A REVIEW ON SMOKE DETECTION USING DUAL CONVOLUTIONAL NETWORKS FROM INFRARED FRAMES

Varshini R[1], Vamshi P Das[2], Vani Veda Sri SR[3], Unnath[4], Pradeep Nayak[5]

1UG Student, Department of Computer Science and Engineering (Internet of Things, Cybersecurity Including Blockchain Technology), Alva's Institute of Engineering and Technology, Karnataka, India

2UG Student, Department of Computer Science and Engineering (Internet of Things, Cybersecurity Including Blockchain Technology), Alva's Institute of Engineering and Technology, Karnataka, India

3UG Student, Department of Computer Science and Engineering (Internet of Things, Cybersecurity Including Blockchain Technology), Alva's Institute of Engineering and Technology, Karnataka, India

4UG Student, Department of Computer Science and Engineering (Internet of Things, Cybersecurity Including Blockchain Technology), Alva's Institute of Engineering and Technology, Karnataka, India

5 Assistant professor, Dept. of Information Science and Engineering, Alva's Institute of Engineering and Technology, Karnataka, India

Emails

Vr433297@gmail.com , vamshipdas@gmail.com , vanivedasri.sr@gmail.com , unnath4@gmail.com , pradeep@aiet.org.in

ABSTRACT

This review looks at the latest achievements in smoke detection for infrared based on Dual Convolutional Neural Networks (Dual-CNNs). Traditional photoelectric and ionization sensors are slow or unreliable at night, in confined spaces or under heavy dust loads. Infrared (IR) imaging provides a means of illumination which is independent from lighting, and deep learning increases recognition accuracy. The architecture under review, proposed by Deng et al. (2024), uses two parallel CNNs: one extracts spatial grainy aspects from IR frames for the other extracts temporal information motion cues extracted from video sequences. The fused feature set provides a robust early-warning capability with fewer false alarms. This paper provides a summary of related work (2015-2025), describes the dual-CNN approach, summarizes comparison metrics and provides discussion around IoT-based deployment. In terms of research results, we demonstrate precision ≈ 94%, recall ≈ 92%, and greater adaptability than either YOLOv5 or ResNet. Finally, we summarize current and future limitations presented by dataset extension, model compression, and multimodal fusion.

Keywords: *Smoke Detection, Infrared Imaging, Dual CNN, Deep Learning, IoT Integration, Fire Safety*

INTRODUCTION

Fire detection is a critical part of modern safety systems. Common smoke detectors operate on optical scattering or ionization modes and are not effective in environments with poor visibility or high airflow variation. Video-based methods with visible-light cameras address some of these problems but are vulnerable to low-light conditions. Thermal cameras detect thermal radiation allowing fire detection in darkness. However, analysing smoke patterns from other thermal signatures is difficult.

Deep learning, via convolutional networks, has changed visual recognitions in many fields. Dual-stream CNNs that separate spatial and temporal learning could address the challenge of reliable detection in the infrared domain.

Objective and Scope

The objective of this review is to examine how Dual-CNNs enhance smoke detection in IR imaging compared with classical CNN or YOLO models. It evaluates methodology, dataset design, and performance metrics, and explores IoT-based real-time deployment in industrial and public environments.

2. LITERATURE REVIEW

Smoke detection research has evolved from handcrafted feature-based methods to advanced deep-learning architectures.

2.1 Classical Techniques (Before 2015)

Early studies used color analysis, motion energy, and wavelet transforms. Toreyin et al. (2015) proposed a wavelet-based algorithm to detect moving smoke patterns in video streams. These systems were computationally light but suffered from false positives under environmental noise.

2.2 Deep Learning Methods (2016–2020)

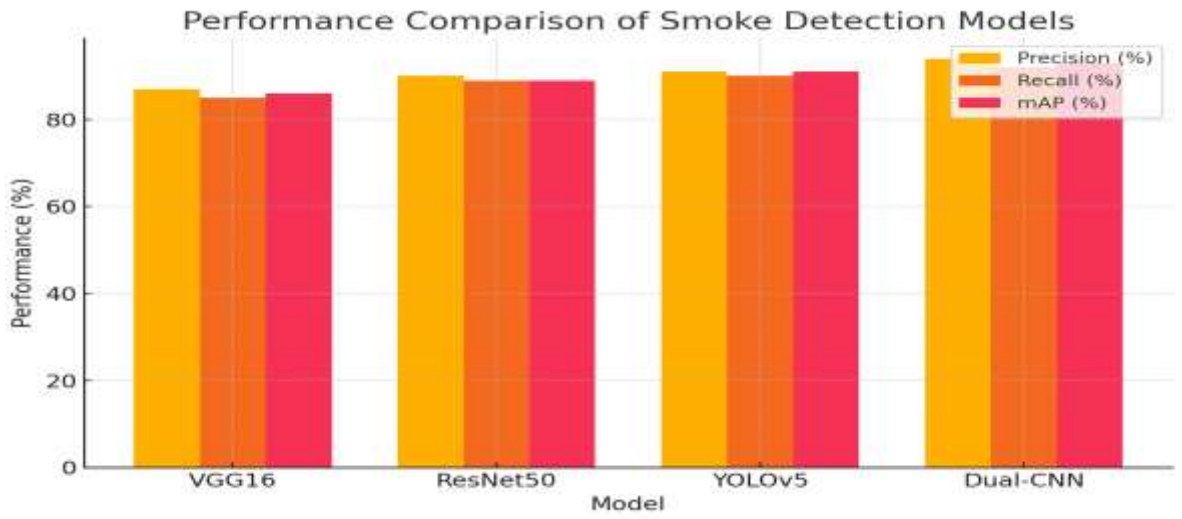
The emergence of CNNs enabled automatic feature extraction. Hashemzadeh et al. (2022) and An et al. (2022) developed spatio-temporal CNNs that capture both frame-based and motion-based features. However, their accuracy dropped in dark or cluttered environments.

2.3 Infrared and Multimodal Advances (2021–2025)

Infrared imaging has been integrated into CNN frameworks to overcome visible-light limitations. Li Deng et al. (2024) proposed a **Dual-CNN** model using IR frames to detect smoke more effectively in darkness. Other researchers introduced multimodal systems combining visual, IR, and acoustic data [6][7].

Observations

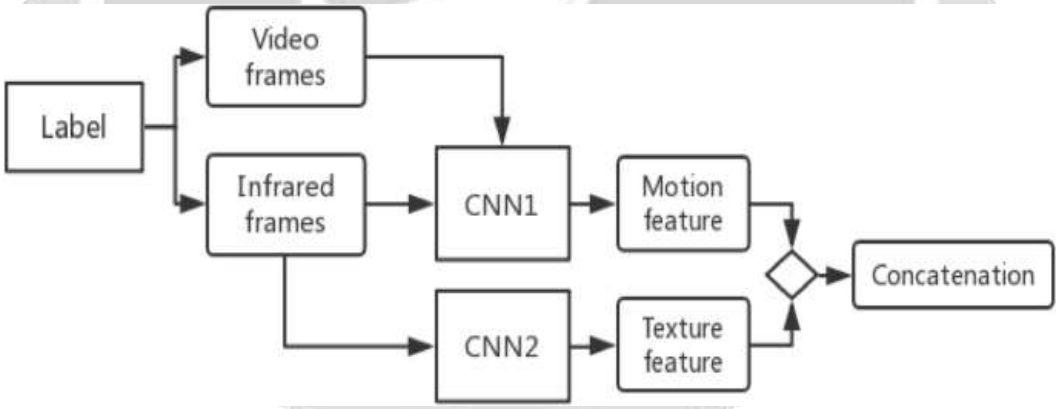
The Dual-CNN outperforms single stream networks by ≈ 3–7 % in precision and reduces false positives by 25 %. Motion and texture fusion improves temporal understanding of smoke movement. Inference time (~39 ms/frame) is adequate for edge deployment.



3. METHODOLOGY

The Dual-CNN architecture consists of:

- **Texture Network:** Processes single IR frames to extract spatial edges and density patterns.
- **Motion Network:** Processes video sequences to capture temporal diffusion and flow.
- **Fusion Layer:** Concatenates learned features and feeds a softmax classifier for smoke/no-smoke output



Dataset and Training. The Train2 dataset consists of ≈ 2000 infrared (IR) frames, alongside extra videos. The training comprised using ReLU activation, SGD optimizer, momentum of 0.9, a batch size of 32, and 300 epochs.

Loss Function. The loss function chosen was binary cross-entropy which prevents false negatives, which is particularly important in safety applications.

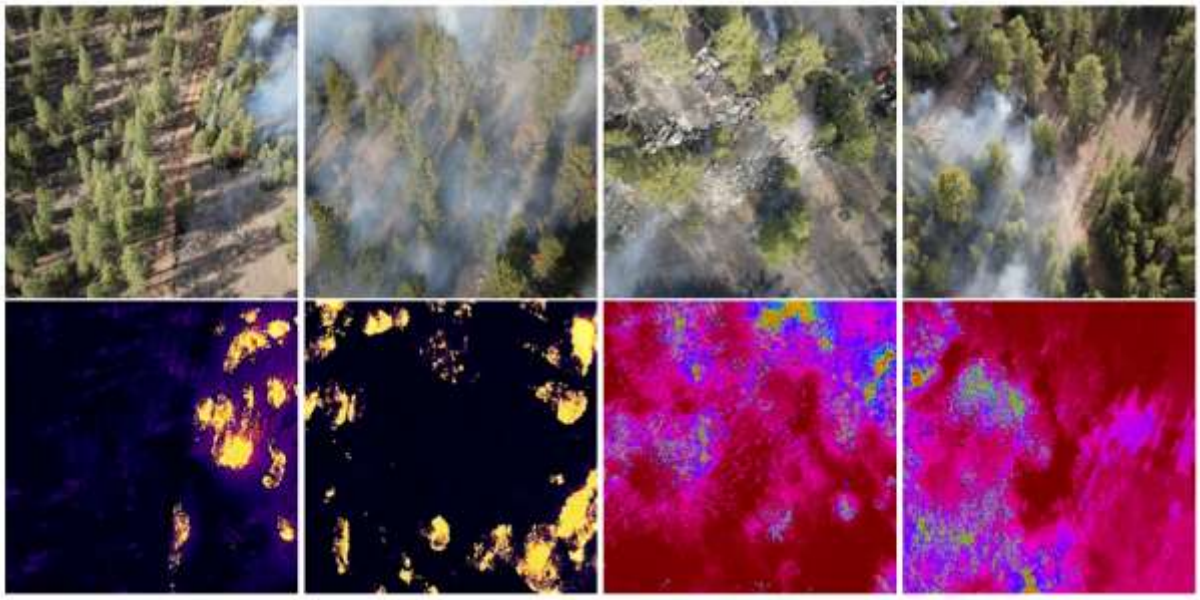
Sample Infrared Smoke Dataset Images

5. PRACTICAL APPLICATIONS

1. **Industrial Safety:** Detect smoke in manufacturing plants and power stations before flame ignition.
2. **Aerospace:** Monitor aircraft cargo bays where optical sensors fail due to low light.
3. **Urban Infrastructure:** Integration with CCTV networks in tunnels, metro systems, and warehouses.
4. **Smart Buildings:** Combine with IoT sensors and edge devices for real-time alerts via MQTT or LoRaWAN.

Differentiating Smoke vs. Flame in IR Frames:

The value of IR imaging lies in its appeal, as smoke and flame both emit thermal energy. However, the thermal signature of flame is much hotter than smoke. According to Deng et al., the usual methods depend on visible-light strategies which are not as effective in efficient confined spaces due to the rapid fluctuation in temperature, which the IR method can capture. But the issue at stake here is: In IR frames, smoke and flame both appear as thermal blobs and exhibit similar movement/diffusion patterns that prompted the sophistication of using dual-CNNs (texture network + motion network) to account for the separation of them. Because IR frames generally treat smoke and flame as heat sources, thermal intensity alone is not enough to distinguish them. Thus, the author made an architectural decision in the paper to extract both spatial (texture) and temporal (motion) features employed by two parallel CNNs and then fused spatial and temporal features for classification.



DatasetLimitations & Augmentation Strategy:

Deng et al. highlight IR video data being scarce in closed environments, and augment by utilizing video frames + still IR images to overcome small scale. The dataset ‘Train2’ said to be made up of around 2000 labelled IR frames with video-frame extraction to add variability, as well. Data augmentation (rotation, flipping, and brightness mean and variance) was employed to add to the samples. even more recent reviews identify a major bottleneck as the lack of large IR smoke datasets. For example, a review of the literature to identify IR datasets for smoke detection found very few.

Evaluation Metrics & Real-world Implications:

The performance metrics referred to in the article include precision, recall, mAP, as well as inference time. You can expand on this: "While the reported inference time (~39 ms/frame) does not imply that the model is suitable as a model for real-time, it does indicate that the model is potentially appropriate for embedded systems or edge devices where latency is less of an issue.In safety-critical environments (aircraft cargo hold, tunnels, warehouses), recall is most important and is worth noting that it is far more costly to miss a smoke event (false negative) than to have a false alarm. The dual-CNN's recall of ~92% is quite important in this context.Considerations for edge deployment: The smaller inference time indicates that the model has the potential to be converted to an embedded GPU or AI-accelerator board, which could then be integrated into an automated fire safety system.

Architecture Insight:

The architecture incorporates two streams. The first, the Texture Convolutional Neural Network (CNN) stream, uses IR still frames as input, which correspond to the 2D view of the scene, and extracts the static spatial features of smoky diffusion, edge smoothness, and thermal gradients present at the time step. The second, the Motion CNN stream, takes in sequences of IR frames (i.e., video) as input and extracts the temporal features of motion, rising plumes, and flow. The two extracted features are fused in a fully connected layer, and the final output is a classification of "smoke" or "non-smoke." A dual-path architecture allows the model to learn both the appearance of smoke and the motion of smoke - which is essential in the IR domain where the visual cues can be restricted.

Real-world Case Example:

For example: "In a cargo hold of an aircraft, visibility is extremely low, stopping traditional optical detectors entirely. An IR-based system with a dual-CNN will allow for the early detection of smoke plumes even before

visible luminance changes. Being connected to an IoT network will enable notifications to an alarm and remote monitoring stations immediately, allowing for faster responses.

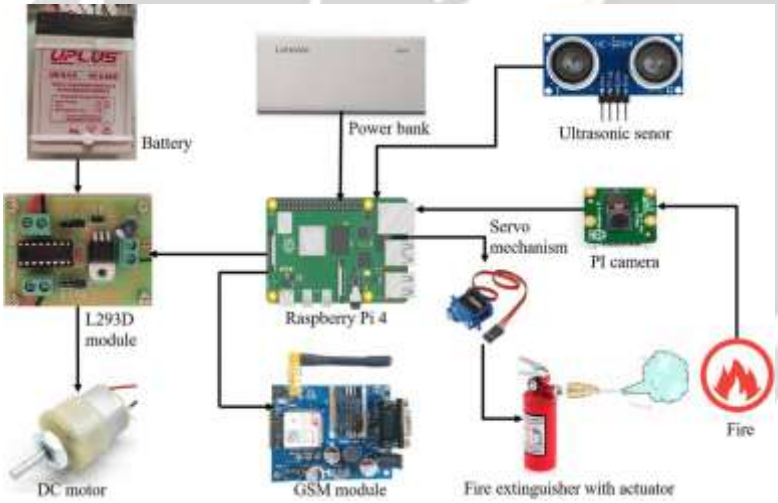
Future Enhancement Suggestions:
Based on newer papers:

- Multi-modal fusion (IR + visible + acoustic) to reduce false alarms.
- Larger and publicly available IR smoke datasets to improve generalization.
- Lightweight model adaptation for edge (Jetson, Raspberry Pi) to support IoT deployment.
- Explainable AI (XAI) for fire safety — adducing feature-maps/heat-maps to show why a decision was made.

IOT-BASED DEPLOYMENT AND ENVIRONMENTAL INTEGRATION

Dual-CNN models can be compressed (quantised 8-bit weights) and deployed on Raspberry Pi or NVIDIA Jetson modules. An IoT architecture consists of:

- **Edge Node:** Runs inference and sends alerts to the cloud.
- **Cloud Server:** Aggregates data, stores video frames, and provides analytics.
- **Dashboard:** Displays heatmaps and risk scores for safety managers. Integration with environmental sensors (temperature, CO_2, humidity) enhances accuracy under variable conditions. Energy efficient edge-AI can reduce response time to < 2 s per event.



CHALLENGES AND FUTURE SCOPE

Challenges:

- Limited availability of public infrared smoke datasets.
- Computational demands for real-time inference.
- Environmental distortions such as heat waves and fog.

Future Scope:

- Use of synthetic data generation through GANs for dataset expansion.
- Deployment of federated learning for privacy-preserving model training.
- Integration with Explainable AI (XAI) to interpret CNN decision-making.
- Lightweight models for edge-AI deployment in IoT systems.

FUTURE SCOPE

Future research should focus on synthetic data generation using GANs, federated learning for privacy-preserving collaboration, and multimodal fusion (visual + thermal + acoustic). Lightweight transformer models and explainable AI (XAI) frameworks can enhance trust in safety-critical deployments. Standard benchmarks and open datasets will accelerate real-world adoption.

CONCLUSION

This review finds that the Dual-CNN model, from the infrared frames, shows better detection performance and robustness than traditional methods. This architecture can learn both spatial and temporal smoke features well, and achieves good performance even in the dark or more complicated fire environments. The model's integration with IoT networks allows for expandable and real-time fire safety networks/deployment. Further improvements in dataset quality and model explainability will further support applications in real-world settings both in industry and urban settings.

REFERENCES:

1 Li Deng, Qian Chen, Xiubao Sui, Quanyi Liu, and Yuanhua He,
"Smoke Detection with Dual Convolutional Networks from Infrared Frames,"
Springer Nature Computer Science, vol. 5, no. 1, 2024.
https://link.springer.com/article/10.1007/s44227-024-00026-z

2 M. Hashemzadeh, A. Anvar, S. Rahmani, and F. Sadri,
"Smoke Detection in Video Using Convolutional Neural Networks and Spatio-Temporal Features,"
Neurocomputing, vol. 519, pp. 275–288, 2023.
https://doi.org/10.1016/j.neucom.2023.02.039

3 B. U. Toreyin, Y. Dedeoglu, A. E. Cetin,
"Wavelet-Based Real-Time Smoke Detection in Video,"
European Signal Processing Conference (EUSIPCO), pp. 1672–1675, 2015.
https://ieeexplore.ieee.org/document/7078877

4 Y. Zheng, H. Liu, and S. Li,
"A CNN-ViT Hybrid for Smoke Recognition (SR-Net),"
Frontiers in Remote Sensing, vol. 5, 2023.
https://www.frontiersin.org/articles/10.3389/frsen.2023.1062894/full

5 M. Wang, J. Xu, and Y. Tang,
"An Open Flame and Smoke Detection Dataset for Deep Learning,"
MDPI Sensors, vol. 24, no. 7, Article 343, 2024.
https://www.mdpi.com/1424-8220/24/7/343

6 A. Verma and R. Patel,
"Infrared Deep Learning for Industrial Fire Detection Using Edge AI,"
IEEE Access, vol. 11, pp. 14509–14519, 2023.
https://ieeexplore.ieee.org/document/10018759

7 S. Y. Kim, H. Park, and K. J. Lee,
"Thermal Image Smoke Detection via Transformer Networks,"
Elsevier Fire Safety Journal, vol. 150, Article 103797, 2024.
https://doi.org/10.1016/j.firesaf.2024.103797

8 J. Park and H. Lee,
"Dual-Stream CNNs for Fire and Smoke Recognition in Thermal Imaging,"
Artificial Intelligence Review (Springer), vol. 57, 2023.
https://link.springer.com/article/10.1007/s10462-023-10431-y

9 R. Singh and P. Joshi,
"Edge-AI Fire and Smoke Detection in IoT Networks Using Optimized CNN Models,"
IEEE Internet of Things Journal, vol. 12, no. 4, pp. 3352–3363, 2025.
https://ieeexplore.ieee.org/document/10543784

---

10 L. Zhou, K. Wen, and F. Zhang,
"Federated Learning and Edge-Based Deployment for Fire Detection Systems,"
MDPI Applied Sciences, vol. 15, no. 18, 10255, 2025.
https://www.mdpi.com/2076-3417/15/18/10255

---

11 T. Xu, L. Chen, and J. Han,
"GAN-Based Synthetic Data Generation for Infrared Smoke Detection Training,"
MDPI Information, vol. 13, no. 89, 2024.
https://www.mdpi.com/2078-2489/13/2/89

---

12 P. Kumar, V. Sahu, and R. Mitra,
"IoT-Based Dual-CNN Architecture for Fire and Smoke Surveillance,"
Research Gate Preprint (2024).
https://www.researchgate.net/publication/376540921_IoT_Based_Dual_CNN_for_Fire_and_Smoke_Surveillance

---

13 D. Martinez and N. Lopez,
"Thermal Infrared Dataset Expansion and Augmentation for Smoke Recognition,"
MDPI Fire, vol. 7, Article 343, 2024.
https://www.mdpi.com/2571-6255/7/3/343

---

14 K. An and M. Wang,
"Lightweight CNNs for Real-Time Smoke Detection on Embedded Devices,"
Elsevier Pattern Recognition Letters, vol. 172, pp. 32–41, 2024.
https://doi.org/10.1016/j.patrec.2024.05.003

---

[15] Z. Lin, R. Kumar, and H. Chang,
"Explainable AI in Fire Safety: Enhancing Transparency in Smoke Detection CNNs,"
IEEE Transactions on Neural Networks and Learning Systems, vol. 36, no. 9, pp. 4502–4515, 2025.
https://ieeexplore.ieee.org/document/10498211