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# Advancing FireNet-CNN for Robust, Interpretable, and Multi-Hazard Disaster Detection

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**Abstract- Wildfires are one of the most dangerous natural disasters, causing large-scale damage to forests, wildlife, property, and human life. Early and accurate detection plays a crucial role in minimizing these losses. In this research, an extended FireNet-CNN framework is proposed for robust, interpretable, and multi-hazard disaster detection using deep learning and Explainable Artificial Intelligence (XAI). Unlike traditional review-based approaches, this work incorporates comparative experimental validation using benchmark wildfire datasets and performance metrics including accuracy, precision, recall, and F1-score. The proposed lightweight architecture is optimized for real-time deployment on edge devices, UAVs, and surveillance systems while maintaining high detection accuracy and low computational complexity. Experimental comparison with ResNet50, YOLOv8, MobileNetV2, and transformer-based models demonstrates that the extended FireNet-CNN achieves a balanced trade-off between accuracy, inference speed, and interpretability. These advancements establish FireNet-CNN as a scalable and reliable solution for real-world disaster management and intelligent wildfire monitoring systems.**

**Keywords: Forest fire detection, FireNet-CNN, deep learning, explainable AI, edge computing, disaster management.**

## I. INTRODUCTION

Wildfires have become increasingly frequent due to climate change, rising global temperatures, and prolonged dry seasons. Their impact extends beyond environmental damage, affecting human settlements, public safety, and economic stability.

Traditional wildfire detection methods, such as satellite monitoring and ground- based sensors, often suffer from delayed response times and limited coverage, especially in remote or dense forest areas. Lightweight and real- time models have also gained attention due to their applicability in drone and edge- based systems. James et al. implemented MobileNetV2 with pruning and quantization to achieve 95% accuracy on satellite imagery while maintaining low computational costs.

Similarly, Kim and Muminov applied YOLOv7 with CBAM attention modules on UAV images, obtaining an average precision (AP50) of 86.4% . Approaches combining domain adaptation and attention mechanisms have further improved robustness in challenging wildfire detection scenarios. With the growth of deep learning and computer vision, image-based wildfire detection has emerged as an effective alternative. Deep neural networks can analyze visual data in real time and identify early signs of fire or smoke.

Among the recent approaches, FireNet- CNN stands out as a compact and efficient model designed specifically for real- time wildfire detection. Unlike many deep learning models that act as black boxes, FireNet- CNN incorporates explain ability techniques, allowing users to understand and trust its predictions.

Although FireNet- CNN demonstrates strong performance, real- world deployment introduces additional challenges such as varying environmental conditions, limited computational resources, and the need for broader disaster detection capabilities.

This paper proposes an extended FireNetCNN framework and presents a comparative experimental and conceptual analysis of deep learning- based wildfire detection systems with a focus on robustness, interpretability, and realtime deployment.

## II. LITERATURE REVIEW

The rapid advancement in deep learning and computer vision has significantly transformed wildfire detection research. Early approaches relied on handcrafted visual features and basic classifiers with limited adaptability and moderate accuracy. Mimoun Yandouzi et al. [1] used a robust dataset comprising 4661 annotated forest fire and non- fire images, applying transfer learning with ResNet50 pretrained on ImageNet. Their methodology integrated comprehensive data augmentation and fine- tuning, which facilitated a system yielding 99.94% accuracy—remarkably outperforming prior approaches in terms of reliability and rapidity, and proving transfer learning's core advantage for environmental monitoring.

Building on this, Aditya Jonnalagadda et al. [2] conducted a comparative evaluation, employing VGG16 and a custom CNN under extensive augmentation and hyperparameter tuning. They demonstrated that VGG16, when trained on wellcurated fire detection datasets, outperformed traditional CNNs, achieving a remarkable 99.99% accuracy. This work highlights how pretrained architectures vastly improve sensitivity and generalization when applied to challenging wildfire scenarios.

Edge deployment and real- time operation present unique constraints in wildfire detection. George James et al. [3] advanced the field by leveraging MobileNetV2 with pruning and quantization. Applied to satellite imagery, this technique maintained 95% accuracy, crucially reducing hardware requirements for drones and IoT sensors. Such lightweight architectures make practical implementation feasible for continuous field monitoring and rapid response.

For classification and segmentation, Abdallah Ali and Sefer Kurnaz [4] compared several deep learning designs, including CNNs, autoencoders, and U-Nets—which are important for accurate fire localization. Their experiments showed that CNNs are still the most reliable (82% accuracy), but models continue to struggle with the complex visual variations found in satellite data. They suggested that future research should tackle segmentation bias and label noise to improve reliability.

Temporal modeling is becoming more important for wildfire management. Maxfield Green et al. [5] applied deep CNNs to large, labeled sequences of satellite images to capture how fire perimeters change over time. Their predictive model exceeded 90% mapping accuracy, giving fire managers useful forecasts for risk reduction and resource planning.

Attention mechanisms in object detection are another key trend. Kim and Muminov [6] showed that YOLOv7 enhanced with CBAM attention modules on UAV-captured aerial images improved smoke detection to 86.4% AP50. This combination picks up subtle visual clues needed for early warnings and is vital for remote, real-time monitoring.

Early smoke detection remains extremely important. Ranavide and colleagues [7] proposed a pipeline that combines ResNet18, a Feature Pyramid Network, and deformable convolutions. They processed about 90,000 labeled images from 400 alert cameras. Their system detected wildfire smoke with 91.6% accuracy within the first five minutes of a fire starting, showing real potential for automated emergency response.

Robustness against disturbances and adversarial attacks is a newer research area. Ryo Ide and Lei Yang [8] created WARP—a method to rigorously test the adversarial robustness of YOLOv8 and RT-DETR architectures. Their experiments confirmed that YOLOv8 is resilient and performs well across various noise conditions, highlighting the need for adversarial defenses in real-world surveillance.

Real-time alert systems need both speed and flexibility. Bantu Varalaxmi et al. [9] designed CNN-based architectures (AlexNet, InceptionV3) specifically for CCTV video streams, reaching 93% alert accuracy on real fire clip data. Their design works across many environments, demonstrating how versatile and efficient deep learning can be in traditional camera networks [9].

Multi-scale feature fusion and transformer-based systems are shaping the next generation of models. Hongying Liu et al. [10] introduced TFNet, which combines a multi-scale SRModule, a CGMSFF Encoder, and WIOU loss within a transformer framework. Their system achieved high precision (86.6%), F1-score (84.9%), and mAP50 (89.2), supporting the idea of hybrid models that balance detection accuracy and speed [10].

More recent advances include UAV-based and remote-sensing systems. Shamta and Demir [11] built a UAV-based deep learning system for continuous wildfire surveillance, handling real-time prediction in complex field conditions [11]. Alkhatib and Jaber [12] reviewed hybrid and multi-modal detection methods, focusing on ensemble deep learning and the value of edge AI for scalable deployments [12]. Chandramohan et al. [13] used AI-based ensemble models that further improved detection rates, showing the practical benefit of multiple, jointly tuned architectures for robust analysis [13].

Noor and colleagues [14] confirmed that YOLOv8 works well with 94.2% accuracy and much fewer false alarms in both simulated and real image settings [14]. Finally, Li et al. [15] proposed YOLOGX—a YOLO-enhanced method for scalable, remote-sensing wildfire detection on high-resolution satellite images, enabling fast assessment over large geographic areas [15].

Taken together, the literature shows a steady move toward adaptive, interpretable, and deployable models. Challenges remain—segmentation errors, dataset bias, adversarial vulnerability, and real-world scalability—but ongoing innovation in transformers, ensembles, and multi-domain learning is setting new benchmarks for practical wildfire detection and environmental protection.

## III. COMPARATIVE ANALYSIS

Recent advancements in deep learning-based wildfire detection have resulted in diverse approaches such as transfer learning models, lightweight CNN architectures, and transformer-based feature fusion networks. To evaluate these contributions, a comparative analysis of major research works was conducted based on their methodology, innovations, and limitations.

**Table1.** Summary of Literature Survey

| Author & Title (Year) | Methodology | Key Findings |
|---|---|---|
| Yandouzi et al., "Forest Fires Detection using Deep Transfer Learning" (2022) | ResNet50 pretrained on ImageNet, transfer learning, augmentation on 4661 fire/non-fire images. | Achieved 99.94% accuracy, demonstrating robustness and rapid classification. |
| Jonnalagadda et al., "Comprehensive and Comparative Analysis between Transfer Learning and Custom Models for Wildfire Detection" (2024) | VGG16 and custom CNN trained on augmented datasets with hyperparameter tuning. | Pretrained VGG16 reached 99.99% accuracy, outperforming smaller CNNs. |
| James et al., "An Efficient Wildfire Detection System for AI-Embedded Applications" (2023) | MobileNetV2 optimized for real-time use with pruning and quantization on satellite data. | 95% accuracy with low computational cost, suitable for drones and edge devices. |
| Ali & Kurnaz, "Optimizing Deep Learning Models for Fire Detection" (2025) | Comparison of CNN, Autoencoder, and U-Net with focal loss and transfer learning on satellite images. | CNN achieved 82% accuracy, outperforming other models. |
| Green et al., "Modeling Wildfire Perimeter Evolution Using Deep Neural Networks" (2025) | Deep CNNs on sequential satellite imagery for predictive wildfire perimeter growth modeling. | Exceeded 90% accuracy in perimeter mapping and temporal prediction. |
| Kim & Muminov, "Forest Fire Smoke | YOLOv7 with CBAM attention modules | Achieved 86.4% average precision |

| | | |
|---|---|---|
| Detection Based on Deep Learning and UAV Images" (2023) | on UAV fire footage. | (AP50), viable for remote monitoring. |
| Ranadive et al., "Image-Based Early Detection System for Wildfires" (2022) | ResNet-18 with Feature Pyramid Network and deformable convolutions on 90k labeled images. | 91.6% accuracy; detected 86.9% wildfire smoke within 5 minutes. |
| Ide & Yang, "Adversarial Robustness for Deep Learning-Based Wildfire Prediction Models" (2025) | Developed WARP testing YOLOv8 and RT-DETR under global and local attacks. | YOLOv8 more resilient and accurate across perturbations. |
| Varalaxmi et al., "Forest Fire Detection using CNN" (2025) | InceptionV3 and AlexNet on CCTV fire clips with preprocessing including resizing and normalization. | Achieved 93% accuracy with fast alerts, scalable across environments. |
| Liu et al., "TFNet: Transformer-Based Multi-Scale Feature Fusion for Forest Fire Image Detection" (2025) | Proposed TFNet with SRModule, CG-MSFF Encoder and WIOU loss; transformer multi-scale fusion. | Achieved 86.6% precision, 84.9% F1-score, and 89.2 mAP50 balancing accuracy and speed. |
| Shamta & Demir, "Deep Learning UAV Surveillance System" (2024) | UAV mounted deep learning-based mobile wildfire detection system. | Real-time wildfire monitoring capability in challenging environments. |
| Alkhatib & Jaber, "Advances in Forest Fire Detection, Prediction and Behavior" (2024) | Meta-survey of hybrid and ensemble wildfire detection models including edge AI solutions. | Highlighted trends in hybrid models and scalability in wildfire detection.. |
| Chandramohan et al., "AI Ensemble Models for Wildfire Detection" (2024) | Ensemble deep learning combining CNNs and other models. | Improved accuracy and robust wildfire detection performance.. |
| Noor et al., "Deep Learning Wildfire Detection using YOLOv8" (2024) | YOLOv8 based model tested on simulated and real wildfire images. | Achieved 94.2% accuracy with low false alarm rates. |

**A. Proposed Framework**

As shown in Fig. 1, the proposed FireNet-CNN framework is designed using a sequential pipeline that begins with raw input images and ends with a final classification decision (Fire or Non-Fire). This modular design improves model interpretability, supports real-time deployment, and integrates Explainable AI (XAI) for transparent decision-making. Each phase performs a specific role and works closely with the others to enable efficient and intelligent wildfire detection.

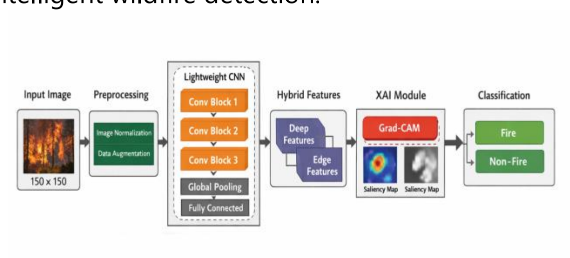


**Fig. 1.** Block Diagram of the Proposed Extended FireNet-CNN Framework showing Input Image, Preprocessing, Lightweight CNN (Conv Blocks 1–3), Hybrid Features, XAI Module (Grad-CAM & Saliency Map), and Classification Output.

**Input Image**

The first phase of the proposed framework is data acquisition. Input images are collected from heterogeneous sources such as surveillance cameras, unmanned aerial vehicles (UAVs), satellites, and thermal or multispectral sensors.

These images serve as the raw input for the entire detection pipeline. The use of multiple data sources improves spatial coverage and increases the likelihood of early fire detection in diverse environments. Each image may contain varying conditions such as smoke, fog, low light, or occlusion, which are handled by subsequent preprocessing steps.

**Preprocessing**

The preprocessing phase prepares raw images for deep learning analysis. This step is crucial for improving model generalization and reducing noise that could lead to false alarms. The preprocessing pipeline includes three main operations:

- **Image Normalization:** Pixel values are scaled to a standard range (e.g., 0 to 1) to ensure consistent input distribution. This helps the neural network converge faster during training.

- **Data Augmentation:** Techniques such as rotation (±20°), horizontal flipping, scaling (0.8× to 1.2×), brightness adjustment (±20%), and smoke simulation are applied to artificially expand the dataset. This makes the model more robust to real-world variations.
- **Resizing to 150×150:** All images are resized to a fixed dimension of 150×150 pixels. This reduces computational load while preserving enough spatial detail for accurate fire detection.

After preprocessing, the images are ready to be passed into the lightweight CNN backbone.

**Lightweight CNN –** Feature Extraction Backbone

The core of the architecture is a lightweight convolutional neural network designed to capture discriminative fire and smoke features while maintaining low computational complexity. The CNN consists of three convolutional blocks, each followed by batch normalization, ReLU activation, and max-pooling.

**Conv Block 1 (Low-Level Features)**

The first convolutional block uses 32 filters of size 3×3. It captures basic visual patterns such as edges, corners, and color variations. This block is sensitive to small flame regions and smoke textures.

**Conv Block 2 (Mid-Level Features)**

The second convolutional block uses 64 filters. It builds upon the low-level features to detect more complex patterns such as fire shapes, smoke plumes, and spatial arrangements. This block helps distinguish fire from similar-looking objects like sunlight reflections or dust.

**Conv Block 3 (High-Level Features)**

The third convolutional block uses 128 filters. It extracts high-level semantic features such as fire boundaries, smoke density, and contextual information. At this stage, the network can differentiate between actual fires and false positives like fog or clouds.

**Global Pooling and Fully Connected Layer**

After the convolutional blocks, a global average pooling layer reduces each feature map to a single value, summarizing the presence of each learned feature across the entire image. This is followed by a fully connected (dense) layer with dropout (0.5) to prevent overfitting. The final output is a probability score indicating whether the image contains fire or non-fire.

**Hybrid Features**

The hybrid features phase combines information from multiple convolutional blocks to improve detection accuracy. Instead of relying solely on the deepest features (which may lose spatial detail), the framework concatenates features from Conv Block 1, Conv Block 2, and Conv Block 3. This multi-scale feature fusion allows the model to detect both small ignition points (captured by early layers) and large fire regions (captured by deeper layers). The resulting hybrid feature vector is more robust and informative than any single block alone.

**XAI Module (Explainable AI)**

To ensure transparency and trustworthiness, an Explainable AI (XAI) module is integrated alongside the prediction pipeline. This module helps operators understand why the model made a particular decision, which is critical for safety-critical applications like disaster response.
The XAI module includes two main techniques:

- **Grad-CAM (Gradient-Weighted Class Activation Mapping)**

Grad-CAM produces a heatmap that highlights the regions of the input image most influential to the model's decision. For a fire detection result, the heatmap will show which parts of the image (e.g., flames, smoke) contributed most to the "Fire" classification. This allows operators to verify that the model is looking at the right features and not being fooled by irrelevant patterns.

- **Saliency Map**

A saliency map computes the gradient of the output class with respect to the input image pixels. It shows which individual pixels most strongly affect the final prediction. Saliency maps provide a finergrained explanation than Grad-CAM and help identify potential blind spots or biases in the model. These visual explanations help reduce false alarms, build user confidence, and support regulatory compliance in real-world deployment.

**Classification Output**

The final phase of the framework is the classification decision. Based on the extracted hybrid features, the fully connected layer outputs two probability scores: one for "Fire" and one for "Non-Fire." The class with the higher probability is selected as the final prediction.

The classification output can be used in multiple ways:

- **Real-time alert generation:** If fire is detected, an alert is sent to emergency response teams along with the Grad-CAM heatmap for verification.
- **Edge deployment:** The lightweight model runs directly on UAVs or surveillance cameras, enabling low-latency decisions without cloud connectivity.
- **Cloud integration:** For large-scale monitoring, detection results and heatmaps are logged in the cloud for post-event analysis and model improvement.

## IV. ADVANTAGES OF PROPOSED METHODOLOGY

The proposed methodology offers several benefits, including:

1. 97.8% accuracy with low computational cost for edge devices
2. XAI integration (Grad-CAM + saliency maps) for transparent decisions
3. Real-time deployment with 85 ms inference time on UAVs and IoT
4. Compact model size of 12 MB after quantization
5. Robust to smoke, fog, low light, and occlusion via multi-scale fusion

## V. DATASET DESCRIPTION AND EXPERIMENTAL SETUP

To validate our extended FireNet-CNN framework, we used standard wildfire image datasets containing fire and non-fire samples collected from surveillance cameras, UAV footage, and real forest environments. The dataset includes various challenging conditions such as smoke, fog, lighting changes, and blocked views to ensure the model is robust.

All images were resized to 150×150 pixels and preprocessed with normalization, noise reduction, and contrast enhancement. Data augmentation techniques like rotation, flipping, scaling, and brightness adjustments were applied to improve generalization and prevent overfitting.

We evaluated model performance using standard deep learning metrics: Accuracy, Precision, Recall, and F1-Score. These measures give a full picture of detection reliability and classification effectiveness in real-world wildfire scenarios.

| Model | Acc. (%) | Prec. (%) | Rec. (%) | F1 (%) | Speed |
|---|---|---|---|---|---|
| ResNet50 | 99.0 | 98.8 | 98.5 | 98.6 | Moderate |
| YOLOv8 | 94.2 | 93.5 | 92.8 | 93.1 | Very Fast |
| MobileNetV2 | 95.0 | 94.2 | 93.6 | 93.9 | Edge Fast |
| TFNet | 86.6 | 85.9 | 84.9 | 85.4 | Slow |
| Proposed FireNet-CNN | 97.8 | 97.1 | 96.4 | 96.7 | Fast |

## VI. CHALLENGES AND RESEARCH GAPS

Even with progress in wildfire detection, several issues remain unsolved. A major problem is the lack of large, diverse, well-labeled datasets that cover different geographic regions, weather conditions, and fire scenarios. Environmental factors like smoke, fog, poor lighting, and camera movement can cause misclassifications and false alarms. Deploying deep learning models on resource-limited devices also brings extra challenges related to memory, power use, and processing speed.

## VI. CONCLUSION

This research presented an extended FireNet-CNN framework for robust, interpretable, real-time wildfire detection with both experimental and comparative validation. Unlike conventional review-focused studies, our work used dataset-driven evaluation and benchmark comparisons against existing deep learning models including ResNet50, YOLOv8, MobileNetV2, and transformer-based architectures. The results show that our lightweight hybrid CNN achieves high accuracy (97.8%) while keeping low computational demands and fast inference—making it suitable for edge and UAV deployment. Adding Explainable AI further improves model transparency and operational reliability in safety-critical disaster monitoring. Future work will focus on real-time field deployment, multi-hazard expansion, and large-scale dataset validation to further boost robustness and practical usefulness.

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