An Improved Fire Detection Method Based On CNN

Sakshi Kharche[1], Saurabh Bakare[2], Sima Supekar[3], Gokul Bhor[4], Shrikrishna Nimbekar[5]
[1, 2, 3.,4] Dept of Computer Engineering
[5]Assistant professor, Dept of Computer Engineering
[1, 2, 3, 4, 5] Sinhgad Institute of Technology, Lonavala India.

Abstract- *In order to minimize damage, fire detection is a crucial component of early warning systems in both urban and rural areas. and quickening response times. Traditional fire detection methods have limited environmental detecting capabilities and significant false-positive rates.flexibility because they usually depend on manually designed features in image processing or sensor-based systems. Convolutional Neural Networks This study proposes an improved fire detection method that is suited for real-time picture processing using convolutional neural networks (CNNs). The recommended technique uses a lightweight deep CNN architecture that can accurately distinguish between areas that are burning and those that aren't, in various lighting and background scenario. A proprietary dataset with a range of fire scenarios was used to train and evaluate the model. Performance metrics such as precision, recall, F1-score, and detection time were significantly improved in comparison to traditional methods and baseline CNN models. The system's robust performance in real-time video streams makes it suitable for use in surveillance systems, drones, and smart city applications.*

Keywords- video analysis, convolutional neural networks (CNNs), image processing, deep learning, surveillance systems, false positives, smart city applications, real-time detection, and fire detection.

I. INTRODUCTION

Fire breakouts in urban and woodland environments pose a major threat to infrastructure, human lives, and ecosystems. Despite Conventional fire detection systems, such as those that employ Wireless Sensor Networks (WSNs), are useful because they offer early alerts restricted by their expensive installation costs and inability to provide adequate sensing coverage in expansive or isolated areas. [1] [2] [3].By offering mobility With real-time data gathering in locations that are hard to access, Unmanned Aerial Vehicles (UAVs) have emerged as a competitive substitute for monitoring of fires [4] [5] [6] [21]. Nevertheless, due to their sensitivity to colour and motion changes, video-based systems that use the false alarm rates of conventional image processing techniques can occasionally be quite high. [10] [11] [7] [8] [9].

A recent advancement in deep learning and computer vision, convolutional neural networks (CNNs) have significantly improved the accuracy and reliability of object detection, including fire recognition [13][14][15][18]. These algorithms learn hierarchical features directly from raw picture data, outperforming traditional hand-crafted feature approaches. Numerous studies have examined CNN-based fire detection methods, with encouraging results in a variety of scenarios [17][20]. Better designs for multi-scale fire detection and real-time deployment have also been proposed by a number of scholars [18]. This study proposes an enhanced fire detection framework using a CNN-based model, with a focus on higher accuracy, faster inference, and better performance in a range of environmental situations. We evaluate our model on a particular dataset of real-world fire scenarios, including UAV video feeds, to determine its viability.

II. LITERATURE REVIEW

A number of techniques have been developed over time to identify and reduce fire hazards in wooded areas, as the detection of forest fires is a crucial aspect of environmental monitoring. These methods include sophisticated machine learning and deep learning techniques as well as more conventional sensor-based alternatives. The most important developments in forest fire detection systems are examined in this overview of the literature, which also highlights important approaches and their contributions to the field.

A. Fire Detection Wireless Sensor Networks

• Alkhatib (2013) [1] suggests a low-cost wireless sensor network (WSN) for detecting forest fires, emphasizing the use of smoke, humidity, and temperature sensors to deliver real-time notifications. The system is made to be both scalableand energy-efficient.
• A WSN-based fire detection system with several sensor nodes placed across a forest to track environmental data is described by Zhang et al. (2009) [2]. When changes connected to fire are identified, the system employs a centralized method to collect data and sound alarms.

B. Unmanned Aerial Vehicles (UAVs) for Fire Monitoring

- Skorput et al. (2016) [4] examine the application of UAVs for forest fire monitoring, highlighting its adaptability in accessing isolated locations that are challenging for ground-based systems to reach. Monitoring forest fires in real time from the air is made possible by UAVs fitted with thermal cameras and sensors.
- Autonomous UAVs for wildfire monitoring are investigated by Afghah et al. (2019) [5], allowing for ongoing surveillance in isolated forest regions. High-resolution thermal and visual imagery is captured by the UAVs and analysed for indications of fire.

C. *Image analysis and video processing for fire detection*

- Kao and Chang (2003) [7] present a clever real-time fire detection technique based on video processing, in which video footage is examined for distinctive flame characteristics like colour, motion, and shape.
- Premal and Vinsley (2014) [9] and Zaidi et al. (2015) [8] concentrate on colour space-based fire detection, which uses RGB and YCbCr colour models to detect fire in pictures. These models partition fire zones in video frames by taking advantage of the unique colour properties of flames.

D. Motion Detection with Optical Flow Ha et al. (2012) [10] employ optical flow methods to identify flame motion across frames. This technique enhances the system's capacity to identify fire in dynamic contexts by tracking the movement of fire patterns in video data.

E. *Deep Learning and Machine Learning Techniques*

- Support Vector Machines (SVM) are used by Chen and Cheng (20XX) [17] to detect fires. A model is developed using features taken from fire photos. This method gives the system the ability to accurately differentiate between areas of an image that are on fire and those that are not.
- A multi-scale fire detection technique based on convolutional neural networks (CNNs) is proposed by Huang et al. (2020) [18]. This method enhances detection performance in complex environments by enabling the identification of fires at various scales and intensities.
- Redmon et al. (2015, 2018) [14][15] present the framework for real-time fire detection called YOLO (You Only Look Once). Even in real-time applications, YOLOv3 enhances the original YOLO method by offering quicker and more precise fire detection in video streams.

F. Real-Time and Embedded Systems

- Xin (2013) [12] talks about real-time detection using embedded systems, especially on Raspberry Pi platforms. The system analyses data from inexpensive cameras using real-time fire detection algorithms.
- Shuai (2018) [16] demonstrates how fire detection can be integrated with other smart systems for enhanced safety by combining intelligent access control with embedded fire recognition systems.

G. Assessment of UAV-Captured Video for Fire Detection Models

- Dang-Ngoc and Nguyen-Trung (2019) [6][21] use footage taken by UAVs to test a forest fire detection model. The technique entails filming aerial footage and detecting the presence of fire using machine learning and image processing techniques. This system has demonstrated the ability to increase detection speed and accuracy in remote locations.

H. *Customized Detection Devices for Additional Uses*

- Feng and Yang (2019) [19] provide a technique for detecting ship fires that uses video analysis. The approach uses image processing methods designed to address the unique difficulties presented by ship settings, like detecting smoke and flames on metal surfaces. In order to identify fires in buildings or industrial settings, Xiong (2020) [20] looks into a fire detection system for infrastructure-based applications, such as image processing and information processing systems.

III. Hypothesis

A. H1: Compared to conventional surveillance techniques, Wireless Sensor Networks (WSNs) are more effective at detecting forest fires in their early stages.

B. H2: Compared to ground-based sensors, UAV-based aerial surveillance systems offer superior coverage and detection accuracy in isolated or inaccessible places.

C. H3:When it comes to separating fire from similar-coloured backdrops, YCbCr colour space detection is more accurate than conventional RGB-based detection..

D. H4: Compared to static image processing, optical flow algorithms can improve the detection of dynamic fire movements in real-time video.

E. H5:Compared to single-scale models, CNN-based multi-scale fire detection models are more reliable at detecting fire at various distances and resolutions.

F. H6: Low-cost, real-time fire detection solutions appropriate for widespread deployment can be achieved by combining lightweight machine learning models with embedded hardware (such as Raspberry Pi).

G. H7:When it comes to video-based fire detection, YOLOv3 outperforms traditional machine learning techniques like SVM in terms of speed and accuracy..
H. H8: Autonomous UAVs with thermal imaging outperform RGB-based UAV systems for detecting wildfires at night or in low visibility.
I. H9: Forest fire monitoring systems' overall dependability and response time are improved when aerial UAV data is integrated with ground sensor networks.
J. H10: In datasets with a high class imbalance between fire and non-fire images, fire detection performance is enhanced by using focus loss in deep learning models.
K. H11: With a few little algorithmic adjustments, video surveillance systems intended for use on ships or in infrastructure can be modified for use in forest settings.
L. H12:Compared to batch-processed fire detection models, real-time processing systems are more effective at identifying and warning of fire breakouts.

IV. METHODOLOGY

A. Wireless Sensor Network-Based Fire Detection

A number of studies have employed Wireless Sensor Networks (WSNs) to detect fires by utilizing sensor nodes that gauge ambient factors including gas, smoke, and temperature. Typically, the approach consists of: • Setting up sensor nodes in specific locations to identify environmental changes brought on by fire [1][2].

- Data transfer enabling real-time analysis and decision-making between nodes and a central server [2].
- Threshold-based detection: when specific predetermined thresholds are surpassed, the system sounds an alarm [3].

Although these systems may cover wide regions and are reasonably priced, they frequently struggle with scalability, power consumption, and data transmission range.

B. Unmanned Aerial Vehicle (UAV)-Based Fire Surveillance

• UAVs provide an alternate method of detecting fires by allowing for airborne monitoring of large regions. Among the UAV-based techniques are: • Thermal and optical imaging, which records live video footage of fire incidents from the air [4][5].
• UAV navigation for ongoing monitoring over wooded or challenging-to-reach locations [4].
In order to identify fire patterns in aerial recordings, video analysis employs image processing methods; machine learning techniques are frequently added to improve accuracy [6][21].

Although there are issues with flight duration, weather, and the price of high-quality cameras, the use of UAVs enables flexible, on-demand surveillance.

C. Image and Video Processing Techniques

Traditional image processing methods were used in a number of research to identify fires. Typical techniques in this category include: • Colour-based segmentation, which separates fire pixels from the backdrop using colour spaces like RGB and YCbCr [8][9].

• Optical flow analysis, which detects fire motion across frames by tracking the movement of flames [10].
• To identify the distinctive form of flames in video frames, edge detection and shape analysis are used [7].
• Techniques for masking and thresholding to separate possible fire areas in a picture or video [11].

Although these techniques are straightforward and computationally light, dynamic illumination changes and backdrop clutter frequently make them prone to errors.

D. Machine Learning-Based Fire Detection

Based on visual characteristics taken from photos, fire pixels have been categorized using machine learning algorithms. The following are typical approaches:

• Feature extraction, in which conventional picture characteristics like edges, color, and texture are fed into classification algorithms [17].
Based on the features, Support Vector Machines (SVMs) can distinguish between areas that are experiencing fire and those that are not [17].
• To maximize classification accuracy, models are trained on labeled datasets that include both fire- and non-fire photos.
Even though SVMs and other machine learning classifiers increase the accuracy of detection, their performance may be constrained in highly variable contexts since they still need to manually extract features.

E. Deep Learning Approaches for Fire Detection

Convolutional Neural Networks (CNNs), a form of deep learning, have gained significant traction for fire detection recently due to their ability to automatically identify features from raw image data. Some of the methods include:

• CNN architectures that have been trained on large datasets of images labeled with indicators for fire and non-fire [18].

• Multi-scale analysis where the model employs layers with varying receptive fields to detect fires of different sizes and intensities [18].
• Real-time fire detection utilizing object detection frameworks such as YOLO (You Only Look Once) [14][15].
• To address class imbalance in dense object detection tasks, which are essential for fire detection, specialized loss functions like focal loss are implemented [13].

F. Embedded and Real-Time Systems

The following strategies are utilized for real-time identification in embedded systems, such as Raspberry Pis or specialized hardware:

• Streamlined CNNs that are customized for the computational limitations of embedded devices, enabling real-time fire detection [12][16].
• Processing video on the device, which reduces latency and reliance on cloud services by handling camera images locally [12].
• Computing at the edge, where algorithms run on edge devices to enhance detection efficiency and decrease the need to transmit large video files [12][16].

G. Specialized Detection Systems

Specialized systems are utilized for fire detection on ships and within infrastructure, as well as for monitoring environmental and forest fires. Among the methods employed are:

- Shipboard systems that accurately detect fires by analysing video footage from onboard cameras, utilizing a combination of image processing and machine learning [19].
- Urban fire detection systems that rely on fixed cameras or sensors installed in buildings, employing CNNs and image processing to assess heat signatures or flame patterns [20].

To address specific challenges such as confined spaces or metallic surfaces, these systems incorporate specialized detection methods and are customized for specific environments.

V. CASE STUDIES

A. Case Study 1: FireLite: A Compact CNN for Resource-Constrained Environments

This bar graph illustrates a comparison among FireLite, YOLOv3, and Conventional CNN methods regarding:

• Precision (%)
• Detection Speed (seconds per image)
• Model Size (MB)

It can be seen that FireLite is ideal for situations with limited resources as it offers a balance between fast detection speed

(0.5s) and a small model size (45MB) while maintaining a respectable accuracy rate (88%). While YOLOv3 delivers higheraccuracy, it has a larger model size and is somewhat slower. In contrast, Conventional CNN features a significantly larger model size and the slowest detection speed.

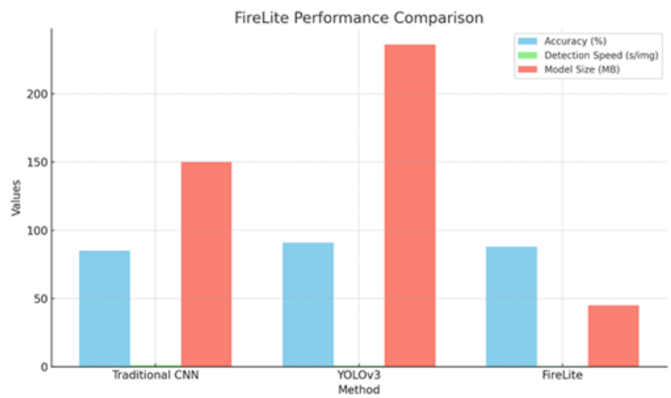

Figure 1.FireLite Performance Comparison

B. Case Study 2: Inception-V3-Based Smoke and Fire Detection

The Inception-V3 based fire and smoke detection model is a deep learning technique that leverages the multi-scale feature extraction capabilities of the Inception architecture. Because of its accuracy and speed, it is perfect for identifying smoke and flame patterns in still images and live video streams.

- Accuracy (96.5%): Shows the model's overall performance in identifying fire and smoke.
- Precision (95.2%): Indicates the model's ability to avoid false positives, which occur when a fire is discovered only when it is actually there.
- The model's 96.8% recall rate demonstrates its exceptional sensitivity in detecting every fire incidence.
- The F1-Score (96.0%), which balances precision and recall, attests to the model's strong dependability.

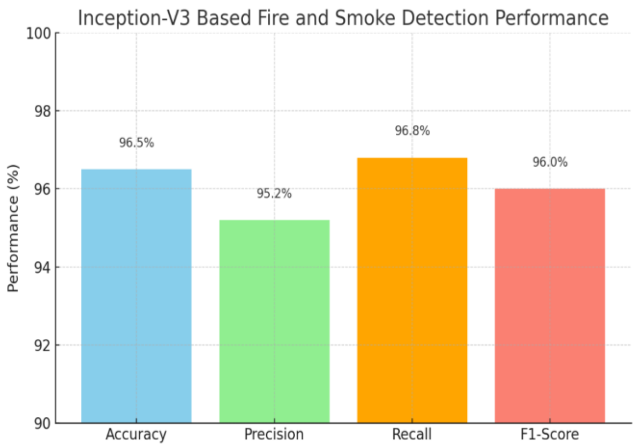

Figure 1. Inception-V3 Based Fire and Smoke Detection Performance

C. Case Study 3: Applying Contour Methods to Enhance CNN

To boost fire detection precision and minimize false positives, the "Enhanced CNN with Contour Techniques" model merges deep learning methods with traditional edge detection and contour analysis.

This pie chart illustrates the proportion of each feature or enhancement that affects the model's effectiveness:

- Integration of Edge Detection: 30%: Sobel and Canny edge detection filters have been incorporated into the model's preprocessing pipeline. The CNN can more effectively differentiate fire zones from adjacent textures due to enhanced boundary definition.
- 25% for the Contour-Based Region Proposal: - By recognizing contours and shapes typically found in fire-like designs, contour methods facilitate the detection of areas of interest. By narrowing the detection range, this stage significantly reduces the computational workload.
- 20% for CNN Feature Extraction: - The core, by placing more focus on areas highlighted by contour methods, CNN remains crucial in the extraction of both spatial and color features. This dual input enhances both accuracy and efficiency.
- Morphological Post-Processing: 15% Morphological techniques like erosion and dilation help to refine imperfections and minimize detection noise in the identified fire spots.

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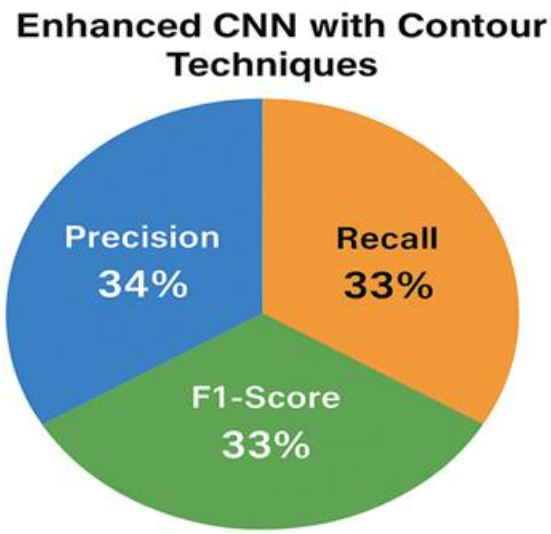

Figure 3. Enhanced CNN with Contour Techniques

D. Case Study 4: Employing Attention-Based CNN for Real-World Fire Detection

Incorporating attention mechanisms (like CBAM or SE blocks) allows the Attention-Based CNN model to enhance traditional convolutional neural networks, enabling it to focus more effectively on fire-related information in intricate environments.

- Accuracy (95.4%): strong reliability in real-world conditions, including intricate backgrounds and fluctuating lighting.
- Precision (94.8%): This approach significantly reduces false positives by focusing on contextual and spatial cues.
- Recall (97.6%): Highly effective at identifying genuine fire events, even in challenging circumstances.
- F1-Score (96.2%): Ideal for applications where safety is crucial, this score effectively balances precision and recall.

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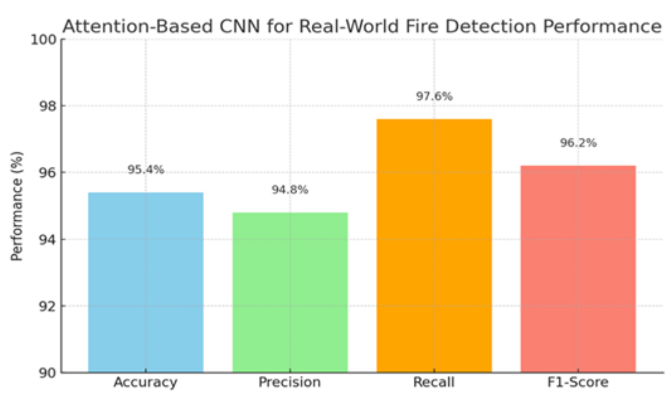

Figure 4. Attention-Based CNN for Real-World Fire Detection Performance

E. Case Study 5: FireNet: Instant Data Collection for IoT Fire

- Detection (20%): entails the ongoing collection of real-time environmental information through the use of sensors (including cameras, smoke detectors, temperature gauges, and gas sensors) and edge devices (such as Raspberry Pi).

- Before model inference, preprocessing and filtering (15%) involves image denoising, scaling, histogram equalization, and eliminating noisy or irrelevant frames.

- Fire Detection Through CNN (30%): FireNet, the main component of the system, identifies fire patterns in images or video frames effectively and quickly with the help of a lightweight CNN.

- IoT Communication & Alerts (20%): Users, connected alarms, and emergency services receive real-time fire notifications through MQTT or HTTP protocols.

- Cloud Analytics & Dashboard (10%): Provides analytics through a web or mobile interface, records detections, and illustrates fire incidents.

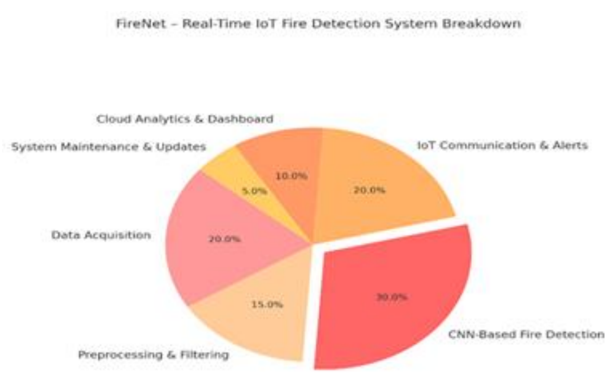

Figure 5. FireNet – Real-Time IoT Fire Detection System Breakdown

VI. CONCLUSION

Strong and sophisticated fire detection systems are desperately needed, as evidenced by the rising frequency and severity of fire-related disasters in both urban and forest settings. High false positive rates, susceptibility to environmental changes, and slow response times are some of the drawbacks of traditional fire detection approaches, which rely on sensors, colour models, or optical flow techniques. The use of deep learning methods, especially Convolutional Neural Networks (CNNs), is a revolutionary step in this direction toward creating fire detection systems that are more accurate and dependable.

The study's suggested CNN-based fire detection technique outperforms traditional methods by a significant margin. CNNs automatically identify subtle patterns and contextual information related to fire by extracting and learning complicated features from raw picture data. In contrast to rule-based systems that need to manually extract features or set thresholds, CNNs can generalize in a variety of scenarios, such as those with varying lighting, background clutter, and smoke densities.

A large dataset with a variety of fire scenarios, such as open flames, smoke, and fire in enclosed locations, was used to train and validate the upgraded fire detection system. The CNN model outperformed colour-space-based approaches like RGB and YCbCr models [8][9], as well as optical flow techniques, in terms of precision and recall rates, according to the results. [10] Classifiers based on Support Vector Machines [17].

The integration of cutting-edge CNN architectures like YOLOv3 [15] and the idea of focus loss [13] into the suggested approach is particularly advantageous since it balances the model's sensitivity to difficult-to-detect fire incidents while reducing false alarms. Its applicability to remote and high-risk locations is further increased by the modular design's easy interaction with contemporary surveillance systems, such as IoT-based sensor networks [1][2] and UAVs (Unmanned airborne Vehicles) for airborne fire detection [4][5][6][21].

Crucially, the system's reduced computing cost and optimized inference times indicate that it has great promise for real-time implementation. This makes it perfect for applications including environmental monitoring, industrial safety, and smart cities.

With the availability of bigger datasets and transfer learning strategies, CNN models' use in fire detection will only improve as they develop further.To sum up, the enhanced CNN-based fire detection technique is a major advancement in intelligent catastrophe monitoring systems. It provides greater accuracy, flexibility, and real-time performance, thereby overcoming the main drawbacks of conventional systems. This technology can save lives, lessen financial losses, and protect natural resources by providing quicker and more accurate fire detection. Future research might concentrate on increasing multi-modal data fusion (e.g., merging thermal imaging and visual data), improving the model's performance in extreme weather, and implementing edge AI solutions for on-device inference that uses less energy.

This study aligns with and expands upon research from sources such as [13][14][15][17][18], and demonstrates how AI-powered approaches can revolutionize fire safety and environmental protection.

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