iJRASET
International Journal For Research in Applied Science and Engineering Technology


INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: III Month of publication: March 2025

DOI: https://doi.org/10.22214/ijraset.2025.67910

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 13 Issue III Mar 2025- Available at www.ijraset.com*

# Power Predictive Modeling for Fire Hazards Using Machine Learning

Rashika M E
*Faculty, Government Tool Room and Training Centre, Bengaluru*

***Abstract: This paper presents a fire prediction protocol that integrates deep learning techniques with Internet of Things (IoT) infrastructure for rapid fire detection and enhanced safety measures. The proposed system utilizes an optimized YOLO model for real-time flame detection by processing video and images based on color, temperature, and shape analysis, achieving an accuracy of up to 81% in fire hazard detection. It incorporates flame and smoke sensors for hazard detection, triggering local alerts via a buzzer and LED, and providing remote warnings to users through a Telegram bot. The system architecture encompasses sensor selection, design, and hardware / software implementation using the Arduino IDE. Test results demonstrate improved response time and notification reliability, validating the system's efficiency in enhancing fire safety.***
***Keywords: Fire Prediction, Deep Learning, YOLO, IoT, Sensor Integration, Real-time Detection, Telegram Bot.***

## I. INTRODUCTION

Fire safety and the early detection of potential fire hazards are crucial in both residential and industrial settings. Traditional fire detection systems often suffer from delayed response times and limited remote monitoring capabilities. This project aims to develop a system for fire and smoke detection using flame and MQ2 sensors. By integrating these sensors with deep learning techniques, specifically optimized YOLO models, and incorporating Telegram alerts, the system aims to enhance the accuracy and reliability of fire detection. The motivation for this project stems from the growing need for improved fire detection systems that can provide both local and remote alerts, a capability offered by modern IoT solutions.

The research questions guiding this investigation include: What techniques are applicable in flame detection, such as color models and deep learning techniques like Convolution Neural Networks (CNNs)? How effective are these methods in terms of performance? Which technique, shallow or deep learning, performs better in fire detection, and is deep learning beneficial for this purpose? How can IoT technology be integrated with deep learning based detection methods to facilitate live hazard monitoring and alert triggering?

The contributions of this report include:

*1)* A holistic fire detection system combining shallow learning (color models and RGB/HSI combination) and deep learning (CNNs).
*2)* Integration of IoT infrastructure for real-time monitoring and alerts.
*3)* Utilization of an optimized YOLO model to investigate the improvement in flame detection accuracy through deep learning. The training set includes 172 flame images, augmented to 1,720.
*4)* An IoT based alert system using flame and MQ2 smoke sensors connected to an Arduino.
*5)* Features of the system include real time monitoring, local alerts (buzzer and LED), instant Telegram notifications, and remote monitoring.
*6)* The system architecture comprises flame and smoke sensors, Arduino microcontroller, remote instant notifications, and a local alarm system.

The objectives of this report are to design an integrated fire detection and alerting system including: Advanced machine learning techniques for flame detection, utilizing color based models and CNNs, including the optimized YOLO framework and a comparison between shallow and deep learning; A sensor based detection system using flame and smoke sensors for real time monitoring, control, and immediate Telegram alerts; A hybrid system combining deep learning based fire prediction, physical sensors, and a remote notification system for comprehensive hazard monitoring. This research seeks to improve fire detection time and provide real time alerts through advanced machine learning techniques.

## II. LITERATURE SURVEY

Flame detection is a critical aspect of fire safety management, with various methods aimed at enhancing detection precision and response time. This survey focuses on flame detection techniques, including color models, motion models, and shape models, as well as deep learning methods and the integration of IoT technology with a Telegram bot for real time alerts.

### A. *Study of Articles*

1) Color Model for Fire Detection: This study explores the use of HSI, RGB, and YCyCbCr color spaces for flame recognition in digital images, achieving detection rates exceeding 99%.
2) Deep Learning for Flame Detection: This paper highlights the benefits of deep learning techniques, particularly CNNs, showing over 98% accuracy in flame detection.
3) IoT Based Fire Detection Using Gas and Smoke Sensors: This article discusses the implementation of IoT based MQ-2 gas sensors for real time fire detection.
4) Image-Based Smoke Detection Using Machine Learning: This research focuses on detecting smoke in digital images using SVMs, showing over 95% accuracy.
5) Hybrid IoT and Deep Learning for Prediction in Fire: This article presents a hybrid fire prediction system that integrates IoT devices with deep learning models, indicating maximum accuracy in fire prediction.
6) Motion-Based Flame Detection: This paper introduces a new approach for flame detection based on motion analysis in videos.
7) Sensor Fusion for Fire Detection: This paper addresses the integration of multiple sensors to enhance fire detection precision using a Bayesian network based approach.
8) CNNs for Image-Based Fire Detection: The main focus of this article is the use of CNNs in image data processing for fire detection, achieving over 97% accuracy.
9) Edge Computing for Fire Detection Using IoT: This research explores the application of edge computing to enable IoT based fire detection systems, improving system performance during emergencies.
10) Multi-Spectral Flame Detection: This article discusses the use of multi spectral imaging for flame detection, performing significantly better in detecting fire in various environments with fewer false alarms.
11) Comparison and Summary A comparison of the reviewed articles highlights the diverse approaches and advancements in flame detection technologies. The integration of IoT technology with sensors and deep learning models, along with remote alerting mechanisms like Telegram bots, shows significant potential for improving fire response systems.

| Article | Problem Addressed | Implementation and Results | Limitations/Future Scope |
|---|---|---|---|
| A: Color Model for Fire Detection (Yang et al., 2007) | Flame detection in digital images using color spaces | Combined HSI, RGB, and YCbCr models; achieved greater than 99% accuracy. | Limited robustness to environmental noise; future scope includes integrating with deep learning models. |
| B: Deep Learning for Flame Detection (Wan et al., 2014) | Enhancing detection accuracy using CNNs | Used CNNs with layer wise training; achieved greater than 98% accuracy with reduced false alarms. | Requires extensive Computational resources; future work involves edge based processing. |
| C: IoT-based Fire Detection (Elprocus, 2023) | Real time fire detection using sensors | Utilized MQ-2 sensors; achieved reliable fire detection with real-time monitoring. | Accuracy depends on sensor placement; integrating with predictive analytics can enhance performance. |
| D: Image-Based Smoke Detection (Koet al., 2009) | Smoke detection in digital images using SVMs | The method uses SVMs to classify fire pixels based on spectral and temporal features with (approx) 95% accuracy. | This system tends to generate false positives in foggy or low light situations, whereas future work needs to introduce some more temporal features to enhance robustness. |

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 13 Issue III Mar 2025- Available at www.ijraset.com*

| | | | |
|---|---|---|---|
| E: Hybrid IoT And Deep Learning for Fire Prediction (Kong et al., 2016) | Combining IoT sensors and deep learning for fire prediction | Used multi layered ANN with real-time sensor data; achieved high accuracy in fire prediction. | High latency due to centralized processing; edge computing can address this limitation. |
| F: Motion-Based Flame Detection (Qi & Ebert, 2009) | Detecting flames in videos using motion analysis | Optical flow techniques provided accurate detection in dynamic environments. | Computationally expensive for real-time applications; scope for optimization through lightweight algorithms. |
| F:Sensor Fusion for Fire Detection (Celiketal., 2007) | Enhancing accuracy through multi sensor data fusion | Bayesian networks fused flame, smoke, and temperature data; improved reliability. | Sensor cost and complexity; scope for reducing system complexity without compromising accuracy. |
| G: CNNs for Fire Detection (Chan et al., 2015) | Accurate flame classification using CNNs | Convolution layers extracted features; achieved greater than 97% accuracy. | Limited by data set diversity; future work involves expanding datasets and applying transfer learning techniques. |
| H: Edge Computing for IoT Fire Detection (Schmidhuber, 2015) | Reducing latency in IoT fire detection systems | Local edge processing reduced cloud dependency; improved real time detection. | Limited processing power at the edge; future scope involves incorporating hybrid edge cloud architectures. |
| I: Multi-Spectral Flame Detection (Celik & Demirel, 2009) | Flame detection across multiple wavelengths | Multi spectral imaging enhanced accuracy in diverse conditions with fewer false alarms. | High hardware costs; potential for integrating with low cost imaging techniques like infrared cameras. |

## III. SOFTWARE AND HARDWARE REQUIREMENTS

The fire detection system requires specific software and hardware components to ensure real time detection, sensor integration, and effective alerting.

### A. *Functional Requirements*

1) Real-Time Detection: The system must detect flames and smoke promptly.
2) Sensor Integration: The system must integrate multiple sensors, including gas sensors and smoke sensors.
3) Hardware Requirements and Alert Process: The system must detect flames using a flame sensor connected to the ESP8266 microcontroller, sending alerts via a Telegram bot and activating local alerts (LED and buzzer) upon detection.

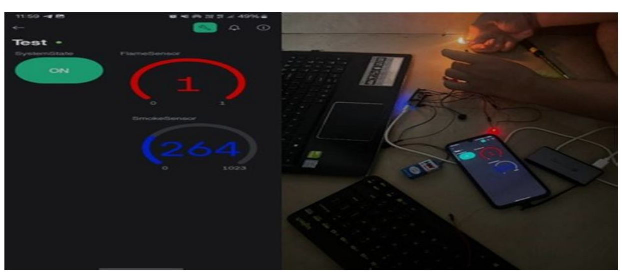


Figure A.1: Different regions of a fire flame

### B. *Non-Functional Requirements*

1) Safety Requirements: The system must minimize false alarms and achieve a detection accuracy rate of over 95%.
2) Performance Requirements: Image data should be processed with minimal latency for timely alerts.
3) Color Space Models: HSI, combination of RGB and HSI, and YCbCr models enhance flame detection.
4) Deep Learning: CNNs are particularly effective for image classification and object recognition.
5) Telegram Bot Integration: Ensures timely alerts and provides a user friendly interface.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 13 Issue III Mar 2025- Available at www.ijraset.com*

### *C. Hardware and Software Requirements*

1) Hardware Requirements: Flame sensor, smoke sensor (MQ-2), microcontroller (ESP8266), power supply, local alarm system (LED and buzzer).
2) Software Requirements: Arduino IDE for microcontroller coding. Python 3.9+, Tensor Flow/Keras, OpenCV, NumPy, pandas, Telegram API for the deep learning model and alert system.

Gas Sensors: Such as MQ-2 or MQ-7 for detecting combustible gases.

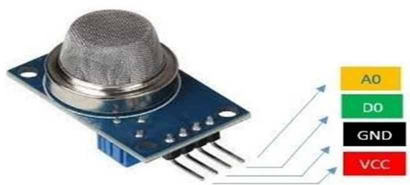



Figure C.1: MQ-2 Smoke Sensor

Smoke Sensors: Optical or ionization smoke detectors for detecting smoke particles.

Figure C.2: Flame Sensor [Digital]

Figure C.3: Node MCU/ESP8266

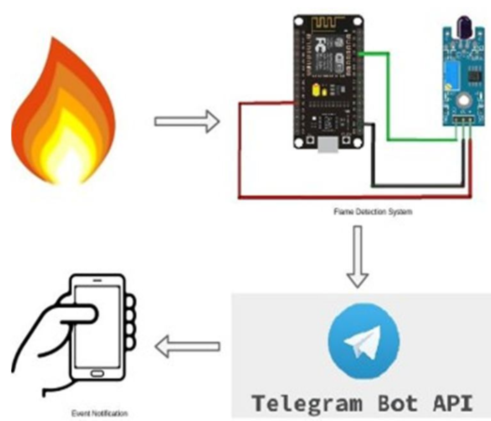



Figure C.4: Alert Mechanism

### *D. Performance Requirements*

The model achieved an accuracy of 81%.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
*ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538*
*Volume 13 Issue III Mar 2025- Available at www.ijraset.com*

## IV. SYSTEM DESIGN

The fire detection system integrates IoT based hardware and deep learning algorithms to provide a robust solution for fire detection and forecasting. The system employs a dual approach: IoT Implementation for real time sensor data processing and Deep Learning Integration using a CNN model to analyze image data. Key features include real-time detection via IoT sensors, advanced prediction using CNNs, and alerts through a Telegram bot for remote monitoring.

1) Shallow Learning Design: Three color based models (RGB, HSI, and their combination) are used to extract fire flames from images.
2) Design of Deep Learning Model: An optimized YOLO v5 model is used for real time object detection, trained on a data set of 172 flame images, augmented to 1,720.

## V. IMPLEMENTATION

This project implements a system integrating hardware components with real time functionality, a deep learning model, and alert signals. Flame and smoke sensors are combined with a YOLO based model for accurate fire identification.

### *A. Hardware Installation*

Includes flame sensor, smoke sensor (MQ-2), microcontroller (ESP8266), power supply, and a local alarm system (LED and buzzer).

#### *1) Architectural Diagram*

This section provides an overview of the system's architecture and its implementation process. Figures V.1 and V.2 illustrate the architectural designs for hardware and the integration of hardware and software, respectively.

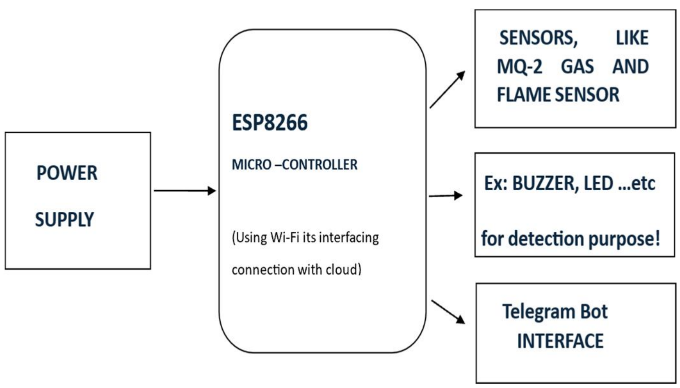



Figure V.1: Architectural Design of Hardware

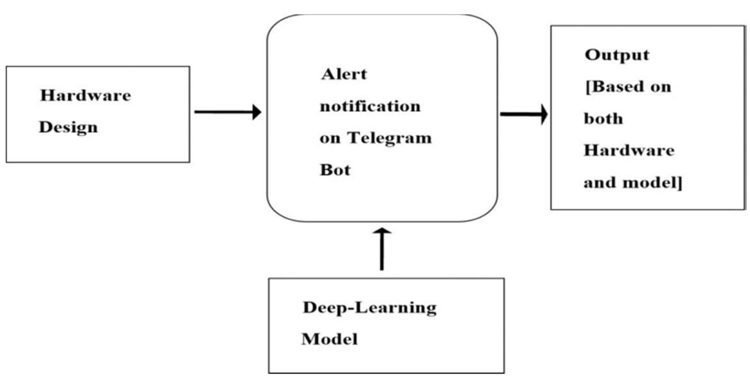



Figure V.2: Architectural Design of Hardware and Software Working Together

### *B. Software Implementation*

1) Deep Learning Model: An optimized YOLO v5 model was trained using Python 3.9, Tensor Flow/ Keras, and Open CV, achieving an accuracy of 81%.
2) Data Integration: Sensor data is transmitted and combined with deep learning model predictions.
3) Alert Mechanism: A Telegram bot alerts users through the Telegram API.

### C. Code Used
The ESP8266 microcontroller was coded using Arduino IDE.

### D. System Integration
Hardware and software coordination ensures sensor data synchronization with deep learning predictions, with local alerts activating immediately upon sensor detection.

### E. Testing and Validations
Hardware, software, and system testing were conducted.

### F. Training Dataset
The data set consisted of 172 fire flame images, augmented to 1,720.


Figure F.1: Training samples based on image enhancement

Training involves 20 epochs of pre-training and 40 epochs of formal training, totaling 60 epochs (10,320 training iterations)

## VI. RESULTS AND DISCUSSION
The implemented fire detection system showed a significant improvement in response time and accuracy compared to traditional methods. The optimized YOLO model achieved 81 percent accuracy for flame detection. The IoT based notification system reliably delivered real time alerts via the Telegram bot. The system underwent rigorous testing under various conditions. Key strengths included reliable data transmission and rapid detection. Limitations such as occasional false positives and sensor instability were noted for future improvements.

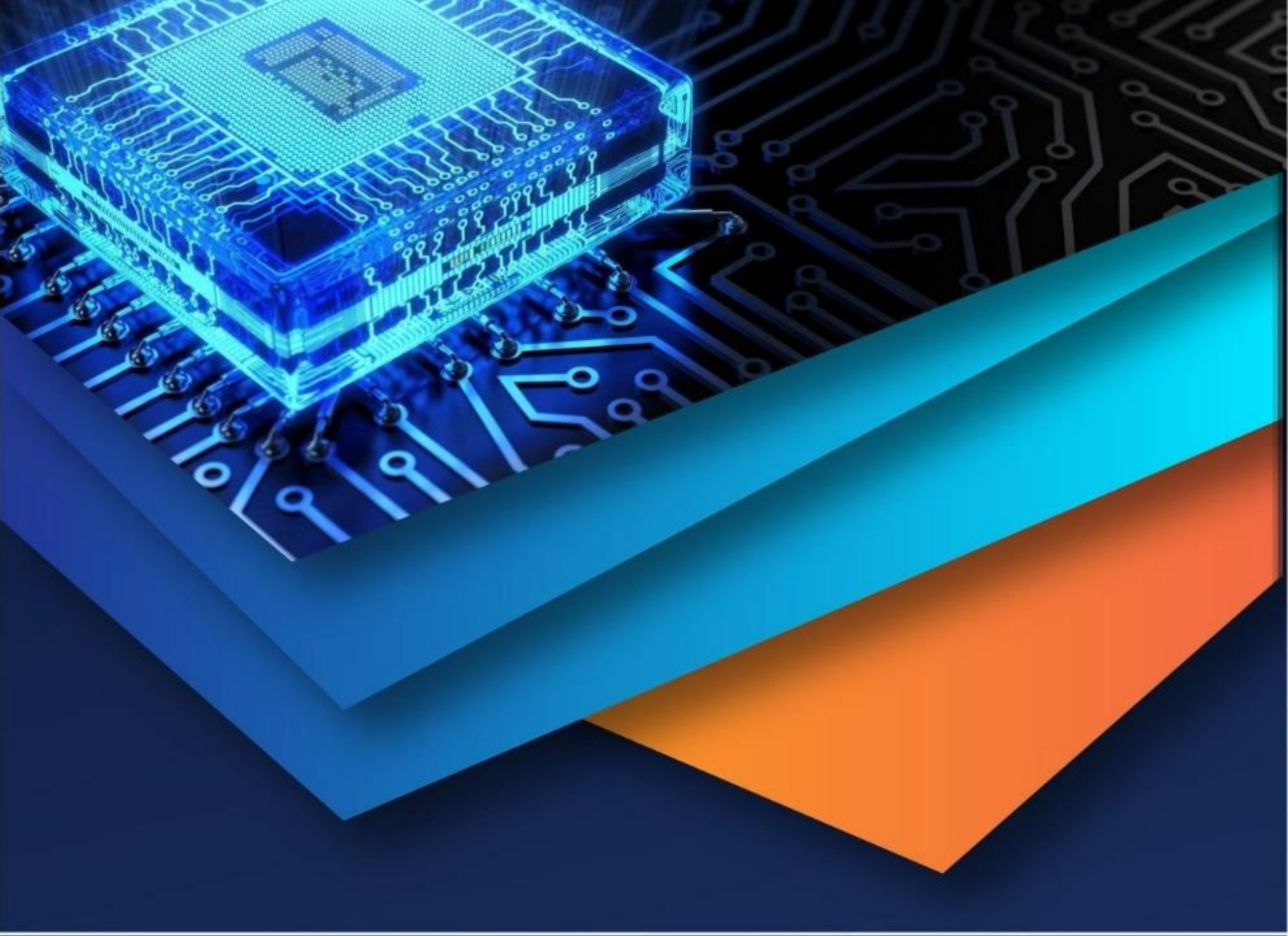
## VII. CONCLUSION
The Machine Learning Driven Protocol for Fire Prediction project successfully integrated hardware based IoT implementations and advanced machine learning techniques to develop efficient and scalable fire detection and alerting system. The system effectively combines real time data collection from sensors with machine learning algorithms for fire prediction and a Telegram bot for immediate user notifications. The project explored both shallow and deep learning methods, with deep learning showing superior performance. The integration of IoT and machine learning provides a synergistic approach to address real world fire detection challenges.

### A. Future Works
Include incorporation of additional sensors, real time image processing, edge computing implementation, advanced notification mechanisms, expanded dataset and integration with firefighting systems, energy optimization, and deployment in diverse environments.

## VIII. ACKNOWLEDGMENT
The authors would like to acknowledge the resources and support provided by Government Tool Room and Training Centre, Bengaluru.

## REFERENCES
[1] Demirel, Hasan. (2009). Fire detection in video sequences using a generic color model. Fire Safety Journal. 44. 147-158. 10.1016/j.firesaf.2008.05.005.
[2] Shen, Dongqing & Chen, Xin & Nguyen, Minh & Yan, Wei. (2018). Flame detection using deep learning. 416-420. 10.1109/IC- CAR.2018.8384711.
[3] Agarwal, T. (2019, August 12). MQ2 Gas Sensor - Working Principle & its Applications. ElProCus - Electronic Projects for Engineering Students. https://www.elprocus.com/an introduction to mq2 gas sensor
[4] Qureshi, Waqar & Ekpanyapong, Mongkol & Dailey, Matthew & Rinsurongkawong, Suchet & Malenichev, Anton & Krasotkina, Olga. (2015). QuickBlaze: Early Fire Detection Using a Combined Video Processing Approach. Fire Technology. 52. 10.1007/s10694-015-0489- 7.

[5] Khan F, Xu Z, Sun J, Khan FM, Ahmed A, Zhao Y. Recent Advances in Sensors for Fire Detection. Sensors (Basel). 2022 Apr 26;22(9):3310. doi: 10.3390/s22093310. PMID: 35590999; PMCID: PMC9100504.
[6] Lv J, Qi Y, Huang L, Zong K, Du W. A fire detection system based on one-chip computer. Journal of Computational Methods in Sciences and Engineering. 2024;24(4-5):2227-2239. doi:10.3233/JCM-247254
[7] Cetin, A. E., Dimitropoulos, K., Gouverneur, B., Grammalidis, N., Gu¨nay, O., Habiboˇglu, Y. H., To¨reyin, B. U., & Verstockt, S.(n.d.). Video fire detection – Review. Digital Signal Processing, 23(6), 1827–1843.
https://doi.org/10.1016/j.dsp.2013.07.003
[8] Khan, F., Xu, Z., Sun, J., Khan, F. M., Ahmed, A., & Zhao, Y. (2022). Recent advances in sensors for fire detection. Sensors, 22(9), 3310. https://doi.org/10.3390/s22093310
[9] Shen, D., Chen, X., Nguyen, M., & Yan, W. Q. (2018). Flame detection using deep learning. Flame Detection Using Deep Learning, 416–420. https://doi.org/10.1109/iccar.2018.8384711
[10] C¸ elik, T., & Demirel, H. (n.d.). Fire detection in video sequences using a generic color model. Fire Safety Journal, 44(2), 147–158. https://doi.org/10.1016/j.firesaf.2008.05.005



10.22214/IJRASET

INDEX COPERNICUS

45.98

ISRA JIF

IMPACT FACTOR: 7.129

SJIFactor Scientific Journal Impact Factor

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

ISI

# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY