Fire Detection Using CCTV Surveillance

Abhay Adapanwar[1], Sejal Ranka[2], Sakshi Gore[3], Nidhi Bhosale[4], Amruta Bharamgude[5]

Department of Computer Engineering, Sinhgad Academy of Engineering, Pune

---***---

Abstract - This study investigates the development and implementation of a Real-Time Fire Detection System using Video Analytics, an advanced monitoring framework designed to enhance safety and surveillance through intelligent video-based analysis. The system utilizes live camera feeds as input and applies a combination of image processing and deep learning techniques to automatically detect fire in real time. The framework leverages Convolutional Neural Networks (CNN) for accurate classification and color-based image processing to identify fire-like regions based on visual characteristics such as color, intensity, and flickering behavior. The camera continuously captures video frames that are processed using OpenCV to extract color and motion features, which are then passed through the CNN model for precise classification. When fire is detected, the system highlights the affected region within the frame and immediately displays an alert message on the monitoring interface. This non-intrusive, sensor-free system offers a cost-effective, reliable, and efficient way to detect fire compared to traditional smoke or heat-based systems. It ensures rapid response and reduces the likelihood of false alarms by integrating deep learning-based classification with image analysis. The system is suitable for real-time applications in industrial areas, smart homes, public places, and surveillance systems, where early fire detection is crucial for preventing damage and ensuring safety.

Key Words: topological data analysis, graph neural networks, credit risk assessment, supply chain finance, BallMapper, SME bankruptcy prediction

1.Introduction

Fire is one of the most destructive hazards that can lead to severe loss of life, property, and the environment. Early detection of fire plays a vital role in minimizing its impact and enabling quick response actions. Conventional fire detection systems primarily rely on smoke sensors, heat detectors, or infrared sensors. While these sensor-based systems are effective to an extent, they often suffer from drawbacks such as slow response time, high installation costs, and susceptibility to false alarms caused by dust, humidity, or electrical interference. With the increasing demand for intelligent and automated safety solutions, video-based fire detection systems have emerged as a promising alternative.

The rapid advancements in computer vision and deep learning have made it possible to analyze video streams in real time to identify potential fire incidents. Video surveillance cameras, already deployed in most public and private infrastructures, can be leveraged as input sources for continuous monitoring. By applying image processing and machine learning techniques, these systems can detect visual indicators of fire such as color, motion, brightness, and flicker patterns directly from live camera feeds. In this study, a Real-Time Fire Detection System using Video Analytics is proposed to overcome the limitations of traditional systems. The framework integrates OpenCV-based color and motion feature extraction with Convolutional Neural Network (CNN) classification to accurately detect fire occurrences in real time. The CNN model is trained on diverse fire and non-fire image datasets to enhance accuracy and reduce false positives. Upon detection, the system highlights the fire-affected region within the frame and immediately generates an alert, ensuring rapid response and improved safety. The proposed system offers several advantages such as non-intrusive monitoring, cost-effectiveness, and scalability for use in smart cities, industrial facilities, transportation hubs, and residential complexes. By combining traditional image processing with modern deep learning algorithms, this system provides an efficient, automated, and intelligent approach to fire detection, contributing significantly to the field of surveillance-based safety systems.

2. Literature Review

2.1 Traditional Fire Detection Systems

Conventional fire detection techniques such as smoke sensors, heat detectors, and infrared sensors have been widely used for decades.

These systems are effective for closed indoor environments but often suffer from slow response time and false alarms due to dust, humidity, or temperature fluctuations.

They require physical installation of multiple sensors, making them costly and difficult to maintain in large or open areas.

2.2 Image Processing-Based Approaches

Early research focused on using computer vision and color-based segmentation to detect fire from images or videos.

Color models such as RGB and HSV were used to isolate fire-like regions based on hue, saturation, and brightness.

Although effective in controlled conditions, these approaches were sensitive to lighting variations, reflections, and other moving objects, leading to reduced reliability.

2.3 Feature Extraction and Motion Analysis

To improve detection accuracy, researchers introduced motion and flicker analysis to differentiate fire from static bright objects.
Additional features like texture and edge patterns were extracted to characterize flame behavior.
However, manual feature design limited scalability and adaptability to diverse environments

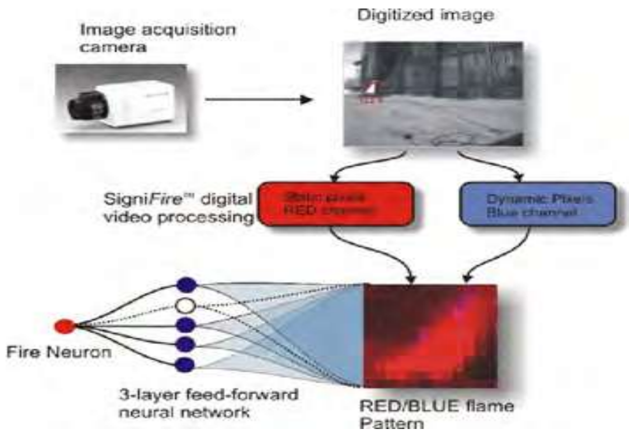
2.4 Machine Learning-Based Detection
Machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Random Forests were employed to classify fire and non-fire regions.
These models required manual feature extraction but provided better classification accuracy than purely rule-based systems.
The performance of these models was still dependent on the quality and diversity of the input dataset.

2.5 Deep Learning Approaches
The introduction of Convolutional Neural Networks (CNNs) revolutionized video-based fire detection.
CNNs automatically extract spatial and visual features from large image datasets, reducing the need for manual feature design.
Studies have shown that CNN-based models achieve higher accuracy, faster detection, and better generalization across various lighting and background conditions.

2.6 Hybrid Techniques
Recent research combines traditional image processing with deep learning to balance computational speed and accuracy.
For example, color and motion detection using OpenCV can pre-filter potential fire regions, which are then analyzed by CNN models for final classification.
This two-stage process helps reduce false positives and improves real-time performance.

2.7 Real-Time Implementation Studies
Several frameworks have integrated OpenCV with CNN architectures for processing live video feeds from CCTV cameras.
These systems detect fire in continuous frames and generate immediate alerts on detection.
They are being tested in smart city surveillance, industrial monitoring, and home safety applications.

2.8 Summary of Literature Findings
The research trend shows a clear evolution from sensor-based to video-based and finally to AI-driven detection systems.
Deep learning models, especially CNNs, have proven to be the most reliable and efficient for real-time applications.
Combining image processing and deep learning enables faster, more accurate, and scalable fire detection suitable for modern surveillance systems.



3. Methodology

The proposed Real-Time Fire Detection System using Video Analytics is designed to process live video feeds, extract relevant features, and classify the presence of fire using deep learning. The methodology involves several key stages, as described below.

3.1 **System Overview**

Video Frame Capture -The live CCTV feed is divided into continuous frames that act as input to the system.
Region Detection - Using colour thresholding and contour detection in OpenCV, the system isolates areas resembling fire based on hue and saturation values.
NN Classification - The extracted region is passed through a Convolutional Neural Network trained on a dataset containing fire and non-fire images. The CNN outputs a classification probability.
Alert Generation - If fire is detected, the system highlights the fire area with a bounding box and displays an alert message on the screen.
Logging and Monitoring – Detected events are logged with timestamps for further analysis or integration with automated response systems.

3.2 Algorithm Steps
1. Capture live video feed from CCTV camera.
2. Extract individual frames for analysis.
3. Convert frames to HSV color model and filter noise.
4. Apply thresholding to detect color regions typical of fire.
5. Feed detected regions into CNN for classification.
6. If probability > threshold, label frame as “Fire Detected”.
7. Display alert and highlight fire area on monitoring interface.

3.3 Tools and Technologies Used
Programming Language : Python

Libraries: OpenCV, TensorFlow/Keras, NumPy
Hardware: CCTV camera, high-performance CPU/GPU for model inference.
Dataset: Publicly available fire image datasets and custom video recorings.

3.4 Data Preparation
The CNN model requires a diverse and well-labelled dataset for training and evaluation.

1. Dataset Sources: The dataset used combines publically available fire datasets (such as Kaggle's Fire Dataset, Foggia's Video Fire Database) along with custom video samples collected from CCTV recordings.
2. Data Pre-processing: Each image is resized to a uniform dimension (typically 128×128 or 224×224 pixels), normalized, and augmented through rotation, flipping, and brightness variation to improve model generalization.
3. Labeling: The dataset is divided into two categories "Fire" and "Non-Fire" — with balanced samples for effective training.

4. Implementation

The working of the Fire Detection System involves the coordinated functioning of several modules that operate in real time. The process begins when the camera captures continuous video frames of the environment. Each frame undergoes preprocessing using OpenCV to eliminate noise and enhance quality. The image is converted to HSV color space, which allows more effective detection of fire colors compared to RGB. Using defined thresholds for hue, saturation, and brightness, the system extracts potential fire regions.**N**ext, the Convolutional Neural Network (CNN) model, which has been pre-trained with a large dataset of fire and non-fire images, processes these regions to classify whether they contain fire. The CNN model uses convolutional layers to analyze spatial patterns, pooling layers to reduce complexity, and activation functions to capture non-linear characteristics of fire textures. Once the model confirms the presence of fire, a rectangular bounding box is drawn around the flame area, and a "Fire Detected" alert appears on the display screen. This real-time monitoring continues as long as the system is active. If no fire is present, the system does not trigger any alert and keeps analyzing subsequent frames. The algorithm is efficient enough to process multiple frames per second, ensuring near-instantaneous detection. This automated mechanism eliminates the need for manual observation and offers a reliable way to detect and respond to potential fire hazards in any environment.

5. Results and Discussion

From the overall review of existing research, it is evident that modern fire detection systems are increasingly shifting toward the use of video-based analytics combined with artificial intelligence. The survey shows that most of the proposed models rely on a hybrid framework, where traditional image processing methods are integrated with deep learning algorithms to achieve accurate and reliable detection. In almost all studies, fire detection begins with preprocessing of video frames, where color segmentation and conversion from RGB to HSV color space are carried out to clearly highlight fire-like regions. This conversion helps in identifying shades of red, orange, and yellow more accurately and reduces the impact of lighting variations in the environment. Following this step, Convolutional Neural Networks (CNNs) are applied to analyze and classify the processed frames. These CNNs are trained using datasets containing both fire and non-fire images so that the model can recognize fine visual patterns like texture, intensity, and movement. In some improved systems, Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks are also used to capture the flickering and dynamic behavior of fire, which helps the system differentiate real flames from other bright or reflective objects. The studies reviewed in this survey clearly indicate that video-based approaches perform better than traditional sensor-based fire detectors. Many researchers have reported detection accuracies exceeding 95%, which demonstrates a high level of precision and reliability under different lighting and environmental conditions. Since these systems rely on camera feeds, they can detect visible flames in real time, resulting in a faster response compared to smoke or heat-based sensors that need physical contact with the fire. Moreover, the combination of image analysis with deep learning significantly lowers the chances of false alarms, as the model is trained to recognize the unique movement and color features of flames and ignore similar objects such as sunlight reflections or electric light sources.

6. Future Scope

The proposed Real-Time Fire Detection System using CCTV surveillance has demonstrated effective performance in detecting fire events with high accuracy. However, there is considerable potential for further improvement and expansion of its functionality. The future scope of this research can be outlined as follows:
1. Integration with IoT and Cloud Platforms
The system can be integrated with Internet of Things (IoT) devices to enable remote monitoring and control.
Cloud-based data storage and processing can facilitate centralized fire monitoring across multiple locations, making large-scale deployment feasible for smart cities and industrial zones.

2. Incorporation of Smoke and Thermal Analysis
Future versions can include additional features such as smoke detection or thermal imaging for enhanced accuracy.
Combining visible light detection with infrared or thermal cameras can help identify fire at earlier stages and under poor lighting conditions.
3. Deployment on Edge Devices
To improve real-time performance and reduce network latency, the system can be optimized for deployment on edge computing devices like Raspberry Pi, NVIDIA Jetson, or Google Coral.
4. Deployment on Edge Devices
More advanced neural network models such as EfficientNet, YOLO, or Vision Transformers (ViT) can be explored for better accuracy and speed.
Transfer learning techniques can be used to fine-tune pretrained models for fire detection, reducing the need for large custom datasets.
5. MultiHazard Detection
The system can be extended to detect other hazards such as smoke, gas leaks, or explosions.
A multi-hazard detection framework will enhance its applicability in industrial and urban surveillance systems.
6. Integration with Drone Surveillance
Drones equipped with cameras can use the same detection algorithm for aerial fire monitoring in forests, agricultural lands, and large industrial zones.
This will significantly improve early detection in areas not covered by fixed CCTV infrastructure.
7. Research on False Alarm Reduction
Future research can focus on fine-tuning the system to minimize false detections caused by reflections, vehicle lights, or sunlight.
Advanced temporal analysis and background modeling can help the system distinguish real fire events from misleading visual cues.

8.Conclusions:

This survey highlights the growing importance of video analytics and artificial intelligence in developing efficient and intelligent fire detection systems. Traditional fire alarms that rely on smoke, heat, or gas sensors are often limited by delayed response times and a higher chance of false alerts. In contrast, the studies reviewed clearly show that computer vision–based systems can detect fire visually and in real time, offering faster and more reliable warnings. The integration of image processing with deep learning models such as CNNs and RNNs allows the system to accurately recognize fire characteristics like color, texture, and flickering motion even under varying lighting conditions. Furthermore, the modular design and scalability of these systems make them highly adaptable for deployment in a wide range of environments, from industrial settings to smart homes. The use of open-source tools and low-cost hardware, such as Raspberry Pi cameras, also makes these solutions practical and affordable. However, despite the promising results, challenges remain in handling complex backgrounds, smoke detection, and ensuring consistent accuracy across different video sources

9. Acknowledgement

The author would like to express sincere gratitude to the project guide and faculty members of the Computer Science Department for their constant guidance, valuable suggestions, and encouragement throughout the preparation of this survey paper. Special thanks are also extended to the researchers and authors of the referenced works, whose studies and innovations have provided significant insights into the development of real-time fire detection systems using video analytics and artificial intelligence.

10. References

[1] T. Celik, H. Ozkaramanli, and H. Demirel, "Fire and smoke detection without sensors: Image processing based approach," *2007 15th European Signal Processing Conference*, 2007, pp. 1794–1798.

[2] G. Toreyin and A. E. Cetin, "Wildfire detection using LMS based active learning," *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2009, pp. 1461–1464.

[3] P. Dimitropoulos, K. Karpouzis, and S. Kollias, "Flame detection for video-based early fire alarm systems," *Fire Safety Journal*, vol. 44, no. 2, pp. 183–195, 2009.

[4] B. Ko, K. Cheong, and J. Nam, "Fire detection based on vision sensor and support vector machines," *Fire Safety Journal*, vol. 44, no. 3, pp. 322–329, 2009.

[5] Z. Yuan, J. Shi, and Y. Gu, "A real-time video fire flame and smoke detection algorithm," *Procedia Engineering*, vol. 62, pp. 891–898, 2013.

[6] Y. Muhammad and A. Ahmed, "CNN-based real-time fire detection system using surveillance video," *International Journal of Computer Applications*, vol. 180, no. 17, pp. 1–6, 2018.

[7] M. Chino, J. Escobar, and M. Avila, "Fire detection using convolutional neural networks for surveillance systems," *IEEE Latin America Transactions*, vol. 17, no. 9, pp. 1438–1444, 2019.

[8] W. Muhammad, M. Nazir, and S. M. Anwar, "Vision-

based fire detection using deep learning," *Multimedia Tools and Applications*, vol. 80, pp. 24823–24845, 2021.

[9] R. Zhou, J. Wang, and X. Huang, "An intelligent video surveillance system for fire detection using deep convolutional neural networks," *Sensors*, vol. 20, no. 22, pp. 6420–6428, 2020.

[10] N. Li, D. Xu, and L. Chen, "Video-based real-time fire detection using deep learning," *IEEE Access*, vol. 9, pp. 14115–14127, 2021.