



A Hybrid Deep Learning Model for Robust and Real-Time Fire Detection

¹Achimba Terfa, ²Nongu Anthonia Doofan, ³Kumba Jeremiah Torver, ⁴Shinyi Michael Ngutor

^{1&2}Department of Computer Science, Federal Polytechnic Wannune, Benue State.

³Department of Computer Engineering, Federal Polytechnic Wannune, Benue State.

⁴Department of Mathematics and Computer Science, University of Mkar, Mkar, Benue State.

Abstract

Fire outbreaks pose serious threats to human life, property, and infrastructure, while conventional detection systems often suffer from false alarms and reduced performance under challenging environmental conditions. This study proposes a hybrid deep learning-based fire detection model that integrates ResNet50 and MobileViT for effective spatial and contextual feature extraction. YOLOv8 is employed to detect fire and smoke using adaptive confidence thresholds, improving detection reliability under varying conditions. To further enhance robustness, multimodal sensor fusion incorporating infrared, thermal, gas, and temperature sensors is implemented, with Kalman filtering applied to reduce sensor noise and improve measurement stability. Generative Adversarial Networks (GANs) are also used to generate synthetic fire scenarios to address limitations associated with insufficient training data. The proposed system is designed for real-time deployment on edge computing platforms, including Raspberry Pi and Jetson Nano, while LoRaWAN enables long-range alert transmission in low-connectivity environments. Experimental results demonstrate an accuracy of 97.6% and precision of 96.1%, indicating the effectiveness of the proposed approach for reliable real-time fire detection. The system offers potential applications in residential, industrial, and other high-risk environments.

Keywords: Real-Time Fire Detection, Deep Learning, Edge Computing, Multi-Sensor Fusion, Generative Adversarial Networks (GANs)

I. Introduction

Fires remain one of the most destructive hazards, endangering human life, damaging property, and causing serious harm to the environment. Their occurrence can lead to tragic outcomes, including fatalities, economic setbacks, environmental degradation, and the destruction of critical infrastructure. In both residential and industrial settings, fire incidents often result in irreversible property losses and operational downtimes. In natural ecosystems, wildfires contribute significantly to forest loss, air contamination, and the decline of biodiversity (Kumar et al., 2022; Raihan, 2023). The speed at which fires can spread, combined with delays in recognizing and responding to them, intensifies their impact. Therefore, early and dependable detection is essential for minimizing potential harm and supporting timely intervention efforts. With fire incidents becoming more frequent and more severe in recent years, the demand for intelligent, responsive, and real-time detection systems has grown more urgent (Yang et al., 2024).

Traditional systems like smoke and heat detectors are often constrained by limited range, delayed responses, and a high incidence of false alarms, especially in complex or extreme conditions like fog, low-light, or dense smoke environments. These limitations can lead to catastrophic consequences, especially in scenarios where early detection is critical (Gaur et al., 2019; Karishma et al., 2019). In recent years, deep learning algorithms have been employed to enhance fire detection capabilities. Convolutional Neural Networks (CNNs) and object detection

models like YOLO have shown promise in identifying fire and smoke in images and videos. However, these models often require substantial computational resources, making them less suitable for real-time applications on edge devices (Vasconcelos et al., 2024). Moreover, their performance can degrade in challenging environments due to factors such as poor lighting, occlusions, and varying fire appearances. They are also limited by the quality and diversity of training datasets, which may not adequately represent all possible fire scenarios, leading to poor generalization in real-world conditions. Additionally, many of these systems depend heavily on stable internet connectivity for cloud-based processing and updates, which is not always guaranteed, especially in remote or underdeveloped areas. Environmental factors, including extreme weather conditions like heavy smoke or fog, may still impact the accuracy and reliability of detection (Sinchai et al., 2024).

The proposed model systematically addresses the limitations of previous deep learning-based fire detection systems. To mitigate computational complexity and enable real-time operation, the model employs lightweight CNN and Vision Transformer architectures optimized through model compression techniques, making it suitable for deployment on edge devices with limited processing power. The issue of dataset limitations is tackled by training the model on a diverse and augmented multimodal dataset that includes various fire scenarios across different environments, lighting conditions, and intensities. To reduce reliance on constant internet connectivity, the model is designed for local inference, allowing it to function efficiently even in areas with poor or intermittent network access. The integration of multiple sensors—such as thermal, infrared, and gas detectors—ensures robustness and enhances detection accuracy in visually impaired conditions like fog, smoke, or low light. Additionally, the model incorporates adaptive thresholding and contextual attention mechanisms to maintain performance under extreme environmental factors, including heavy smoke and adverse weather. Together, these innovations make the enhanced system a comprehensive and resilient solution for accurate, fast, and reliable fire detection in real-world scenarios.

II. Related Works

A Study on AI-Integrated Fire Alarm and Detection A review of AI-enhanced fire alarm and detection technologies was conducted in (Hanif, 2023), emphasizing the urgent need to improve fire safety through more accurate and reliable detection mechanisms. This research investigates how artificial intelligence can be leveraged to reduce the incidence of false alarms and increase detection precision. The paper categorizes existing AI-driven fire detection solutions based on their use of algorithmic processing, sensor integration, pattern recognition, decision-making frameworks, predictive analytics, and smart infrastructure compatibility. However, the study remains theoretical, lacking empirical trials or real-world system deployment. Despite showcasing the strengths of AI, it overlooks concerns related to computational overhead, data protection, and the robustness of AI systems under extreme conditions.

Another study, outlined in (Karishma et al., 2019), introduced an AI-centered fire detection and suppression model, primarily addressing the drawbacks of conventional systems—namely their susceptibility to false alarms and delayed response. This system integrates computer vision and embedded technologies to enhance both detection reliability and automated fire response. The methodology combines software and hardware components to deliver real-time detection, incorporating computer vision, embedded systems, and practical testing. Nonetheless, limitations include the absence of wireless communication, limited testing scenarios, and hardware restrictions.

The work in (Lee et al., 2024) proposed an advanced fire detection and suppression solution specifically designed for autonomous maritime vessels. Motivated by the increasing demand for self-reliant safety systems in shipping, the model employs a combination of RGB, IR, and UV sensors, coupled with reinforcement learning algorithms, to manage fire suppression in unstable sea environments. While promising, the model's real-world application is limited, particularly in diverse sea conditions, and focuses solely on early-stage fires within specific motion parameters.

In (Remmelzwaal, 2023), a study was presented focusing on early wildfire detection using AI-enhanced object recognition. The proposed approach integrates solar-powered panoramic cameras with real-time AI-driven image analysis to detect fires promptly and alert emergency services. Challenges include insufficient testing in actual wildfire scenarios, limitations in camera positioning, dependency on internet connectivity, and susceptibility to environmental disturbances causing false alarms.

Research in (Marandi, 2018) reviewed AI, machine learning, and wireless sensor networks (WSNs) in the context of fire detection. The study emphasizes efficient sensor selection and AI-powered classification to boost detection accuracy. Wireless sensor networks and machine learning classification techniques were evaluated for performance in terms of accuracy and processing time. Nevertheless, the system was hindered by restricted field testing, sensor limitations, computational inefficiencies, and false positives.

Authors in (Frizzi et al., 2021) developed a CNN-based semantic segmentation system for detecting smoke and fire in RGB imagery. Their model, based on a modified VGG16 architecture, replaces the typical fully connected layers with a 7×7 convolutional layer for improved generalization, followed by up-sampling layers to refine segmentation outputs. While offering real-time visual assistance for firefighting, this solution faces challenges in separating fire from smoke, maintaining low false positives, and coping with computational demands.

The study in (Gocmen et al., 2024) analyzed different CNN architectures for fire detection to identify the most effective models in image-based detection scenarios. The research compared deep learning models, applied transfer learning techniques, and used forest fire datasets to enhance detection capabilities. However, challenges such as limited data availability, computational burden, false detections, and the absence of live testing environments were observed.

In (Surabhi & Babu, 2024), researchers proposed a fire detection system leveraging image processing and HAAR cascade classifiers to enhance response time and detection accuracy. The solution includes real-time video analysis, fire detection mechanisms, alarm systems, and IoT-based notifications. Limitations involved a narrow testing scope, visibility dependence, basic AI modeling, and false detection issues.

A forest fire detection framework based on "Learning Without Forgetting" (LwF) was introduced in (Sathishkumar et al., 2023), aiming to address the shortcomings of traditional fire monitoring systems. The model retained prior learning while adapting to new data (from the BowFire dataset) to improve classification across various conditions. Despite this advancement, the approach still faced obstacles like limited field testing, imbalanced data, and high rates of misclassification under certain environmental scenarios.

Study (Avazov et al., 2023) presented a real-time AI-supported forest fire detection and alert system that integrates deep learning (YOLOv5) and IoT devices. The model is trained to distinguish between actual fires and fire-like stimuli such as bright lights. While effective in many cases, the system contends with connectivity limitations, false alarms, inadequate field testing, and significant computational requirements.

From the above review, it is evident that AI-based fire detection systems are still evolving and face several notable challenges. Many of the systems have not been rigorously tested in real-world settings, leading to concerns over their reliability. False alarms—both positive and negative—remain problematic due to environmental noise and the limitations of current models in distinguishing fire from other heat or light sources. Computational resource constraints restrict deployment on low-powered devices, while most systems depend heavily on visual data, ignoring multi-sensor fusion that could offer greater robustness. Furthermore, some systems are designed for detection only, lacking sophisticated suppression mechanisms. Internet connectivity remains a hurdle in remote locations, affecting timely alerts. Environmental conditions such as fog, smoke, and lighting variations further reduce accuracy, and frequent retraining of AI models is often required to adapt to evolving fire scenarios. These limitations highlight the pressing need for a more adaptive, scalable, and sensor-diverse fire detection system.

III. Methodology

A. Architecture

The Architecture of the system is structured into several integrated modules designed to collaboratively detect, validate, and respond to fire emergencies effectively. The modules are discussed below.

a. Data Acquisition Module

This module is responsible for collecting raw input data from various sources, including RGB cameras, infrared sensors, thermal imagers, and gas detectors. These sources enable the system to capture visual, thermal, and chemical signatures associated with fire outbreaks. In addition to static sensors, real-time surveillance feeds are also incorporated to provide continuous monitoring, ensuring comprehensive environmental coverage for early fire detection.

b. Data Augmentation Module.

To address the limitations of static datasets and improve model generalization, this module utilizes Generative Adversarial Networks (GANs) to create synthetic fire scenarios. This includes variations in lighting, smoke density, reflections, and environmental backgrounds. By combining real and synthetic images, this module enriches the training dataset, enhancing the model's ability to recognize fire in diverse and challenging conditions.

c. Processing Module.

This module performs lightweight yet effective analysis of input images using a combination of ResNet50 and MobileViT architectures. ResNet50 is employed to extract detailed spatial patterns characteristic of fire, while MobileViT captures global contextual information with reduced computational load. A fusion mechanism integrates features from both models, yielding a robust representation that balances accuracy with processing efficiency, which is essential for deployment on resource-constrained edge devices.

d. Fire Detection Module.

For the actual identification of fire and smoke, this module employs the YOLOv8 object detection algorithm. This component analyzes the fused feature representations to detect potential fire outbreaks with high speed and precision. To ensure reliability in different environmental conditions such as fog, low-light, or dense smoke, an adaptive thresholding strategy dynamically adjusts the detection sensitivity, thereby reducing false positives and improving performance under extreme conditions.

e. Multi-Sensor Fusion Module.

This module enhances detection accuracy by integrating data from multiple sensor modalities. This includes information from infrared and thermal cameras, as well as gas sensors and temperature readings. By applying a dynamic fusion mechanism, which adjusts sensor contributions based on reliability, the system achieves accurate detection even in visually obstructed or noisy environments. This multi-sensor approach is particularly beneficial in scenarios where traditional vision-based systems may fail.

f. Decision-Making Module.

At the core of the system's logic, this module determines whether to trigger a fire alert. This decision is based on the combined analysis of visual detection outputs and sensor fusion results. When the probability of fire presence exceeds a predefined threshold, the system generates an alert, ensuring that only verified fire events lead to emergency responses.

g. Edge Processing and Communication Module.

To enable reliable and real-time operation, especially in environments with unstable internet connectivity, this module handles all detection tasks locally using low-power devices such as Raspberry Pi and NVIDIA Jetson Nano. This module supports offline alert generation and employs Long Range Wide Area Network (LoRaWAN) communication protocol to transmit alerts over long distances. In the event of network failure, alerts are cached locally and transmitted once connectivity is restored, maintaining the reliability of the alert system.

h. Alert and Response Module.

This module is responsible for delivering timely fire warnings to relevant stakeholders or emergency systems. It works in tandem with the communication infrastructure to ensure alerts are dispatched instantly, and it incorporates a redundancy mechanism to guarantee that no critical alert is lost, even during temporary network disruptions.

B. Work flow

The Enhanced model begins by collecting data from RGB cameras, thermal and infrared sensors, and gas detectors to capture a comprehensive range of fire indicators. This data is augmented using GANs to simulate diverse fire scenarios, improving the model's ability to generalize. Feature extraction is then performed using a combination of ResNet50 and MobileViT, which together produce a balanced and efficient representation of fire-related features. These features are analyzed by the YOLOv8-based fire detection module, with adaptive thresholding applied to maintain accuracy in challenging conditions. Multi-sensor fusion then combines data from all sources to enhance detection reliability. A decision-making module evaluates this fused data to determine if a fire alert should be triggered. Detection is processed locally on edge devices, and alerts are transmitted using LoRaWAN,

ensuring continued operation even without internet connectivity. Finally, alerts are delivered through a robust communication module, ensuring timely response and minimizing the risk of undetected fire events.

C. Mathematical Formulation for the enhanced model

a. Feature Extraction & Lightweight Processing.

The feature extraction process involves ResNet50 and MobileViT. ResNet50 extracts spatial fire patterns from input images. MobileViT (Lightweight Transformer) reduces computational overhead while maintaining high accuracy. Model Compression (quantization & pruning) reduces the size of ViT and YOLOv8, optimizing them for deployment on edge devices. This strategy reduces computational cost, making the model more suitable for real-time processing on IoT and embedded devices.

Given an input image I , feature maps F_{CNN} and F_{ViT} are extracted as follows:

$$F_{\text{CNN}} = \Phi_{\text{ResNet50}}(I) \quad (1)$$

$$F_{\text{ViT}} = \Phi_{\text{MobileViT}}(I) \quad (2)$$

Where:

- $\Phi_{\text{ResNet50}}(\cdot)$ extracts spatial features.
- $\Phi_{\text{MobileViT}}(\cdot)$ extracts global contextual information while reducing computational complexity.

The final feature representation is a weighted fusion of the two feature maps:

$$F_{\text{Hybrid}} = \alpha F_{\text{CNN}} + \beta F_{\text{ViT}} \quad (3)$$

where α and β are adaptive fusion weights optimized during training.

b. Fire Detection with YOLOv8 and Adaptive Thresholding.

YOLOv8 detects fire and smoke in real time with high precision. Adaptive Confidence Thresholding dynamically adjusts detection sensitivity based on environmental conditions (e.g., low-light, fog, or dense smoke). This addresses the issue of false positives due to reflections and environmental noise, ensuring reliable fire detection.

YOLOv8 detects fire with a confidence score C_f :

$$C_f = \sigma(W_f \cdot X_f + b_f) \quad (4)$$

Where:

- X_f represents input image features,
- W_f and b_f are learnable parameters,
- $\sigma(\cdot)$ is the Sigmoid activation function

To handle extreme environments, we introduce an adaptive confidence threshold T_f dynamically adjusted based on environmental factors E (fog, smoke, lighting):

$$T_f = T_0 + \gamma E \quad (5)$$

Where:

- T_0 is the base threshold,

- γ is an adaptive factor.

Fire is detected if:

$$C_f \geq T_f \quad (6)$$

c. Multi-Sensor Fusion for Extreme Conditions.

To improve fire detection in low-visibility environments, we fuse infrared (IR), thermal imaging, and gas sensor data. Infrared (IR) and Thermal Imaging enhances detection in low-visibility conditions such as smoke, fog, and night time scenarios. Gas Sensors and Temperature Sensors provides early fire warnings even before visible flames appear. Kalman Filtering fuses multiple sensor readings to minimize false detections.

This strategy addresses performance degradation in extreme environments by ensuring accurate detection under challenging conditions.

Each sensor provides a probability score for fire presence:

$$P_{IR} = f_{IR}(I_{IR}), P_{Thermal} = f_{Thermal}(I_{Thermal}), P_{Gas} = f_{Gas}(S_{Gas}) \quad (7)$$

The final fused fire detection score P_{Fire} is computed using weighted sensor fusion with Kalman filtering:

$$P_{Fire} = w_1 P_{YOLO} + w_2 P_{IR} + w_3 P_{Thermal} + w_4 P_{Gas} \quad (8)$$

Where:

- P_{YOLO} is the probability score from YOLOv8, based on visual fire/smoke detection
- P_{IR} is the probability score from the infrared sensor, detecting heat signatures
- $P_{Thermal}$ is the Probability score from the thermal camera, based on temperature mapping
- P_{Gas} is the probability score from the gas sensor, based on chemical signatures
- w_i are the sensor reliability weights dynamically adjusted using Kalman filtering.

Fire is confirmed if:

$$P_{Fire} \geq \theta \quad (9)$$

Where θ represents a critical decision threshold, optimized during system calibration. It acts as a cut-off value to decide whether the combined evidence from all sensors is strong enough to confirm a fire event.

d. IoT-Based Edge Processing and Offline Alert Mechanism.

Since real-time fire alerts depend on network availability, we introduce edge caching and LoRaWAN communication. Edge AI Deployment (Raspberry Pi, NVIDIA Jetson Nano) enables real-time fire detection without requiring cloud dependency. LoRaWAN Communication and Edge Caching stores alerts temporarily in case of network failures, ensuring alerts are always delivered.

This strategy addresses dependency on stable internet, making the system operational even in remote areas or during network disruptions.

An alert A is generated when fire detection probability exceeds a critical threshold θ_c :

$$A = \begin{cases} 1, & P_{Fire} \geq \theta_c \\ 0, & P_{Fire} < \theta_c \end{cases} \quad (10)$$

For offline alert storage, LoRaWAN stores alerts A_t when network connectivity N_t is lost:

$$A_t = A \cdot (1 - N_t) \quad (11)$$

Where $N_t = 1$ when the network is available and $N_t = 0$ when offline.

e. Dataset Augmentation using GANs.

To improve robustness, we introduce GAN-based synthetic data augmentation. GANs (Generative Adversarial Networks) synthesize additional fire scenarios (e.g., reflections, fog, and diverse backgrounds) to improve model generalization.

With Real-Time Surveillance Footage Integration, the model trains on dynamically collected real-world fire detection data, instead of relying on static datasets.

This strategy addresses Dataset limitations, ensuring the model generalizes well across different fire scenarios.

Given a real fire image I_r , a Generative Adversarial Network (GAN) produces synthetic samples I_s :

$$I_s = G(I_r, z) \quad (12)$$

Where:

- $G(\cdot)$ is the generator network,
- z is a random noise vector

The final augmented dataset is a mix of real and synthetic images:

$$D_{aug} = D_{real} \cup D_{GAN} \quad (13)$$

IV. System Implementation

The implementation of the enhanced model focuses on building a hybrid, real-time fire detection system optimized for edge deployment. The system was developed in a modular fashion to support integration, scalability, and performance across different environmental conditions.

A. Hardware Components

The implementation of the enhanced fire detection system utilized edge-friendly and low-power hardware platforms suitable for real-time, remote deployment. Raspberry Pi 4 and NVIDIA Jetson Nano were employed as the primary edge devices for running the detection and decision-making modules. These devices were connected to multiple types of sensors, including RGB cameras, thermal imagers, infrared (IR) sensors, gas detectors, and temperature sensors, for comprehensive environmental data acquisition. Communication hardware such as LoRaWAN modules and GSM shields were integrated to facilitate long-range and redundant transmission of fire alerts in areas with unstable or limited network connectivity.

B. Software Components

The software stack was built using Python as the core programming language. Deep learning models were implemented using PyTorch, TensorFlow, and Keras. YOLOv8 was integrated through the Ultralytics framework for object detection, while ResNet50 and MobileViT were used for spatial and contextual feature extraction respectively. OpenCV handled image processing tasks, and the GAN used for data augmentation was built using Keras and trained on an NVIDIA GPU. Communication and data handling were managed using Message Queuing Telemetry Transport (MQTT) for local messaging, and LoRaWAN communication was programmed using the Arduino IDE. Model compression techniques, including pruning and quantization, were applied using PyTorch's built-in utilities to optimize the models for edge deployment.

C. Dataset and Training Configurations

a. Data Sources

The dataset used for training and evaluation was primarily sourced from the FIRE Dataset (Fire and Smoke Dataset) available on Kaggle, which contains labeled images of fire and smoke in various environmental conditions, including both indoor and outdoor scenarios. Additionally, the dataset was augmented with sensor data collected from the deployed hardware components, including RGB and thermal images, temperature variations, gas levels, and infrared signatures. These diverse sources provided comprehensive data for training the model to detect fire under various challenging conditions. Furthermore, synthetic fire scenes were generated using a GAN model to simulate various lighting, smoke density, and background conditions, enhancing the dataset and improving model generalization.

b. Data Augmentation

To increase data diversity, synthetic fire scenes were generated using a trained GAN model. These augmentations introduced variability in smoke density, lighting, weather conditions, and background complexity, enriching the dataset and improving the model's generalization capabilities.

c. Data Split

The complete dataset was divided into training, validation, and testing sets using a standard 70:15:15 ratio. Care was taken to ensure that augmented and original images were evenly distributed across the splits to prevent data leakage and ensure robust evaluation.

V. Performance Evaluation

To assess the effectiveness of the enhanced model, a comprehensive performance evaluation was conducted, focusing on key metrics such as accuracy, precision, recall, F1-score, false positive rate (FPR), inference time, and energy efficiency across various deployment conditions. The model was tested on a combination of real-world and GAN-augmented datasets, ensuring diversity in environmental conditions, lighting, and fire scenarios.

A. Evaluation Metrics

The following standard performance metrics were used:

- **Accuracy (Acc):** Measures overall correctness of predictions.
- **Precision (P):** Reflects the proportion of true fire detections among all fire predictions.
- **Recall (R):** Represents the proportion of actual fires correctly detected.
- **F1-Score:** Harmonic mean of precision and recall.
- **False Positive Rate (FPR):** Measures the rate of incorrect fire detections.
- **Inference Time:** Measures how quickly the model responds, critical for real-time applications.
- **Energy Efficiency:** Assesses suitability for edge devices by analyzing resource consumption.

B. Experimental Setup

The model was deployed and tested on two edge platforms: Raspberry Pi4 and NVIDIA Jetson Nano

Testing datasets included:

- Real-world fire and smoke image data from the FIRE Dataset on Kaggle.
- Synthetic fire scenarios generated using the GAN module, introducing variations in smoke density, light intensity, fog, and environmental backgrounds.

C. Results

Table 1 presents a comparative evaluation of the proposed enhanced system based on detection accuracy, processing speed, and overall operational efficiency.

Table 1. Evaluation of Detection Accuracy, Speed, and Efficiency for the Proposed Enhanced system

Metric	YOLOv8 Only	Proposed system
Accuracy (%)	91.3	97.6
Precision (%)	88.9	96.1
Recall (%)	85.7	97.4
F1-Score (%)	87.2	96.7
False Positive Rate (%)	6.5	1.8
Avg. Inference Time (ms)	73	39
Energy Usage (Jetson Nano, W)	9.5	5.8

D. Performance under Challenging Conditions

The model was also evaluated under extreme environmental conditions (e.g., fog, dense smoke, low light). Results showed that:

- YOLOv8 alone struggled with a 14% increase in FPR under fog.
- The enhanced model, due to its multi-sensor fusion and adaptive thresholding, maintained high accuracy and recall (above 94%) with minimal false alarms.

E. Edge Deployment Performance

On both Raspberry Pi and Jetson Nano, the enhanced model achieved real-time inference capability (25–30 FPS) while consuming under 6W of power, validating its edge-friendly design. The model compression techniques (pruning and quantization) played a significant role in reducing latency and resource demand without sacrificing accuracy.

F. Comparative Analysis

Compared to prior models reviewed in Section 2.0, enhanced model outperforms in terms of:

- Robustness to environmental variability
- Accuracy and generalization due to GAN-based augmentation
- Real-time operability with low latency
- Offline detection and alerting capabilities using LoRaWAN

VI. Conclusion

This research presented a hybrid and modular fire detection framework optimized for real-time deployment on edge devices. By integrating lightweight deep learning models (ResNet50 and MobileViT), YOLOv8-based adaptive fire detection, GAN-based dataset augmentation, and multi-sensor fusion using Kalman filtering, the system effectively addresses the shortcomings of traditional and existing AI-based fire detection systems. The proposed architecture ensures robust and accurate detection across diverse and challenging environments, including low-light, foggy, and high-smoke conditions.

One of the major strengths of the enhanced model lies in its ability to operate independently of stable internet connectivity. Through the use of edge processing, LoRaWAN communication, and offline alert caching, the system guarantees reliable alert transmission even in remote or infrastructure-poor areas. The experimental evaluation confirms its superior performance over conventional models in terms of accuracy, false positive rate, computational efficiency, and energy consumption, making it highly suitable for real-world, mission-critical deployments.

Future enhancements will focus on integrating active fire suppression modules, improving real-time decision-making using reinforcement learning, and enhancing privacy-preserving mechanisms to ensure ethical use in public surveillance environments. Additionally, long-term field testing and real-world validation in diverse geographic regions will be pursued to further reinforce the model's generalization capabilities and scalability.

References

- Avazov, K., Hyun, A. E., Sami, A. A., Khaitov, A., Abdusalomov, A. B., & Cho, Y. I. (2023). Forest fire detection and notification method based on AI and IoT approaches. *Future Internet*, 15(2), 61. <https://doi.org/10.3390/fi15020061>
- Frizzi, S., Bouchouicha, M., Ginoux, J.-M., Moreau, E., & Sayadi, M. (2021). Convolutional neural network for smoke and fire semantic segmentation. *IET Image Processing*, 15(3), 634–647. <https://doi.org/10.1049/ipr2.12046>
- Gaur, A., Singh, A., Kumar, A., Kulkarni, K. S., Lala, S., Kapoor, K., Srivastava, V., Kumar, A., & Mukhopadhyay, S. C. (2019). Fire sensing technologies: A review. *IEEE Sensors Journal*, 19(9), 3191–3202.
- Gocmen, R., Cibuk, M., & Akin, E. (2024). Comparative analysis of deep learning algorithms in fire detection. *Balkan Journal of Electrical & Computer Engineering*, 12(3), 255–261. <https://doi.org/10.17694/bajece.1533966>
- Hanif, M. K. M. (2023). AI-driven transformation in fire safety: A comprehensive study on AI-integrated fire alarm and detection systems. *International Journal of Science and Research (IJSR)*, 12(8), 125–126. <https://doi.org/10.21275/SR23727132310>
- Karishma, S., Suresh, K., Sireesha, B., & Hussain, S. A. (2019). AI-based fire detection and control system. *Journal of Engineering Science Publications*, 10(11), 456–463. <http://jespublication.com/>
- Kumar, R., Kumar, A., & Saikia, P. (2022). Deforestation and forests degradation impacts on the environment. In *Environmental degradation: Challenges and strategies for mitigation* (pp. 19–46). Springer International Publishing.
- Lee, H., Chung, J. H., Chung, H., Kim, J. H., Yoo, Y., Lim, G. H., & Ruy, W. S. (2024). AI-enhanced fire detection and suppression system for autonomous ships. *International Journal of Naval Architecture and Ocean Engineering*, 16, 100628. <https://doi.org/10.1016/j.ijnaoe.2024.100628>
- Marandi, A. K. (2018). Artificial intelligence (AI) fire detection system: A review. *Journal of Emerging Technologies and Innovative Research (JETIR)*, 5(9), 234–239. <https://www.jetir.org/>
- Raihan, A. (2023). A review of the global climate change impacts, adaptation strategies, and mitigation options in the socio-economic and environmental sectors. *Journal of Environmental Science and Economics*, 2(3), 36–58.
- Rommelzwaal, L. (2023). An AI-based early fire detection system utilizing HD cameras and real-time image analysis. *Artificial Intelligence and Applications*, XX(XX), 1–5.
- Sathishkumar, V. E., Cho, J., Subramanian, M., & Naren, O. S. (2023). Forest fire and smoke detection using deep learning-based learning without forgetting. *Fire Ecology*, 19(9). <https://doi.org/10.1186/s42408-022-00165-0>
- Sinchai, A., Pumanee, P., & Lomwong, R. (2024, November). Enhanced fire detection using deep learning and heat signatures. In *2024 12th International Conference on Control, Mechatronics and Automation (ICCMA)* (pp. 261–266). IEEE.
- Surabhi, K. S., & Babu, A. (2024). Fire detection using AI. *International Journal for Multidisciplinary Research (IJFMR)*, 6(5), 1–8. <https://www.ijfmr.com/>
- Vasconcelos, R. N., Franca Rocha, W. J., Costa, D. P., Duverger, S. G., Santana, M. M. D., Cambui, E. C., & Cordeiro, C. L. (2024). Fire detection with deep learning: A comprehensive review. *Land*, 13(10), 1696.
- Yang, S., Huang, Q., & Yu, M. (2024). Advancements in remote sensing for active fire detection: A review of datasets and methods. *Science of the Total Environment*, 173273.

How to Cite this Article: Achimba, T., Nongu, A. D., Kumba, J. T., & Shinyi, M. N. (2026). *A hybrid Deep Learning Model for Robust and Real-Time Fire Detection*. *International Journal of Engineering, Science, and Environmental Research (IJESER)*, 2(1), 396–407.