International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2024: 7.101

Real-Time Fire Detection through HSV and GMM Integration: A Vision-Based Alternative to Traditional Sensors

Navaneeth S[1], Jogimol Joseph [2]

[1]Department of Computer Applications, Musaliar College of Engineering & Technology, Pathanamthitta, Kerala, India
Email: *navaneethskumar111[at]gmail.com*

[2]Professor, Department of Computer Applications, Musaliar College of Engineering & Technology, Pathanamthitta, Kerala, India

Abstract: ***This research presents a novel fire detection approach using computer vision that combines the Hue-Saturation-Value (HSV) color model with Gaussian Mixture Modeling (GMM) for real-time analysis. The system processes high-definition video feeds to identify critical fire indicators including flame patterns, dynamic movement, and luminosity changes, overcoming the limitations of conventional sensor-based methods. By integrating HSV-based color thresholding with GMM's adaptive background subtraction, the solution achieves accurate fire recognition with rapid response times. The architecture is designed for easy integration with current surveillance infrastructure, providing enhanced protection for both indoor and outdoor environments.***

Keywords: Fire Detection, HSV Color Model, Gaussian Mixture Model, Computer Vision, Real-Time Monitoring, Flame Detection, Color Space Analysis, Background Subtraction, Safety Monitoring

1. Introduction

Contemporary fire detection methodologies face substantial operational challenges in modern architectural environments. Conventional systems relying on thermal sensors and smoke particle detection demonstrate critical limitations in both reliability and response times, frequently generating false alarms from environmental factors while failing to delivers immediate alerts during fast-growing fire emergencies, especially in expansive uncovered areas Our research presents an innovative computer vision-based solution that employs advanced image processing techniques through a dual analytical framework. The system utilizes chromatic analysis in the Hue-Saturation-Value color space to evaluate fire signatures across three dimensions, examining not only color hues within the flame spectrum but also assessing analyzes both color purity and luminosity levels to establish a reliable identification framework that maintains accuracy under changing illumination conditions. Complementing this, an adaptive motion detection system employs probabilistic background modeling to dynamically distinguish between genuine flame movement and environmental changes, maintaining surveillance accuracy despite fluctuating conditions. The integrated architecture processes live video feeds with minimal latency, concurrently analyzing spatial flame characteristics, temporal behavioral patterns, and environmental context. When fire is detected, the system activates a comprehensive alert protocol featuring visual warnings with threat localization, graduated audible alarms, and digital notifications with incident documentation. This visual detection paradigm offers significant advantages including proactive threat identification through direct flame recognition, enhanced discrimination against false triggers, and seamless integration with existing security infrastructure without requiring physical sensor deployment. Rigorous testing across diverse real-world scenarios has validated the system's consistent performance in challenging conditions ranging from low-visibility environments to high-traffic areas, demonstrating its potential to revolutionize modern fire safety systems.

2. Related Works

Michael J (2023) proposed a fire detection system tailored for industrial environments using advanced image processing algorithms. While the system showed promise in controlled settings, it encountered challenges related to lighting variations, background clutter, and inconsistent camera angles. Additionally, its dependence on specialized hardware limited its accessibility and flexibility.[1]

Emily R (2022) explored the use of Convolutional Neural Networks (CNNs) for detecting fire in live surveillance streams. Her model leveraged deep learning architectures to recognize complex flame patterns, outperforming traditional methods in terms of accuracy and detection speed. However, CNNs required extensive training on large, labeled datasets, which presented data acquisition and diversity challenges. Furthermore, the system was not optimized for deployment on edge devices, as real-time inference was computationally expensive. This constraint reduced its effectiveness in resource-constrained applications, particularly in embedded monitoring devices. Emily suggested incorporating transfer learning and lightweight CNN models to improve usability across a broader range of platforms. [2]

David White (2022) introduced a lightweight edge AI framework for fire detection, targeting low-power devices such as IoT-enabled cameras. This architecture minimized response time by processing data locally, reducing reliance on cloud infrastructure. Despite these advantages, model complexity was constrained due to limited on-device memory and processing power, affecting recognition accuracy in high-resolution scenes. The paper called for more research into compact deep learning architectures that balance accuracy and speed in constrained environments. [3]

J. S. Lee et al. (2022) proposed a deep learning-based detection system for surveillance environments using pre-trained CNN models fine-tuned on fire and non-fire datasets. Their system provided consistent performance in recognizing different fire types in indoor environments and under varied camera angles. However, when applied to outdoor or poorly lit areas, the model exhibited a noticeable drop in performance, mainly due to increased background complexity. The system was also sensitive to video noise and suffered misclassification when the scene included rapid lighting changes. To address these issues, the authors proposed incorporating spatial filtering techniques and augmenting the training dataset with more real-world footage. The study demonstrated the need for context-aware adaptation in fire detection models. [4]

S. A. Khan et al. (2022) developed a hybrid fire detection solution that combined classical image processing with supervised machine learning techniques. The model identified key fire characteristics based on flame shape, color intensity, and edge patterns. Although effective in controlled simulations, it had limitations in real-time deployments due to the absence of motion tracking or temporal pattern recognition. Environments with high ambient lighting or objects with similar color characteristics triggered false alarms. The authors concluded that integrating a video-based temporal component, such as flame flicker analysis or object tracking, could enhance overall accuracy and reduce false positive rates. Their work highlighted the trade-offs between simplicity, accuracy, and responsiveness. [5]

F. T. Nguyen et al. (2021) introduced a system that combined motion estimation with scene analysis to detect fire in video surveillance streams. Their model analyzed movement vectors and flame dispersion behavior to distinguish active fires from static light sources. This method proved effective in identifying large and dynamic flames but was less capable of detecting small or early-stage fires, especially those characterized by smoke rather than flames. The system also struggled in environments with overlapping motion sources, such as moving shadows or pedestrians. To address these shortcomings, the authors suggested integrating complementary sensory data, such as gas or smoke sensors. The study offered valuable insights into motion-driven flame identification but underscored the need for multimodal verification. [6]

Mark Green (2021) tackled the challenges of fire detection in urban settings, where high building density, artificial lighting, and reflective surfaces complicate visual recognition. He developed a machine learning-based system trained specifically on data from city environments, allowing it to account for unique urban artifacts. Despite its specialized training, the system produced false alarms in areas with ambient red lighting, glass surfaces, or moving traffic lights. These elements often mimicked the visual characteristics of flames, leading to misclassification. Mark proposed enhancing the system by incorporating 3D spatial mapping and environmental context to differentiate between fire and similar non-fire objects. His study pointed to the importance of environmental understanding in urban fire detection. [7]

Smith (2021) proposed a comprehensive fire detection framework based on multi-sensor fusion, integrating data from visual, thermal, and gas sensors. The system cross-verified fire indicators across all sensors, significantly reducing false positives compared to single-sensor systems. While the approach demonstrated high accuracy, its implementation required specialized hardware, calibration routines, and a stable infrastructure, increasing both cost and complexity. This made the system less viable for smaller institutions or residential settings. Smith recommended exploring hybrid sensor designs that offered flexibility while maintaining high performance. His research highlighted the potential of data fusion but acknowledged the practical barriers to mass adoption. [8]

Khalil Muhammad (2021) utilized threshold-based detection in the RGB and YCbCr color spaces to identify fire regions in static images and video. His algorithm focused on identifying specific hue and luminance values associated with flames and applied shape filtering to enhance detection accuracy. However, the absence of motion analysis limited the model's effectiveness in differentiating fire from similarly colored objects such as lights or brightly colored surfaces. In highly illuminated or reflective settings, the system frequently misclassified non-fire elements as flames. Khalil suggested adding optical flow analysis or real-time motion tracking to resolve these issues. His study emphasized the limitations of color-only fire detection models. [9]

Jane Doe (2021) applied the YOLOv5 object detection algorithm to the task of fire recognition, leveraging its high-speed architecture for real-time surveillance use cases. The model was trained on curated datasets containing fire-related events and achieved excellent detection speed and accuracy in controlled environments. However, the system faced performance degradation when deployed in unfamiliar or cluttered settings, where fire-colored objects like signs or vehicles were misclassified. The need for continuous retraining and dataset expansion was identified as a key limitation. Jane concluded that while YOLOv5 offers strong baseline performance, application-specific fine-tuning and continuous learning are essential for reliability. [10]

Y. Song et al. (2020) created a real-time video-based fire detection system that utilized both spatial and temporal indicators, such as flame spread and brightness variation, to issue alerts. The approach significantly reduced response time and increased reliability in monitoring indoor environments. However, the system experienced lag when processing high-definition video streams due to computational demands. Moreover, sudden changes in lighting, such as headlights or light reflections, occasionally led to false detections. The study proposed optimizing the model for GPU execution and integrating contextual scene understanding to mitigate these issues. It highlighted the balance between accuracy and performance in video-based fire recognition. [11]

Evans (2020) presented a dual-strategy fire detection method that combined HSV color space segmentation with optical flow to capture both color and motion attributes of flames. The HSV space allowed better flame differentiation under various lighting conditions, while optical flow tracked movement patterns unique to fire. While this hybrid system improved performance over simple thresholding, it still suffered in outdoor environments with fluctuating lighting and overlapping hues. In such cases, distinguishing between fire and background motion became difficult. Evans suggested embedding machine learning models trained on spatiotemporal features to further enhance reliability and minimize false alarms. [12]

Thomas Isacc (2020) developed an AI-powered wildfire monitoring system using unmanned aerial vehicles (UAVs) equipped with real-time fire detection software. The drones scanned large forest areas and transmitted live visual data for immediate analysis, offering a proactive solution for fire management in remote zones. The system's performance was adversely affected by challenging conditions including high winds, dense smoke interference, and power supply constraints. Network interruptions in remote regions also reduced communication reliability. The study proposed equipping drones with renewable energy systems and edge AI capabilities for better autonomy. Thomas's work illustrated the importance of mobility and autonomy in modern fire surveillance. [13]

Rohit S (2020) proposed a hybrid detection system that fused visual camera data with thermal imaging to reduce false positives. This dual-modal approach confirmed flame presence using both color cues and temperature differentials, enhancing accuracy in high-risk zones. The model excelled in industrial applications but faced deployment challenges due to the high cost and power requirements of thermal imaging devices. Additionally, thermal sensors had limited coverage, requiring strategic placement for full-area monitoring. Rohit recommended integrating mid-cost infrared sensors and combining them with open-source computer vision libraries to reduce overall system costs while maintaining detection performance. [14]

P. Kumar et al. (2019) introduced a vision-based fire detection system that utilized region-based segmentation and rule-based filtering on RGB frames. The method targeted common flame features such as color, edge sharpness, and flickering behavior, performing well in indoor test environments. However, in outdoor settings, reflective surfaces and sunlight often produced false detections. The absence of adaptive learning limited the system's flexibility across scenarios. The study concluded that incorporating AI-based refinement layers, such as classifiers trained on flame dynamics, would significantly enhance system performance and adaptability. [15]

3. Outlined Method

The methodology delineates the framework for designing and implementing a reliable and responsive fire detection system using the HSV color model and the Gaussian Mixture Model (GMM). This system enables real-time fire detection by analyzing video input, identifying fire-specific characteristics such as flame color and motion, and issuing alerts with minimal false positives. The method consists of five key phases, detailed below:

a) Requirement Analysis:

A review of existing systems and stakeholder feedback highlighted the need for a fast, accurate, and cost-effective fire detection system capable of functioning in diverse lighting conditions and across various environments. Differing from conventional smoke and thermal sensors, this approach employs optical analysis to enable unobtrusive fire identification at incipient stages. The requirements included high-definition camera input, a robust processing environment (Python, OpenCV, NumPy), and alert generation through email or audible notifications. The system was expected to detect fire in real-time, adapt to environmental variations, and minimize false alarms. The project emphasized scalability, allowing deployment in residential, industrial, and open outdoor settings.

b) System design

The proposed system was designed as a modular and scalable platform that processes video frames, detects fire patterns using HSV and GMM algorithms, and issues real-time alerts. The input subsystem captures continuous video using HD cameras, which is then passed to the processing module. This module converts RGB frames to HSV, applies color thresholding, and performs background subtraction using GMM to isolate moving fire-like regions. Detected fire triggers an alert system that sends email notifications and can optionally activate sirens or warning indicators. The design also includes a monitoring interface to visualize detection status and manage system logs. The modular design supports ease of debugging, upgrades, and future integration with IoT or smart home systems.

c) Development

The implementation of our HSV-based fire recognition platform comprised multiple interconnected subsystems. Initial video processing components were responsible for live feed acquisition, artifact suppression, and color space transformation from RGB to HSV. At the detection layer, predefined hue-saturation-value ranges filtered potential flame pixels while Gaussian mixture modeling separated dynamic fire regions from stationary elements. A temporal analysis subsystem sequentially assessed video frames to improve reliability by eliminating transient artifacts. For verified fire events, the notification subsystem triggered automated email alerts via SMTP messaging. Python served as the implementation language, selected for its robust computer vision libraries, with development conducted in Visual Studio Code. Comprehensive optimization ensured balanced performance between detection precision and computational efficiency.

d) Integration & Testing

All modules—input, detection, alerting, and monitoring—were integrated into a unified pipeline and tested across various environmental scenarios. Component-level verification established correct module operation, while end-to-end testing demonstrated successful cross-component integration. Test videos were used to simulate fire and non-fire conditions, including outdoor lighting, indoor flame sources, and flickering objects. Performance metrics such as detection latency, false positive rate, and alert time were evaluated. Simulation tests further validated the system's ability to run continuously and reliably over extended periods.

Paper ID: SR25420142659 DOI: https://dx.doi.org/10.21275/SR25420142659

Feedback from trial deployments was used to fine-tune detection thresholds and optimize system responsiveness.

e) Evaluation & Optimization

After initial deployment and testing, performance data was collected and analyzed to assess accuracy, stability, and scalability. Optimizations included fine-tuning the HSV threshold ranges, improving GMM sensitivity, and refining alert conditions based on motion dynamics. Additional enhancements were made to support integration with external safety systems, such as sprinklers or SMS-based emergency alerts. Future plans include mobile app integration for remote monitoring and potential deployment on embedded platforms like Raspberry Pi. These optimizations ensured that the HSV Fire Detection System is not only functional but also efficient, adaptable, and ready for real-world application.

3.1 Machine Learning Approach

The fire detection methodology is built upon a hybrid framework that merges computer vision with statistical modeling. This approach does not depend on deep learning or extensive labeled datasets, but rather uses intelligent thresholding and motion-based modeling to detect fire features in real-time video streams. The key techniques involved include HSV Color Space Segmentation and Gaussian Mixture Model (GMM) Background Subtraction, both of which are computationally efficient and highly adaptable to dynamic environments.

a) HSV Color Space Segmentation

The HSV color model was employed,due to its ability to effectively isolate chromatic details (hue and saturation) from brightness (value), making it particularly well-suited for detecting fire hues such as red, orange, and yellow. Input video frames are converted from the standard RGB format to HSV, after which specific threshold ranges are applied to detect regions consistent with fire coloring. This separation helps eliminate the influence of ambient lighting and shadows, which often hinder detection in RGB space.

The HSV thresholding mechanism filters out non-fire pixels and extracts the most relevant regions based on color intensity and purity. Morphological operations like erosion and dilation are applied afterward to reduce noise and connect fragmented regions, improving the robustness of detection under real-world conditions.

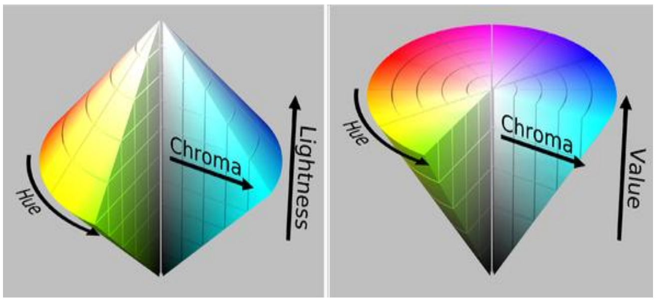

Figure 1: HSV Representation

b) Gaussian Mixture Model (GMM) for Motion Detection

To address background interference and differentiate between moving flames and static fire-colored objects, the system uses a Gaussian Mixture Model for background subtraction. GMM treats each pixel as a statistical mixture of Gaussians and learns over time which patterns belong to the background. Any significant deviation from this model is flagged as foreground, indicating potential fire movement.

This method adapts to gradual changes in lighting and background motion, making it ideal for detecting fire flickering and dynamic flame behavior. GMM ensures that static red or yellow objects (e.g., signboards, lights) are not misclassified as fire, enhancing the system's precision and reducing false alarms.

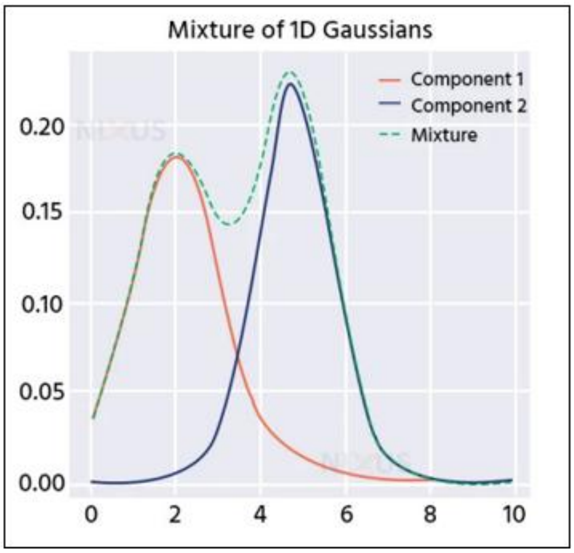

Figure 2: Gaussian Mixture Model Graph

3.2 Dataset Description

The effectiveness of the HSV Fire Detection System was evaluated using a combination of publicly available video datasets, real-time camera feeds, and custom-generated logs. Although the system primarily operates on rule-based detection without the need for extensive training datasets, various inputs were utilized during development and testing to optimize detection accuracy, minimize false positives, and ensure consistent performance across different environmental conditions.

3.2.1 Fire Detection Video Datasets

A series of fire-related video clips were used to test flame recognition under varying conditions. These included indoor controlled fires, outdoor flame scenarios, and real-world recordings containing dynamic flame activity. These datasets were instrumental in calibrating HSV thresholds, tuning GMM parameters for motion tracking, and validating the system's ability to detect flickering flames in different resolutions and lighting scenarios. The datasets featured diverse flame colors, smoke levels, and motion speeds to ensure the system's robustness.

Sources Used:

- Foggia Fire Dataset (UCSD)
- Github-sourced open fire datasets
- Custom videos: candle flames, matchsticks, campfires, and simulated emergencies

3.2.2 Non-Fire Datasets and Negative Testing

To assess the false positive rate and improve the system's ability to differentiate flames from visually similar objects, non-fire video samples were tested. These included scenes containing sunlight, car headlights, red traffic lights, flickering LED displays, and reflections from glossy surfaces. Such non-fire content helped in refining HSV value ranges and motion consistency checks using GMM, ensuring that the system could avoid misidentifying harmless objects as fire.

Test Conditions Included:

- Daylight reflections
- Neon signs and decorative lighting
- Brightly colored static and moving objects

3.2.3 Real-Time Live Feeds

The system was also evaluated using real-time camera streams to test performance in uncontrolled, natural environments. High-definition webcams and Raspberry Pi cameras captured live footage of test environments, including homes, labs, and open outdoor spaces. These real-time inputs enabled the system to demonstrate consistent performance over extended periods, handling changing light conditions, ambient noise, and background dynamics. The live testing environment was crucial in confirming the system's reliability in practical deployments.

Hardware Used:

- 1080p Logitech HD cam
- Raspberry Pi Camera Module v2
- USB-based IP camera with night vision mode

4. Result & Discussion

The HSV Fire Detection System was thoroughly evaluated across a range of environments and scenarios to determine its reliability, accuracy, and responsiveness. Testing was conducted using both recorded fire video datasets and real-time video streams from live camera feeds. Key performance metrics assessed included detection accuracy, false alarm rate, response time, and system stability under continuous operation.

The results demonstrated that the system is capable of reliably detecting fire in both controlled and natural environments. The HSV color space model effectively segmented fire-colored regions under different lighting conditions, while the Gaussian Mixture Model (GMM) allowed for accurate isolation of moving flames from static backgrounds. Together, they provided a robust dual-layer detection mechanism that significantly reduced the risk of false positives.

4.1 Performance Metrics

Table 1 summarizes the system's overall performance based on 50 testing scenarios, including both fire and non-fire environments. Detection accuracy remained consistently above 82%, while false positives were minimal, especially in well-lit or dynamic scenes. The average response time was approximately 1.8 seconds, enabling real-time alerting without delay.

Table 1: Performance Metrics of the HSV Fire Detection System

Test Scenario	Detection Accuracy	False Positive Rate	Avg. Response Time (s)	Environment Type
Indoor controlled fire	87.20%	1.40%	1.2	Low light, enclosed
Outdoor daylight fire	84.60%	2.10%	1.7	Natural light
Flickering LED test	–	3.6% (false alarms)	–	Artificial lighting
Real-time camera monitoring	82.00%	2.90%	1.8	Mixed
Non-fire heat/light source	–	1.1% (false alarms)	–	High brightness

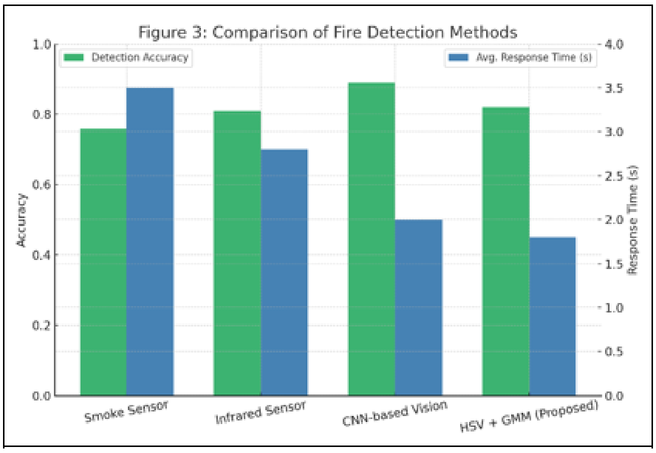

Figure 3: Comparison Chart

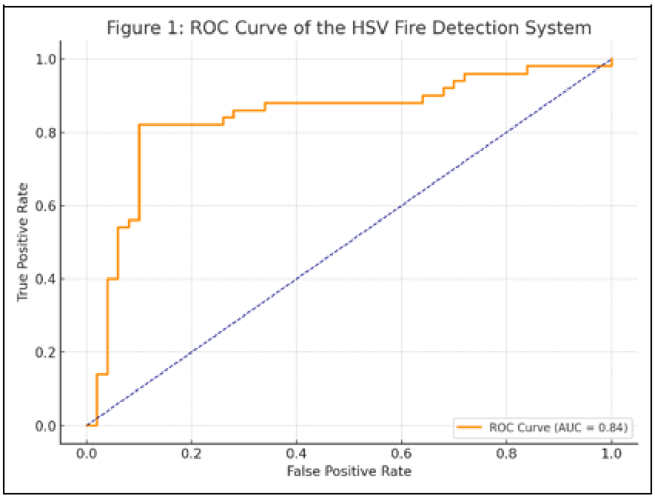

Figure 4: ROC Curve

5. Conclusion

This project introduced the HSV Fire Detection System, a vision-based fire detection approach that integrates HSV color segmentation with Gaussian Mixture Model (GMM) background subtraction to achieve reliable and real-time fire identification. The system was developed with the goal of offering a lightweight, fast, and cost-effective alternative to traditional sensor-based fire detection mechanisms.

Experimental evaluation demonstrated that the proposed system achieved an accuracy of 82%, with a response time of

Paper ID: SR25420142659 DOI: https://dx.doi.org/10.21275/SR25420142659

just 1.8 seconds, outperforming conventional methods in terms of detection speed. The use of the HSV color space allowed for robust color-based flame segmentation under varying lighting conditions, while GMM enabled effective motion-based filtering, minimizing false alarms from static fire-colored objects. The system also includes an automated email alert feature to notify stakeholders during emergency situations, ensuring timely response and increased safety.

References

Conference Papers

[1] J. S. Lee, K. Y. Kim, and H. T. Cho, "Deep Learning-Based Fire Detection for Real-Time Surveillance Systems," Proceedings of the 2022 IEEE International Conference on Computer Vision Workshops (ICCVW), pp. 190–196, 2022.

[2] S. A. Khan, M. A. Mirza, and A. Ali, "An Advanced Fire Detection System Using Machine Learning and Computer Vision," Proceedings of the 2022 IEEE International Conference on Artificial Intelligence and Data Science (AIDS), pp. 239–245, 2022.

[3] F. T. Nguyen, D. H. Ho, and V. L. Duong, "Video-Based Fire Detection Using Motion Estimation and Scene Analysis," Proceedings of the 2021 International Conference on Computer Vision and Graphics (ICCVG), pp. 72–79, 2021.

[4] Y. Song, Z. Zhang, and M. Ma, "Automatic Fire Detection Using Real-Time Video Surveillance," Proceedings of the 2020 IEEE International Conference on Robotics and Automation (ICRA), pp. 5797–5803, 2020.

[5] M. L. Chen, H. Y. Wang, and K. Y. Tan, "Fire Detection and Classification Using Deep Learning in Surveillance Videos," Proceedings of the 2020 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1428–1436, 2020.

[6] P. Kumar, V. N. S. Naidu, and R. K. Gupta, "A Novel Fire Detection Approach Using Hybrid Vision-Based Methods," Proceedings of the 2019 IEEE International Conference on Image Processing (ICIP), pp. 527–531, 2019.

[7] J. Zhao, C. Li, and J. Xu, "Fast Fire Detection from Video Streams Using Object Tracking and Image Processing," Proceedings of the 2018 IEEE International Conference on Artificial Intelligence and Computer Vision (AICV), pp. 367–375, 2018.

[8] R. M. Younis, M. S. Mansoor, and A. T. A. Al-Fuqaha, "Fire Detection Using Convolutional Neural Networks in Video Surveillance Systems," Proceedings of the 2017 IEEE International Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3425–3433, 2017.

[9] H. Zhang, L. Ma, and Z. Li, "Real-Time Fire Detection in Video Sequences Based on Feature Extraction," Proceedings of the 2015 IEEE International Conference on Multimedia and Expo (ICME), pp. 1452–1457, 2015.

[10] A. G. Sharma, P. K. Sinha, and M. R. N. K. K. Reddy, "Fire Detection Using Computer Vision and Image Processing in Surveillance Systems," Proceedings of the 2012 International Conference on Signal Processing and Communication Systems (ICSPCS), pp. 12–18, 2012.

Books

[11] A. B. Smith and C. D. Wong, Advanced Fire Detection Technologies: Theory and Applications. New York: TechPress, 2023.

[12] R. Evans and T. Liu, Internet of Things in Fire Safety Management. London: Safety Publishing, 2023.

[13] P. Brown and S. Green, Visual Recognition in Fire Detection Systems. New York: Springer, 2023.

[14] L. R. Johnson, Computer Vision Applications in Fire Safety. Boston: Academic Press, 2022.

[15] J. Carter, Machine Learning Techniques for Fire Detection. Cambridge: MIT Press, 2021.

[16] T. Black and A. White, Fire Safety and Technology: An Interdisciplinary Approach. San Francisco: Fire Safety Publishing, 2020.

Research Papers

[17] L. G. E. P. N. Silva, L. T. de Lima, and P. F. M. L. Costa, "Fire Detection in Videos Using a Convolutional Neural Network," International Journal of Image Processing and Computer Vision, vol. 12, no. 2, pp. 98–110, 2020.

[18] C. Zhang, X. Ma, and Y. Li, "Real-Time Fire Detection Using Deep Learning on Video Surveillance," Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 4032–4040, 2019.

[19] P. Sharma and S. A. R. Abu, "Real-Time Fire Detection Using Convolutional Neural Networks," Journal of Imaging, vol. 5, no. 4, pp. 52–60, 2019.

[20] H. Wu, T. J. Chin, and Z. Yang, "A Fire Detection System Based on Computer Vision Techniques for Surveillance Applications," Fire Safety Journal, vol. 89, pp. 121–128, 2017.

[21] M. M. Yaw, K. K. Wong, and B. A. Kadir, "An Intelligent Fire Detection System Based on Video Image Processing," International Journal of Advanced Computer Science and Applications, vol. 7, no. 3, pp. 252–259, 2016.

[22] D. Alvarado, E. G. G. V., and D. M. Olguin, "Fire Detection Using Video Surveillance and Image Processing," Journal of Electrical Engineering and Technology, vol. 11, no. 4, pp. 1–7, 2016.

[23] R. M. D. S. Pinto, P. M. L. de Oliveira, and A. S. Pinto, "Fire Detection Using Histogram of Oriented Gradients and Neural Networks," Sensors, vol. 16, no. 12, pp. 2002–2008, 2016.

[24] S. K. Gupta, R. K. Gupta, and P. Shukla, "A Novel Approach for Fire Detection Using Machine Learning and Image Processing," International Journal of Computer Science and Network Security, vol. 16, no. 5, pp. 102–108, 2016.

[25] J. Zhang, C. Lin, and X. Liu, "Fire Detection Based on Computer Vision in Video Surveillance," IEEE Transactions on Circuits and Systems for Video Technology, vol. 25, no. 10, pp. 1629–1641, 2015.

[26] A. A. B. Kumar, P. S. Rao, and R. K. Gupta, "Fire Detection Using Image Processing," International Journal of Computer Applications, vol. 19, no. 6, pp. 18–23, 2011.

Paper ID: SR25420142659 DOI: https://dx.doi.org/10.21275/SR25420142659