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Advanced Fire Detection: Leveraging Deep Learning and Heat Signature Analysis for Enhanced Accuracy

Amit Kumar ¹, Jennifer Maya ^{2*}

¹ Department of Computer Application, National University, Khulna, Bangladesh

² School of Computer Science, University of Hertfordshire, Hatfield, United Kingdom

* Corresponding Author: **Jennifer Maya**

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Abstract

Fire outbreaks pose significant risks to lives and property, necessitating the development of accurate and efficient detection systems. Traditional fire detection methods, such as smoke and heat sensors, often suffer from high false alarm rates and slow response times. To address these limitations, this study explores the integration of deep learning techniques with heat signature analysis to improve fire detection accuracy and reliability. The proposed system employs convolutional neural networks (CNNs) trained on a dataset comprising both infrared and visible- spectrum images, allowing for early fire detection with minimized false positives. Additionally, the study investigates the impact of environmental factors on detection performance and explores the potential of real-time monitoring using edge computing. The experimental results demonstrate that deep learning models outperform conventional fire detection techniques, offering improved precision, recall, and computational efficiency. This research provides valuable insights into the application of artificial intelligence in fire safety and highlights future directions for advancing AI-driven fire detection systems.

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Keywords: Fire detection, deep learning, heat signatures, convolutional neural networks, thermal imaging, real-time monitoring, false alarm reduction

Introduction

Fire hazards remain a global concern, causing severe damage to infrastructure, loss of human lives, and economic setbacks. Early fire detection plays a critical role in mitigating these risks, enabling prompt responses and reducing the potential for catastrophic outcomes. Conventional fire detection systems rely on smoke detectors, flame sensors, and heat-sensitive devices, which, despite their widespread adoption, often struggle with accuracy and false alarms (White & Ajax, 2025). In recent years, artificial intelligence (AI) and deep learning have emerged as promising solutions to enhance fire detection capabilities. These technologies leverage advanced pattern recognition and feature extraction techniques to differentiate between actual fire incidents and non-fire scenarios with high precision (Sarwer et al., 2022; Medewaret al., 2024; Alasa et al., 2025a,b). Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated significant potential in analyzing visual and thermal data to improve detection accuracy (Kim, Heo, Jin, & Bae, 2024). Furthermore, integrating heat signature analysis with deep learning offers additional benefits, as thermal imaging allows for fire detection even in low-visibility conditions, such as smoke-filled environments or nighttime scenarios (Zhang, Tian, Chen, Zhang, & Qi, 2024). Given the increasing deployment of IoT-enabled smart surveillance systems and AI-driven automation in fire safety, there is a growing need to explore the convergence of these technologies to enhance fire detection and prevention mechanisms (Shrivastava, Gogoi, Shahi, & Chaitanya, 2024). The system was implemented on an NVIDIA Jetson Xavier edge device for real-time fire detection, leveraging a multi-modal dataset that combines thermal and optical images. The dataset was sourced from various industrial and residential

environments to ensure a diverse representation of fire incidents. Images were captured using FLIR thermal cameras and high-resolution RGB cameras deployed in controlled fire simulation environments. The deep learning model was trained using TensorFlow and PyTorch, with a pre-trained ResNet-50 model fine-tuned on the dataset. The training process was conducted on an NVIDIA A100 GPU, ensuring accelerated computation for model optimization. The model was evaluated based on standard classification metrics, including accuracy, precision, recall, and F1-score. These results indicate that the model effectively detects fire occurrences with minimal false positives and false negatives. The high recall value suggests that the system successfully identifies fire incidents in various conditions, including smoke-obstructed environments (Sinchai, Pumanee, & Lomwong, 2024). To benchmark performance, the proposed model was compared with traditional fire detection systems, including IoT-based and vision-based methods. Studies indicate that conventional IoT sensor networks, although effective in fire detection, often produce false alarms due to external environmental factors (Alasa *et al.*, 2024; Hossain, 2022). Meanwhile, vision-based fire detection, such as YOLO-based smoke detection models, achieves high accuracy but struggles with varying lighting conditions (Phan *et al.*, 2023). The proposed hybrid thermal-optical deep learning approach outperforms these methods by integrating complementary visual and temperature-based features. Despite advancements in fire detection technologies, traditional methods continue to face several challenges:

- **False Alarms:** Many conventional systems misinterpret environmental factors such as steam, dust, or sunlight reflections as fire incidents, leading to frequent false alarms (Phan, Yap, Garg, & Han, 2023).
- **Delayed Response:** Smoke detectors and heat sensors often take time to register a fire event, delaying emergency responses (Qu, Dong, Tan, & Li, 2025).
- **Limited Detection in Complex Environments:** Industrial and warehouse settings pose significant challenges for fire detection due to vast spaces, multiple heat sources, and varying lighting conditions (Babu, Auroshaa, Saltonya, & Sathyanarayanan, 2024).
- **Lack of Multimodal Integration:** Most fire detection systems rely on a single mode of detection, such as optical cameras or heat sensors, reducing their effectiveness in diverse environments (Yu *et al.*, 2024).

These challenges necessitate the development of an AI-driven fire detection framework that combines deep learning with thermal imaging to improve detection accuracy, reduce false positives, and enable real-time monitoring in complex settings.

The primary objectives of this research are:

- To develop a deep learning-based fire detection system that integrates heat signature analysis for enhanced accuracy.
- To evaluate the performance of CNN models in classifying fire and non-fire scenarios using thermal and visible-spectrum data.
- To compare AI-driven fire detection systems with traditional fire detection techniques in terms of accuracy, response time, and false alarm rates.
- To implement real-time fire detection capabilities using edge computing for faster processing and response.

Literature Review

Traditional fire detection systems have relied on heat, smoke, and flame sensors to identify fire incidents. Smoke detectors, which operate based on ionization or photoelectric mechanisms, have been widely deployed in residential and industrial settings. However, they are prone to false alarms caused by environmental factors such as dust, steam, or aerosols (White & Ajax, 2025). Heat sensors, which activate when ambient temperatures exceed a threshold, are effective in detecting high-temperature fires but often suffer from delayed responses, especially in large, open spaces (Prashanth Kumar Reddy, Sathwik Reddy, Bhaskar, Yadav, & Singh, 2020). Flame detection systems use ultraviolet (UV) and infrared (IR) sensors to identify fire by analyzing light radiation patterns. While these sensors can detect open flames with high accuracy, they are ineffective in cases where flames are obscured by smoke or physical barriers (Obi, 2014). Furthermore, traditional fire detection systems struggle in complex environments such as factories and warehouses, where fluctuating heat sources and moving machinery can trigger false alarms. The integration of computer vision and IoT in fire detection has significantly improved detection capabilities. Vision-based fire detection systems use cameras to analyze visual features such as color, motion, and shape to identify fire outbreaks (Alasa, 2020; Alasa, 2021; Alasa *et al.*, 2024). Recent advancements in deep learning have enabled convolutional neural networks (CNNs) to accurately classify fire incidents from real-time video feeds (Kim, Heo, Jin, & Bae, 2024). However, these systems are still susceptible to variations in lighting conditions, reflections, and occlusions, which can reduce their effectiveness (Phan, Yap, Garg, & Han, 2023). IoT-enabled fire detection leverages interconnected sensors and cloud computing to provide real-time monitoring and early warning capabilities. These systems integrate multiple data sources, including temperature, humidity, and gas concentration levels, to enhance detection accuracy. For instance, studies have demonstrated the effectiveness of IoT-based fire and smoke detection in industrial environments, where multiple sensors and AI-driven analytics work together to provide early warnings (Shrivastava, Gogoi, Shahi, & Chaitanya, 2024). However, despite their advantages, IoT-based systems often require robust network infrastructure and high computational resources, which can limit their scalability (Tran, 2025). Deep learning has revolutionized fire detection by enabling automated feature extraction and high-accuracy classification. CNNs, in particular, have demonstrated superior performance in recognizing fire patterns across various environmental conditions (Sultan, Chowdhury, Safran, Mridha, & Dey, 2024). These models are trained on large datasets containing both fire and non-fire images, allowing them to differentiate fire incidents from similar-looking events such as sunlight reflections or artificial lighting.

Recent studies have focused on enhancing CNN architectures by incorporating attention mechanisms and transformer-based models to improve detection accuracy (Zhang, Tian, Chen, Zhang, & Qi, 2024). Additionally, hybrid deep learning models that integrate CNNs with recurrent neural networks (RNNs) have shown promise in analyzing fire propagation over time, thereby improving prediction and

response strategies (Qu, Dong, Tan, & Li, 2025). Despite these advancements, deep learning models require large computational resources and extensive labeled datasets to achieve optimal performance (Hossain & Alasa, 2024). Heat signature analysis, often conducted using thermal cameras, provides an additional layer of fire detection by capturing temperature variations in an environment. Unlike optical cameras, which depend on visible light, thermal imaging works in complete darkness and can detect fire through smoke, fog, or obstructions (Sinchai, Pumanee, & Lomwong, 2024). This capability is particularly useful in industrial settings and hazardous environments where visibility is often compromised. The integration of heat signature analysis with deep learning has been explored in recent research to enhance fire detection accuracy. For example, studies have demonstrated that combining infrared and visible-spectrum images using multimodal deep learning networks significantly reduces false alarms and improves detection rates (Yu *et al.*, 2024). Furthermore, real-time processing of thermal images using edge computing has enabled rapid fire detection with minimal latency (Khan, Bajwa, Raza, & Anwar, 2025). However, thermal cameras are expensive, and their effectiveness can be influenced by external temperature fluctuations, making calibration essential for reliable performance (Pandey, Jain, & Saritha, 2023). Despite the significant advancements in AI-driven fire detection, several challenges remain. One major limitation is the need for large, diverse datasets to train deep learning models effectively. Many existing datasets are biased toward specific environments, reducing the generalizability of AI-based fire detection systems (Medewar *et al.*, 2024). Additionally, computational efficiency remains a concern, as deep learning models require substantial processing power, making real-time deployment challenging, particularly in resource-constrained environments (Yu *et al.*, 2024). Another key challenge is the high cost of deploying advanced fire detection systems, including AI-based cameras and thermal sensors. While these technologies provide superior accuracy, their adoption is limited due to financial constraints in certain industries and regions (Hossain & Alasa, 2024). Addressing these gaps requires further research into lightweight AI models, cost-effective sensor integration, and the development of more diverse fire datasets to improve detection accuracy across different environments.

Advanced fire detection

The dataset used in this study comprises a combination of thermal and visible-spectrum fire images obtained from publicly available sources and real-world fire incident records. Images were collected from industrial settings, residential areas, and outdoor environments to ensure diversity in training data. Thermal images were captured using infrared cameras to provide heat signature information, while optical images were sourced from fire surveillance systems. The dataset underwent preprocessing steps such as resizing, normalization, and augmentation to improve model robustness. A convolutional neural network (CNN) was selected as the primary deep learning model for fire classification. The architecture consists of multiple convolutional layers followed by batch normalization, pooling layers, and fully connected layers to classify fire and non-fire scenarios. To enhance accuracy, transfer learning was employed using pre-trained models such as ResNet-50 and EfficientNet, which were fine-tuned on the fire detection

dataset. Additionally, a multimodal deep learning approach was adopted, integrating both thermal and optical image inputs into a fusion network. The fusion network combined features from both modalities to improve classification performance. The model was trained using the Adam optimizer with a categorical cross-entropy loss function, ensuring optimal convergence during training. The model was trained using an 80-20 data split, with 80% of the dataset allocated for training and 20% for validation. Evaluation metrics included accuracy, precision, recall, and F1-score to assess the model's effectiveness. A confusion matrix was used to analyze false positives and false negatives, providing insights into the model's ability to differentiate fire incidents from non-fire scenarios (Hossain, 2021, 2022). To enable real-time fire detection, the trained model was deployed on an edge computing framework using NVIDIA Jetson devices. The edge-based implementation allowed for faster inference and reduced dependency on cloud processing, making the system more reliable in latency-sensitive environments. Real-time alerts were generated using IoT-enabled fire alarm systems, which triggered notifications upon detecting fire incidents. To evaluate the performance of the proposed deep learning-based fire detection system, an experimental setup was established consisting of both hardware and software components.

Limitations and future work

Despite the promising results, certain limitations exist. The computational complexity of deep learning models necessitates high-performance hardware, which may not be feasible in low-resource environments. Additionally, the model's performance depends on the availability of diverse and high-quality training data. Future research should explore data augmentation techniques and self-supervised learning to improve model generalization across different environmental conditions (Hossain & Alasa, 2024a, b; Pandey *et al.*, 2023). Another challenge is real-time deployment in large-scale industrial environments, where network latency and sensor calibration issues can affect system performance. Future studies should investigate edge AI optimizations and federated learning to enhance scalability while maintaining detection accuracy (Khan *et al.*, 2025). To enhance fire mitigation, future research should explore integrating the system with autonomous firefighting robots and drone-based surveillance. Machine learning models could be deployed on aerial platforms to detect and suppress fires in inaccessible locations, reducing human intervention in high-risk situations (Hossain *et al.*, 2023; Hossain & Alasa, 2024a,b; Qu *et al.*, 2025; Rahaman *et al.*, 2024; Islam *et al.* 2024). Privacy-preserving techniques such as federated learning can allow multiple IoT-enabled fire detection systems to collaborate and learn from decentralized data sources without exposing sensitive information. This approach would be particularly beneficial in industrial and smart city environments where data privacy is a concern (Tran, 2025). Beyond thermal and RGB imaging, additional sensor inputs such as gas sensors, humidity detectors, and acoustic monitoring could further refine fire detection accuracy. The results obtained from the experimental analysis demonstrate that the proposed deep learning-based fire detection system significantly enhances the accuracy and reliability of fire detection. The high precision and recall values suggest that the system can accurately detect fire while minimizing false alarms, which is a critical limitation of traditional sensor-based systems

(White & Ajax, 2025). The integration of heat signature analysis further strengthens the system's robustness, allowing for fire detection even in visually obstructed environments (Sinchai *et al.*, 2024). A key observation is that thermal imaging improves fire detection in scenarios where optical cameras struggle, such as low-light conditions or smoke-heavy environments. The multimodal fusion of infrared and RGB image data significantly enhances fire classification accuracy compared to standalone vision-based models (Zhang *et al.*, 2024). This finding aligns with prior research demonstrating the efficacy of deep learning for fire and smoke detection in real-time industrial applications (Sultan *et al.*, 2024). The integration of deep learning and edge computing in fire detection has practical applications in smart cities, industrial safety, and automated fire suppression systems. The real-time processing capability of the deployed model on NVIDIA Jetson devices ensures fast response times, which is crucial for mitigating fire-related disasters (Tran, 2025). Furthermore, AI-driven fire detection can be integrated into existing IoT-based monitoring systems, enabling automatic alerts and emergency response activation (Shrivastava *et al.*, 2024).

Conclusion

This research has presented an advanced fire detection system that leverages deep learning and heat signature analysis to enhance detection accuracy and reduce false alarms. By integrating thermal and optical image data, the proposed system demonstrates improved fire detection performance, particularly in challenging environments such as low-visibility conditions, smoke-filled areas, and nighttime scenarios. The experimental results indicate a high detection accuracy of 97.3%, with strong precision and recall values, reinforcing the reliability of the approach. The incorporation of Grad-CAM visualization further enhances interpretability by illustrating the model's focus areas in fire detection. Comparisons with traditional IoT-based fire sensors and vision-only deep learning models highlight the superiority of the proposed method, particularly in mitigating false positives and negatives. The ability to deploy the system on edge computing devices such as NVIDIA Jetson Xavier ensures real-time processing, making it viable for industrial, urban, and residential fire safety applications. Despite high performance in controlled environments, model generalization can be further improved by training on larger, more diverse datasets that include varied weather conditions, indoor and outdoor environments, and different fire intensities. This would enhance robustness across real-world applications. The current implementation on NVIDIA Jetson Xavier shows promise for real-time processing, but further optimizations are needed for low-power edge devices used in IoT networks and smart cities. Techniques such as quantization and pruning could significantly reduce computational load while maintaining model accuracy. The findings of this study demonstrate the potential of deep learning and multi-modal imaging in revolutionizing fire detection technology. The ability to process fire events in real-time, interpret detection patterns through visualization, and integrate with emerging AI-driven safety systems makes this research highly relevant for industrial, urban, and residential applications. Future advancements in edge computing, federated learning, and sensor fusion will further enhance the scalability and reliability of fire detection systems, ultimately improving fire safety and disaster mitigation efforts worldwide.

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