed system is based on an ESP32 microcontroller integrated with multiple environmental sensors. The ESP32 platform was selected due to its built-in wireless connectivity, multiple analog input channels, and suitability for real-time Internet of Things applications. The sensing subsystem consists of several low-cost sensors designed to capture environmental indicators associated with fire events. A DHT11 sensor is used to measure ambient temperature in degrees Celsius and relative humidity in percentage. These environmental parameters are important indicators because fire incidents typically cause rapid temperature increases and humidity variations. A flame sensor is employed to detect infrared radiation emitted by fire sources, providing an early indication of flame presence. In addition, a sound sensor is used to capture abnormal acoustic signals that may occur during fire-related events, such as crackling sounds or structural disturbances.

All sensors operate at a supply voltage of 3.3 V and are connected to the ESP32 microcontroller through its analog-to-digital converter inputs. The integrated hardware configuration of the ESP32 and sensors is illustrated in Figure 2.

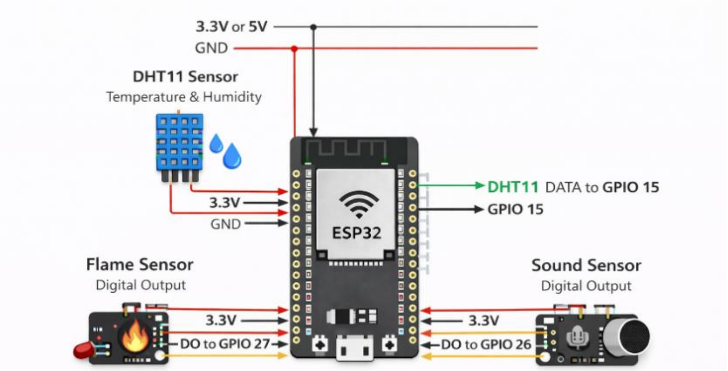


Figure 2. ESP32-based IoT hardware setup with integrated temperature–humidity, flame, and sound sensors

2.2.2. Data Sampling

Sensor measurements are collected at fixed sampling intervals of five seconds. This sampling rate was selected to maintain temporal consistency while minimizing wireless communication overhead and power consumption. Each recorded data sample consists of four environmental attributes: temperature, humidity, flame sensor value, and sound sensor value. The ESP32 microcontroller performs real-time data acquisition and transmits the sensor readings wirelessly to cloud storage through Wi-Fi communication. The transmitted data are stored in a structured database, which forms the dataset used for machine learning model development and evalu.

2.3. Data Labeling Strategy

To support supervised machine learning, each collected data sample was assigned a class label representing the environmental condition observed during data acquisition. Three operational states were defined to represent different fire conditions: Normal, Fire-Risk, and Fire. The Normal state represents safe environmental conditions characterized by stable temperature and humidity levels, the absence of flame detection, and low sound activity. The Fire-Risk state represents early or potential fire scenarios in which flame detection occurs without significant acoustic signals, indicating the possible presence of a small or emerging flame. The Fire state represents active fire conditions characterized by simultaneous flame detection and elevated sound intensity levels. To ensure labeling consistency, threshold-based environmental rules were applied during the data collection process. These rules were defined based on observable environmental patterns and sensor readings recorded during controlled experiments. The labeling process was carefully verified to ensure that each sample accurately represented the corresponding environmental state, thereby improving the reliability of the training dataset.

2.4. Dataset Preprocessing

The final dataset consisted of 1,500 samples, including 700 Normal instances, 400 Fire-Risk instances, and 400 Fire instances. Prior to machine learning model training, several preprocessing steps were applied to ensure data quality and improve model performance. First, timestamp attributes were removed from the dataset to prevent potential data leakage during model training. Next, the dataset was inspected to identify and remove any missing or invalid sensor readings. Feature selection was then performed to retain the most relevant environmental attributes, including temperature, humidity, flame sensor value, and sound sensor value. Finally, the categorical class labels representing the three fire states were encoded into numerical form to enable compatibility with machine learning algorithms. The overall workflow of the proposed system begins with environmental sensing using Internet of Things sensors connected to the ESP32 microcontroller. The collected data are transmitted wirelessly to cloud storage, where preprocessing and labeling procedures are performed. The processed dataset is then used to train and evaluate machine learning models for fire detection.

2.5. Machine Learning Models

Three supervised machine learning classifiers were implemented and compared to evaluate their effectiveness in detecting fire-related environmental conditions. A Decision Tree classifier was first implemented as a baseline model due to its interpretability and low computational complexity. Decision Tree models construct hierarchical decision rules based on feature thresholds and are suitable for embedded systems due to their lightweight structure. A Support Vector Machine classifier with a radial basis function kernel was also employed to capture nonlinear relationships among sensor features. Class weighting was applied to mitigate the effect of class imbalance and ensure fair model learning across all fire states.

Finally, a Random Forest classifier was implemented as the primary model for fire detection. Random Forest is an ensemble learning technique that combines multiple decision trees to improve prediction accuracy and robustness. The model was configured with 200 decision trees, and the final classification output was obtained through a majority voting mechanism among individual trees. This ensemble approach helps reduce overfitting and improves generalization performance when handling sensor noise and environmental variability. Three supervised machine learning classifiers were implemented and compared to evaluate fire detection performance.

2.6. Model Training and Evaluation Metrics

All machine learning models were trained using the same training dataset and evaluated using an independent test dataset to ensure a fair and consistent comparison. The dataset was divided into training and testing subsets to evaluate the generalization performance of each model on unseen data. Model performance was assessed using several standard classification metrics, including accuracy, precision, recall, and F1-score. In addition, confusion matrix analysis was performed to examine the distribution of classification errors across different fire states. The macro-averaged receiver operating characteristic area under the curve was also calculated to evaluate the overall discriminative capability of the classifiers. Among these evaluation metrics, particular emphasis was placed on the recall values for the Fire and Fire-Risk classes. In fire detection systems, false-negative predictions—where actual fire conditions are incorrectly classified as normal—may result in delayed emergency responses and severe safety risks. Therefore, maximizing recall for these critical classes is essential for ensuring reliable fire detection.

2.7. Feature Importance Analysis

Feature importance analysis was conducted using the Random Forest model to identify the contribution of each sensor parameter to fire detection performance. The analysis revealed that temperature and humidity features contribute significantly to classification decisions, followed by sound intensity and flame sensor readings. These findings highlight the importance of combining multiple environmental indicators when detecting fire conditions. The integration of temperature, humidity, acoustic signals, and flame detection enables a more comprehensive representation of environmental dynamics. Consequently, multi-sensor data fusion improves detection robustness and reduces reliance on a single sensing modality, thereby minimizing false alarms.

2.8. Implementation Environment

The Internet of Things firmware was developed using the Arduino Integrated Development Environment and deployed on the ESP32 microcontroller to enable real-time sensor data acquisition and wireless communication. Machine learning experiments were conducted using the Python programming language within a Jupyter Notebook environment. Several scientific computing libraries were utilized during the development process, including Scikit-learn for machine learning model implementation, Pandas for data manipulation, and NumPy for numerical computations. This implementation environment ensures efficient model development, reproducibility, and reliable experimental evaluation.

3. RESULTS AND DISCUSSION

This section presents the experimental results of the proposed IoT-based fire detection system and discusses their implications for intelligent indoor fire monitoring. The evaluation focuses on classification performance, class-wise error behavior, feature contribution, and practical deployment considerations in safety-critical environments.

3.1. Classification Performance Analysis

The proposed system was evaluated using a dataset of 1,500 samples collected from the Internet of Things sensing platform, representing Normal, Fire-Risk, and Fire conditions. All machine learning models were trained using the same feature set consisting of temperature, humidity, flame sensor readings, and sound sensor values to ensure a fair and consistent comparison. The comparative per-class performance of the evaluated classifiers is summarized in Table 1. Both the Decision Tree and Random Forest classifiers achieved an overall accuracy of 95%, outperforming the class-weighted Support Vector Machine model, which achieved an accuracy of 89%. This difference suggests that tree-based models are more effective in capturing nonlinear relationships and feature interactions inherent in multi-sensor environmental data.

Importantly, all evaluated models achieved perfect recall (100%) for the Fire class, indicating that no active fire events were missed during testing. From a safety-critical perspective, this is a crucial requirement, as false negatives in fire detection systems can lead to severe consequences, including delayed emergency response and increased damage.

Although the Decision Tree and Random Forest models achieved the same overall accuracy, their classification behavior differed in terms of stability and error distribution. The Random Forest model demonstrated slightly better balance in detecting Fire-Risk conditions, while maintaining robustness against sensor noise and overlapping feature distributions. This improvement can be attributed to the ensemble learning mechanism, which reduces variance and enhances generalization compared to a single decision tree.

Misclassifications primarily occurred between the Normal and Fire-Risk classes. These transitional states represent early environmental changes before combustion becomes clearly detectable, making them inherently more difficult to classify accurately. This indicates that feature overlap in early-stage fire conditions remains a fundamental challenge, even for machine learning-based approaches. This observation highlights the importance of multi-sensor data fusion in improving the detection of early fire-risk conditions.

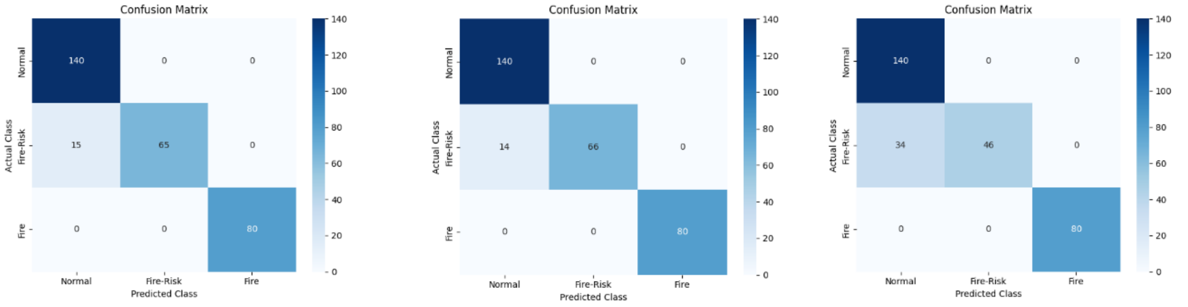
Table 1. Per-Class Performance Comparison of The Evaluated Machine Learning Models

Model	Class	Precision	Recall	F1-score
Decision Tree	Normal	0.91	1.00	0.95
	Fire-Risk	1.00	0.82	0.90
	Fire	1.00	1.00	1.00
	Accuracy			0.95
SVM (Class-Weighted)	Normal	0.80	1.00	0.89
	Fire-Risk	1.00	0.57	0.73
	Fire	1.00	1.00	1.00
	Accuracy			0.89
Random Forest	Normal	0.90	1.00	0.95
	Fire-Risk	1.00	0.81	0.90
	Fire	1.00	1.00	1.00
	Accuracy			0.95

3.2. Confusion Matrix Analysis

The confusion matrix analysis provides deeper insight into model-specific error patterns. Although all models correctly identified Fire instances, the SVM model exhibited a significant limitation by misclassifying a large number of Fire-Risk samples as Normal. This indicates that SVM struggles to construct optimal decision boundaries in regions with high feature overlap, even when class weighting is applied.

In contrast, tree-based models, particularly Random Forest, better partition the feature space by leveraging multiple decision boundaries, resulting in improved discrimination of borderline conditions. This demonstrates the advantage of ensemble-based learning in handling uncertainty and complex feature distributions. Importantly, misclassification between Normal and Fire-Risk states reflects early-stage uncertainty rather than complete model failure, as these conditions often exhibit gradual environmental transitions rather than abrupt changes. Such behavior is expected in real-world fire development scenarios, where environmental parameters evolve progressively rather than instantaneously.



(a) (b) (c)

Figure 3. Confusion matrix comparison of (a) Random Forest, (b) Decision Tree, and (c) class-weighted SVM models on the test dataset.

3.3. Effectiveness of Multi-Sensor Fusion

The experimental results confirm that integrating multiple Internet of Things sensors significantly improves fire detection reliability compared with traditional single-sensor or threshold-based approaches. Environmental parameters such as temperature and humidity provide valuable information for identifying early fire-risk conditions, while flame and sound sensors offer strong signals during active fire events. Feature importance analysis derived from the Random Forest classifier, as shown in Figure 4, indicates that the flame sensor provides the highest contribution to the classification process, followed by humidity, temperature, and sound sensors. This distribution highlights that direct fire indicators dominate during active fire conditions, while environmental sensors contribute more significantly to early-stage detection.

The sound sensor contributes complementary information during combustion events, improving the model’s ability to distinguish fire-related conditions. However, its relatively lower importance suggests sensitivity to environmental noise, which may reduce its reliability as a standalone feature. These findings demonstrate that multi-sensor data fusion provides a more comprehensive representation of environmental conditions and enhances fire detection reliability. By combining heterogeneous sensor inputs, the system mitigates the limitations of individual sensors and improves overall robustness.

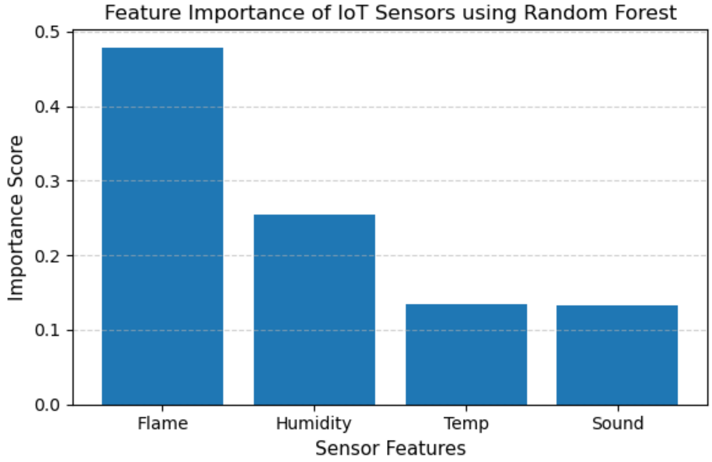


Figure 4. Feature importance scores of IoT sensor variables obtained using the Random Forest classifier.

3.4. Model Comparison and Safety-Critical Behavior

Among the evaluated models, the Random Forest classifier demonstrated the most reliable performance for safety-critical fire detection. Although the Decision Tree classifier achieved the same overall accuracy, Random Forest provides improved stability due to its ensemble learning mechanism. The Support Vector Machine model achieved strong performance in detecting active fire conditions but showed reduced sensitivity in identifying Fire-Risk states. In particular, several Fire-Risk samples were misclassified as Normal conditions. This limitation reduces its effectiveness for early warning applications, where detecting pre-fire conditions is essential. From a safety perspective, maintaining high recall for both Fire and Fire-Risk classes is more important than maximizing overall accuracy. This prioritization reflects real-world requirements, where early detection and risk prevention outweigh minor classification errors. The Random Forest classifier achieves this balance effectively.

3.5. Receiver Operating Characteristic (ROC) Analysis

The macro-averaged ROC curve for the Random Forest classifier is shown in Figure 5. The achieved ROC–AUC value of 0.993 indicates excellent separability among Normal, Fire-Risk, and Fire classes. Such a high ROC–AUC value confirms that the model maintains strong discriminative capability across different classification thresholds, which is essential for reliable operation under varying environmental conditions. This result further validates the robustness of the Random Forest classifier in IoT-based fire detection applications.

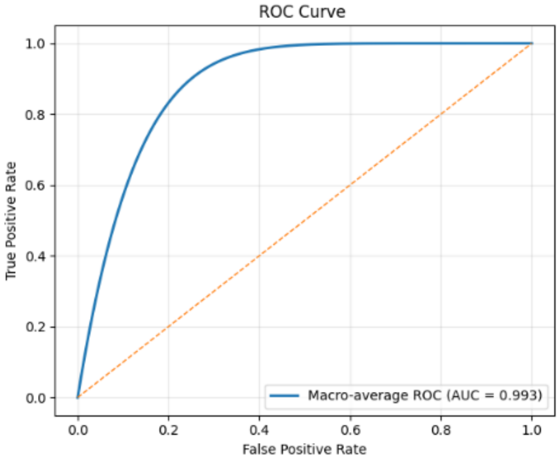


Figure 5. Macro-averaged ROC curve for multi-class fire detection using the Random Forest classifier.

The results of this study support previous findings that multi-sensor data fusion improves fire detection accuracy and reduces false alarms compared to single-sensor systems [9], [23]. The integration of multiple environmental parameters is consistent with studies showing enhanced robustness through heterogeneous sensor data [10], [11], [14]. The strong performance of the Random Forest model also aligns with prior research highlighting the effectiveness of ensemble learning methods [31], [35]. The high accuracy and perfect recall for fire events confirm the reliability of the proposed approach in safety-critical applications, where minimizing missed detections is essential [2], [9]. Moreover, compared to computationally intensive deep learning approaches [29], [41], [42], this method offers a more efficient solution suitable for real-time IoT deployment [22].

The proposed system is computationally lightweight and well suited for deployment on resource-constrained Internet of Things platforms such as the ESP32 microcontroller. Machine learning models can be trained offline and deployed either on edge devices or cloud-based inference systems to enable real-time environmental monitoring and fire detection. In practical applications, the system can be implemented in residential buildings, laboratories, warehouses, and small industrial facilities where early fire detection is critical. For example, in a smart home environment, the system can continuously monitor environmental conditions and trigger early warnings when abnormal temperature or flame signals are detected, allowing occupants to respond before the situation escalates into a severe fire incident. The use of low-cost sensors further enhances system scalability, making it economically feasible for widespread indoor safety monitoring applications.

Building upon these practical advantages, this study contributes a novel approach to intelligent indoor fire detection by integrating multi-sensor IoT data with machine learning–based multi-class classification in a lightweight and edge-deployable framework. Unlike prior studies that predominantly rely on single-sensor mechanisms, static thresholding, or computationally intensive deep learning models, this research introduces a data-driven adaptive classification system capable of distinguishing Normal, Fire-Risk, and Fire conditions in real time. The novelty also lies in the implementation of an efficient ensemble learning model optimized for low-cost hardware such as the ESP32, enabling high detection accuracy while maintaining minimal computational overhead. Furthermore, this study advances existing work by emphasizing early fire-risk identification through multi-sensor data fusion, thereby improving system reliability and reducing false alarms in dynamic indoor environments—an issue that remains a critical limitation in current IoT-based fire detection systems.

Despite these promising results, several limitations must be acknowledged. First, the dataset was collected in a controlled environment, which may not fully capture the variability of real-world indoor conditions such as ventilation, human activity, and external disturbances. Second, the labeling strategy is threshold-based, which may introduce bias into the training data. While effective for initial classification, this approach may limit the model's ability to learn more complex fire progression patterns. Third, the sound sensor shows relatively lower contribution, suggesting sensitivity to environmental noise variations. Therefore, future work should focus on: (1) collecting real-world and large-scale datasets; (2) developing adaptive or semi-supervised labeling strategies; (3) incorporating temporal modeling (e.g., LSTM or time-series analysis) to capture fire evolution over time; and (4) exploring edge-optimized deep learning models to improve performance without increasing computational cost.

4. CONCLUSION

This study presented an intelligent fire detection system that integrates low-cost Internet of Things sensing with machine learning for indoor safety monitoring. By combining multiple environmental sensors—including temperature, humidity, flame intensity, and sound signals—the system provides a comprehensive representation of environmental conditions associated with fire development. The results show that multi-sensor data fusion improves fire detection reliability compared with conventional single-sensor or threshold-based approaches. Machine learning enables the system to identify complex environmental patterns and distinguish between normal conditions, early fire-risk situations, and active fire events, supporting more effective early warning. Among the evaluated models, the Random Forest classifier provided the most reliable performance due to its ensemble learning structure, which improves robustness against sensor noise and environmental variability. The system successfully detected all active fire conditions during testing, demonstrating the effectiveness of combining environmental sensing with intelligent decision-making. The proposed approach is computationally lightweight and cost-effective, making it suitable for deployment in residential buildings, laboratories, and small commercial facilities. However, the dataset was collected under controlled indoor conditions. Future work will focus on expanding data collection in diverse environments, integrating additional sensors such as gas or smoke detectors, and exploring temporal learning models to further enhance fire detection performance. Overall, the integration of Internet of Things sensing and machine learning provides a practical approach for developing intelligent fire detection systems that improve indoor safety and support proactive fire prevention.

ACKNOWLEDGEMENTS

The authors acknowledge the Faculty of Engineering, Computer, and Design at Nusa Putra University, Sukabumi, Indonesia, for their continuous support and resources, which significantly contribute to this research.

AUTHOR CONTRIBUTIONS

Conceptualization, H.A.; Methodology, H.A.; Software, H.A.; Validation, H.A., A.P.J. and D.A.D.; Formal Analysis, H.A.; Investigation, H.A.; Resources, H.A., A.P.J. and D.A.D.; Data Curation, H.A.; Writing – Original Draft Preparation, H.A.; Writing – Review & Editing, H.A.; Visualization, H.A.; Supervision, A.P.J. and D.A.D.; Project Administration, H.A.; Funding Acquisition, A.P.J. and D.A.D.

INFORMED CONSENT STATEMENT

Not applicable.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the preparation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

REFERENCES

[1] S. Medved, “Buildings fires and fire safety,” in *Building Physics: Heat, Ventilation, Moisture, Light, Sound, Fire, and Urban Microclimate*. Cham, Switzerland: Springer, 2021, pp. 407–451, doi: 10.1007/978-3-030-74390-1_6.

[2] V. Kodur, et al., “Fire hazard in buildings: Review, assessment and strategies for improving fire safety,” *PSU Res. Rev.*, vol. 4, no. 1, pp. 1–23, 2020, doi: 10.1108/PRR-12-2018-0033.

[3] M. Yu, et al., “Building fire alarm model based on fire source inversion according to smoke arrival time intervals,” *J. Build. Eng.*, vol. 73, Art. no. 106650, 2023, doi: 10.1016/j.jobe.2023.106650.

[4] R. Kuti, G. Zólyomi, G. László, C. Hajdu, L. Környei, and F. Hajdu, “Examination of effects of indoor fires on building structures and people,” *Heliyon*, vol. 9, no. 1, Art. no. e12720, Jan. 2023, doi: 10.1016/j.heliyon.2022.e12720.

[5] M. L. Ivanov and W. K. Chow, “Fire safety in modern indoor and built environment,” *Indoor Built Environ.*, vol. 32, no. 1, pp. 3–8, Jan. 2023, doi: 10.1177/1420326X221134765.

[6] M. T. Bashir, “Fire protection and prevention in perspective of human, environment and workplace,” *Int. J. Sci. Technol. Res.*, vol. 10, no. 3, pp. 38–42, Mar. 2021. [Online]. Available: https://web.archive.org/web/20210814084738/http://www.ijstr.org/final-print/mar2021/Fire-Protection-And-Prevention-In-Perspective-Of-Human-Environment-And-Workplace.pdf

[7] L. Deng, et al., “Large-space fire detection technology: A review of conventional detector limitations and image-based target detection techniques,” *Fire*, vol. 8, no. 9, Art. no. 358, 2025, doi: 10.3390/fire8090358.

[8] G. Tejaswi, R. Bhavani, S. Srihitha, S. Arshiha, and R. V. S. Sarayu, “Predicting fire alarms using multi-sensor data: A binary classification approach,” *Turkish J. Comput. Math. Educ.*, vol. 15, no. 1, pp. 242–255, 2024, doi: 10.61841/turcomat.v15i1.14617.

[9] C. L. Wu, et al., “False-alarm susceptibility of spot-type smoke detectors under realistic fire and nuisance conditions,” *Fire Saf. J.*, Art. no. 104621, 2025, doi: 10.1016/j.firesaf.2025.104621.

[10] 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 stage,” *Comput. Electr. Eng.*, vol. 101, Art. no. 108046, 2022, doi: 10.1016/j.compeleceng.2022.108046.

[11] J. Baek, et al., “Intelligent multi-sensor detection system for monitoring indoor building fires,” *IEEE Sensors J.*, vol. 21, no. 24, pp. 27982–27992, Dec. 2021, doi: 10.1109/JSEN.2021.3124266.

[12] H. Zhu, et al., “Automotive fire alarm system based on multi-sensor fusion,” in *Proc. Int. Conf. Sensors Inf. Technol.*, 2024, pp. 159–164, doi: 10.1117/12.3029223.

[13] A. Solórzano, et al., “Early fire detection based on gas sensor arrays: Multivariate calibration and validation,” *Sens. Actuators B, Chem.*, vol. 352, Art. no. 130961, 2022, doi: 10.1016/j.snb.2021.130961.

[14] Q. Su, G. Hu, and Z. Liu, “Research on fire detection method of complex space based on multi-sensor data fusion,” *Meas. Sci. Technol.*, vol. 35, no. 8, Art. no. 085107, 2024, doi: 10.1088/1361-6501/ad437d.

[15] A. Rehman, et al., “Smart fire detection and deterrent system for human savior by using Internet of Things (IoT),” *Energies*, vol. 14, no. 17, Art. no. 5500, 2021, doi: 10.3390/en14175500.

[16] S. K. Mekni, “Design and implementation of a smart fire detection and monitoring system based on IoT,” in *Proc. Int. Conf. Appl. Autom. Ind. Diagn.*, 2022, pp. 1–5, doi: 10.1109/ICAAID51067.2022.9799505.

[17] B. E. Raju, K. R. Chandra, K. V. N. Gupta, K. N. V. Rao, R. Devi, and P. V. Kumar, “Fuzzy logic-enhanced multi-sensor hardware module for real-time fire detection and notification,” in *Proc. 7th Int. Conf. Contemp. Comput. Inform. (IC3I)*, 2024, pp. 1–6, doi: 10.1109/IC3I61595.2024.10828880.

[18] A. Al-Dahoud, M. Fezari, A. A. Alkhatib, M. N. Soltani, and A. Al-Dahoud, “Forest fire detection system based on low-cost wireless sensor network and Internet of Things,” *WSEAS Trans. Environ. Dev.*, vol. 19, pp. 506–513, 2023, doi: 10.37394/232015.2023.19.49.

[19] A. A. Almohammedi, et al., “Design and implementation of IoT-enabled intelligent fire detection system using neural networks,” in *Lecture Notes in Computer Science*, vol. 14202, 2023, doi: 10.1007/978-3-031-45140-9_6.

[20] U. Dampage, et al., “Forest fire detection system using wireless sensor networks and machine learning,” *Sci. Rep.*, vol. 12, Art. no. 46, 2022, doi: 10.1038/s41598-021-03882-9.

[21] ././/// J. Desikan, et al., “Hybrid machine learning-based fault-tolerant sensor data fusion and anomaly detection for fire risk mitigation in IIoT environment,” *Sensors*, vol. 25, no. 7, Art. no. 2146, 2025, doi: 10.3390/s25072146.

[22] J. C. N. Bittencourt, D. G. Costa, P. Portugal, and F. Vasques, “Towards lightweight fire detection at the extreme edge based on decision trees,” in *Proc. IEEE 22nd Mediterranean Electrotech. Conf. (MELECON)*, Jun. 2024, pp. 873–878, doi: 10.1109/MELECON56669.2024.10608598.

[23] F. Khan, et al., “Recent advances in sensors for fire detection,” *Sensors*, vol. 22, no. 9, Art. no. 3310, 2022, doi: 10.3390/s22093310.

[24] A. Doshi and Y. Rai, “IoT-based fire and gas monitoring system,” *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 9, no. 7, pp. 3110–3117, 2021, doi: 10.22214/ijraset.2021.37026.

[25] M. N. Khan, et al., “Real-time environmental monitoring using low-cost sensors in smart cities with IoT,” *Int. J. Future Mach. Res.*, vol. 6, pp. 1–11, 2024, doi: 10.36948/ijfmr.2024.v06i01.23163.

[26] R. F. Chisab, A. A. Majeed, and H. S. Hamid, “IoT-based smart wireless communication system for electronic monitoring of environmental parameters with a data-logger,” *Int. J. Electr. Electron. Eng. Telecommun.*, vol. 12, no. 6, pp. 450–458, 2023, doi: 10.18178/ijeetc.12.6.450-458.

[27] S. Chitram, et al., “Enhancing fire and smoke detection using deep learning techniques,” *Eng. Proc.*, vol. 62, no. 1, Art. no. 7, 2024, doi: 10.3390/engproc2024062007.

[28] J. Pincott, et al., “Indoor fire detection utilizing computer vision-based strategies,” *J. Build. Eng.*, vol. 61, Art. no. 105154, 2022, doi: 10.1016/j.jobe.2022.105154.

[29] A. Gaur, et al., “Video flame and smoke based fire detection algorithms: A literature review,” *Fire Technol.*, vol. 56, pp. 1943–1980, 2020, doi: 10.1007/s10694-020-00986-y.

[30] S. Suklabaidya and I. Das, “Processing IoT sensor fire dataset using machine learning techniques,” in *Proc. Int. Conf. Intell. Syst. Adv. Comput. Commun. (ISACC)*, Feb. 2023, pp. 1–7, doi: 10.1109/ISACC56298.2023.10084317.

[31] A. Secilmis, N. Aksu, F. A. Dael, I. Shayea, and A. A. El-Saleh, “Machine learning-based fire detection: A comprehensive review and evaluation of classification models,” *JOIV: Int. J. Inform. Visualization*, vol. 7, no. 3-2, pp. 1982–1988, 2023, doi: 10.30630/joiv.7.3-2.2332.

[32] U. Ahad, Y. Singh, P. Anand, Z. A. Sheikh, and P. K. Singh, “Intrusion detection system model for IoT networks using ensemble learning,” *J. Interconnection Netw.*, vol. 22, no. 3, Art. no. 2145008, 2022, doi: 10.1142/S0219265921450080.

[33] J. Jose and J. E. Judith, “Unveiling the IoT’s dark corners: Anomaly detection enhanced by ensemble modelling,” *Automatika*, vol. 65, no. 2, pp. 584–596, 2024, doi: 10.1080/00051144.2024.2304369.

[34] R. A. Khan, et al., “Fire and smoke detection using capsule network,” *Fire Technol.*, vol. 59, pp. 581–594, 2023, doi: 10.1007/s10694-022-01352-w.

[35] F. Daghero, et al., “Dynamic decision tree ensembles for energy-efficient inference on IoT edge nodes,” *IEEE Internet Things J.*, vol. 11, no. 1, pp. 742–757, 2024, doi: 10.1109/JIOT.2023.3286276.

[36] H. Wang, J. Li, and K. He, “Hierarchical ensemble reduction and learning for resource-constrained computing,” *ACM Trans. Des. Autom. Electron. Syst.*, vol. 25, no. 1, pp. 1–21, 2019, doi: 10.1145/3365224.

[37] S. Uppal, S. Raheja, and N. R. Das, “Fire detection alarm system using deep learning,” in *Proc. 13th Int. Conf. Cloud Comput. Data Sci. Eng. (Confluence)*, Jan. 2023, pp. 54–58, doi: 10.1109/Confluence56041.2023.10048842.

[38] A. Hassan and A. I. Audu, “A lightweight CNN model for vision-based fire detection on embedded systems,” *FUOYE J. Eng. Technol.*, vol. 9, no. 4, pp. 624–628, 2024, doi: 10.4314/fuoyejet.v9i4.9.

[39] S. Sawant, B. Chauhan, S. Kumbhar, G. Chaudhari, and P. Thakar, “Integrated fire detection system using machine learning and IoT,” *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 12, no. 5, pp. 2091–2100, 2024, doi: 10.22214/ijraset.2024.60063.

[40] M. Milli and M. Milli, “Reducing false positives in building fire detection systems via multiple metal oxide sensors,” *IEEE Access*, early access, 2025, doi: 10.1109/ACCESS.2025.3606584.

[41] ,.... N. Dilshad, T. Khan, and J. Song, “Efficient deep learning framework for fire detection in complex surveillance environment,” *Comput. Syst. Sci. Eng.*, vol. 46, no. 1, pp. 749–764, 2023, doi: 10.32604/csse.2023.034475.

[42] A. K. Vishwakarma and M. Deshmukh, “CNNM-FDI: Novel convolutional neural network model for fire detection in images,” *IETE J. Res.*, vol. 71, no. 4, pp. 1105–1118, 2025, doi: 10.1080/03772063.2025.2453877.

[43] N. D. Ismail, et al., “A systematic literature review of vision-based fire detection, prediction and forecasting,” *J. Kejuruteraan*, vol. 37, no. 1, pp. 191–218, 2025, doi: 10.17576/jkukm-2025-37(1)-13.

[44] M. S. Mohammed, A. H. Abbas, and N. A. Abdullah, “Intelligent surveillance systems for fire detection in open areas: A survey,” *Iraqi J. Sci.*, vol. 65, no. 5, pp. 2813–2827, 2024, doi: 10.24996/ijs.2024.65.5.36.

[45] F. A. Nafis, et al., “An efficient IoT-based fire detection system using quantized deep learning model on resource-constrained devices,” in *Proc. 27th Int. Conf. Comput. Inf. Technol. (ICCIT)*, Dec. 2024, pp. 3182–3187, doi: 10.1109/ICCIT64611.2024.11021729.

[46] H. L. Farhan and A. S. Daghal, “Improving the detection and warning fire system on the smart campus area using ANFIS,” *Al-Furat J. Innov. Electron. Comput. Eng.*, vol. 3, no. 2, pp. 422–436, 2024, doi: 10.46649/fjiece.v3.2.28a.7.6.2024.

[47] H. T. Thai, N. Y. Tran-Van, K. H. Le-Minh, and K. H. Le, “An edge-based fire detection system for real-time IoT applications,” in *Proc. IEEE Int. Conf. Commun. Netw. Satell. (COMNETSAT)*, Nov. 2023, pp. 646–651, doi: 10.1109/COMNETSAT59769.2023.10420588.

[48] D. Kaliyev, O. Shvets, S. Grigoryeva, and A. Alimkhanova, “Intelligent forest fire detection using CNN and UAVs,” in *Proc. IEEE 6th Int. Symp. Logist. Ind. Inform. (LINDI)*, Oct. 2024, pp. 131–134, doi: 10.1109/LINDI63813.2024.10820427.

[49] R. D. Shirwaikar and L. Mathews, "CNN-based video surveillance for fire and localization detection," in *Proc. Int. Conf. Cogn. Comput. Inf. Process. (CCIP)*, Dec. 2022, pp. 1–8, doi: 10.1109/CCIP57447.2022.10058625.

[50] S. Khirani, A. Souahlia, A. Rabehi, et al., "Advanced evaluation of pre-trained CNN models for accurate forest fire detection," *Nat. Hazards*, vol. 122, Art. no. 234, 2026, doi: 10.1007/s11069-026-07976-3.