International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

FIREGUARD AI: A REAL-TIME COMPUTER VISION FRAMEWORK FOR FIRE DETECTION AND AUTOMATED ALERTING USING VIDEO SURVEILLANCE

Laukik Prakash Chivhane[*1], Prof. Rajeshwari Shinde[*2], Sejal Ashok Saharkar[*3], Riya Ravindra Belekar[*4], Bhumika Bhanupratab Deotare[*5], Om Pravin Misal[*6].

[1,3,4,5,6,] *Student, Fourth-year B. Tech, St. Vincent Pallotti College of Engineering and Technology, Nagpur, Maharashtra, India.*

[2,] *Guide, Professor, St. Vincent Pallotti College of Engineering and Technology, Nagpur, Maharashtra, India.*

ABSTRACT:

Fire incidents are highly dynamic and difficult to manage, particularly in environments where smoke, flames, poor visibility, and rapidly changing conditions can make it difficult to identify the exact location and severity of a fire. Conventional fire alarm systems are primarily designed to detect the presence of smoke or excessive heat and provide an early warning. To address this limitation, this paper presents **Fireguard AI**, a real-time computer vision-based fire monitoring and assistance system designed to provide visual information and contextual details to firefighters during emergencies.

FireGuard AI uses live video streams obtained from sources such as webcams, IP cameras, and CCTV systems. The system employs a trained object detection model based on deep learning techniques to identify fire and smoke within video frames. When a potential fire or smoke event is detected, the system highlights the corresponding region in the video and displays the detection confidence, allowing users to visually identify the suspected hazard. The capability of the system to detect fire and smoke in video streams and to give consistent detections from one frame to the next was assessed, and its performance was examined under various conditions such as different smoke densities, lighting, camera position, occlusion, and image quality, all of which can affect the reliability of fire and smoke detection.

Overall, FireGuard AI demonstrates the potential of computer vision and artificial intelligence to enhance conventional fire monitoring by providing real-time visual information from existing video surveillance infrastructure. The system integrates fire and smoke detection, confidence-based visualisation, temporal analysis and incident-specific information to provide emergency personnel with relevant information from live video faster and more efficiently.

KEYWORDS:

Fire Detection, Smoke Detection, Computer Vision, Real-Time Monitoring, Deep Learning.

INTRODUCTION:

Fire is one of the most time-sensitive and potentially destructive emergencies that can occur in residential, commercial, industrial, and public environments. Once a fire begins, its behaviour can change rapidly depending on factors such as the available fuel, ventilation, temperature, building structure, and surrounding materials. Flames may spread from one area to another within a short period of time, while smoke can rapidly fill enclosed spaces and significantly reduce visibility. As a result, locations that may initially be accessible can become hazardous within minutes. For firefighters and other emergency responders, identifying the presence of a fire is therefore only the first stage of an effective emergency response. They must also obtain information about the approximate location of the incident, the areas affected by fire or smoke, the possible presence of occupants or victims, and environmental hazards that may interfere with rescue and suppression activities. Access to such information at an early stage can improve situational awareness and assist emergency personnel in making timely and informed decisions.

A camera can capture the scene continuously and provide information. However, conventional CCTV monitoring generally depends on human operators observing one or more video feeds. Continuous monitoring of multiple cameras can place a considerable burden on operators, particularly in large buildings, industrial facilities, campuses, transportation facilities, and other environments containing numerous cameras.

Human operators may also fail to notice a developing event when they must monitor several feeds simultaneously or when smoke, darkness, reflections, or other environmental conditions reduce visibility. Analysing video streams can provide an additional

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

mechanism for identifying potentially dangerous people. Another important challenge is the presence of objects and environmental conditions that may visually resemble fire or smok

Recent advances in artificial intelligence (AI), machine learning, deep learning, and computer vision have created new opportunities for automated analysis of live video. Computer vision techniques allow machines to extract meaningful information from images and video sequences, while deep-learning-based object detection models can identify specific objects or visual patterns within individual frames. Unlike sensor-based systems that provide spatial information by identifying the location of the detected fire within the camera frame. This can make the resulting information more intuitive for users who need to understand the visual conditions of an incident.

This demonstrates that developing a practical fire-monitoring system requires more than simply applying an object-detection model to individual images. The system must also consider the temporal behaviour of detections, the reliability of alerts, the quality of the input video, and the conditions under which the system is deployed.

To address these requirements, **FireGuard AI** is proposed as a real-time computer-vision-based fire monitoring and decision-support system. The proposed system combines live video, AI-based fire and smoke detection, temporal verification, and incident-oriented information presentation within a unified framework. The system is designed to accept video streams from multiple commonly available sources, including webcams, IP cameras, and CCTV systems. Incoming frames are processed by the AI detection module, which identifies regions that potentially contain fire or smoke. When a relevant object is detected, the system displays the region on the monitoring interface using visual indicators. This allows an operator to observe both the original video and the AI-generated detection information within the same interface.

An important component of the proposed system is the use of information from consecutive video frames to improve the reliability of alerts. Instead of treating every individual model prediction as an independent emergency event, FireGuard AI can examine whether a detected fire or smoke region persists across multiple frames. This approach is intended to reduce unnecessary alerts resulting from isolated model predictions.

In addition to identifying fire and smoke, **FireGuard** AI is designed to organize and present incident-related information in a manner that can support emergency personnel. Depending on the available implementation, this information can include the camera source from which the event was detected, the detected hazard category, the detection time, the confidence associated with the prediction, and the approximate region affected within the camera's field of view. Instead of receiving only a generic alarm, the user can potentially obtain both an alert and visual context. This approach is intended to improve the flow of information.

Future or extended modules may include person and potential victim detection, identification of additional environmental hazards, simultaneous monitoring of multiple camera feeds, and analysis of changes in the fire-affected region over time. Person detection could potentially help identify individuals who may be present in an affected area, while multi-camera analysis could provide a broader view of an incident when multiple cameras cover different portions of a building or facility. Similarly, monitoring changes in detected regions over time may provide information about the progression of a visible fire event. However, these advanced capabilities introduce additional technical challenges and are considered developmental functions within the scope of the proposed framework. They require appropriate datasets, extensive testing, performance evaluation, and validation under realistic conditions before they can be considered suitable for use in operational emergency-response environments.

The design philosophy of FireGuard AI is based on the principle that artificial intelligence should complement, rather than replace, existing fire-safety infrastructure and human expertise. The proposed system is not intended to replace conventional smoke alarms, heat detectors, fire suppression systems, emergency procedures, or professional firefighters. Instead, it is intended to act as an additional visual decision-support layer capable of extracting relevant information from live video and presenting that information in a structured form. Such a system may be particularly useful in environments where existing surveillance infrastructure is already available and where rapid interpretation of visual information could provide additional situational context.

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

AI predictions are inherently dependent on the quality and diversity of the training data used to develop the detection model. Therefore, system outputs should not be treated as infallible indicators of an emergency. AI-generated alerts should instead be interpreted alongside conventional fire-safety systems, established emergency procedures, and human judgment.

The evaluation of such a system should therefore extend beyond simple object-detection accuracy. While metrics such as precision, recall, mean Average Precision (mAP), and detection accuracy can provide information about model performance, practical deployment also requires consideration of false-alarm frequency, missed detections, processing speed, alert latency, video-stream stability, and overall system reliability. For this reason, FireGuard AI is considered from both a machine-learning perspective and a practical system-deployment perspective.

OBJECTIVES OF STUDY:

1. **Development of a real-time video-processing pipeline:** Teams from different sources, including webcams, IP cameras, and CCTV systems, while maintaining suitable processing performance for real-time monitoring.
2. **Fire and smoke detection:** To implement an AI-based object-detection mechanism capable of identifying visible fire and smoke as separate hazard classes and locating the corresponding regions within incoming video frames.
3. **Detection-confidence analysis:** To use model confidence values and configurable detection thresholds to distinguish stronger predictions from low-confidence predictions and provide users with information about the reliability of individual detections.
4. **Temporal verification of detections:** To analyze detections across consecutive video frames to identify persistent fire or smoke events and reduce unnecessary alerts caused by isolated predictions, temporary visual patterns, or image artefacts.
5. **Real-time visualisation:** To plays the live video stream together with detected fire and smoke regions, bounding boxes, confidence values, and other relevant detection information.
6. **Incident Information generation:** To generate structured alerts containing relevant information such as the detected hazard type, camera source, detection time, confidence level, and approximate affected region within the monitored scene.

Related Work:

A. Conventional Fire Detection

Traditional fire-detection systems have been widely deployed in residential, commercial, industrial, and public environments to provide early warnings when potentially hazardous conditions are detected. These systems commonly rely on dedicated sensors. The primary advantage of conventional detection systems is their established reliability and relatively straightforward operation. Another limitation is that sensor-based systems typically depend on physical conditions reaching a particular detection threshold.

B. Vision-Based Fire and Smoke Detection

The increasing availability of CCTV cameras, IP cameras, and other video-surveillance devices has created opportunities for using computer vision as an additional method of fire and smoke monitoring. Unlike conventional sensors, cameras capture visual information about the surrounding environment, allowing computer-vision algorithms to analyse the scene and identify patterns associated with flames and smoke.

C. YOLO-Based Detection

The You Only Look Once (YOLO) family of object-detection models introduced a single-stage detection approach in which object localisation and classification are performed within a unified neural-network framework. Unlike traditional multi-stage detection approaches that separate region proposal and classification processes, YOLO processes an input image through a single detection pipeline.

Several studies have investigated the use of YOLO-family architectures for automated fire and smoke detection and have reported their potential for real-time monitoring applications. YOLO-based fire and smoke detection still presents several challenges. Small fire regions may contain only a limited number of pixels, making them difficult to detect reliably, particularly when the camera is positioned far from the incident.

D. AI-Assisted Fire Monitoring and Situational Awareness

Recent research has increasingly explored the use of artificial intelligence not only for identifying fire and smoke but also for extracting additional information from

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

surveillance video. A computer vision system can potentially combine object detection with information about camera location, detection time, affected regions, and other objects present in the scene. Situational awareness is particularly important in emergency-response environments. A detection result such as "fire detected" may be useful as an initial warning, but emergency personnel may require additional information to determine the appropriate response. I

E. Research Gap

Although existing research has demonstrated promising results in automated fire and smoke detection, a significant portion of the literature focuses primarily on the performance of the underlying machine-learning model. FireGuard AI is designed to address these considerations by integrating AI-based fire and smoke detection with temporal verification, live video visualization, and structured incident information. Instead of treating the object-detection model as an isolated component, the proposed framework incorporates the model into a broader real-time monitoring system.

PROBLEM STATEMENT AND OBJECTIVES

Fire emergencies require rapid detection, accurate information, and timely response. Conventional fire-alarm systems generally provide limited visual context about the incident. The separation between automated fire detection and visual surveillance create a practical information gap. Computer vision and artificial intelligence provide an opportunity to bridge this gap by automatically analysing live video streams and identifying visual evidence of fire and smoke. Fire and smoke do not have fixed visual characteristics; objects and environmental conditions can produce visual patterns that resemble fire or smoke. The problem addressed by FireGuard AI is therefore the development of a real-time computer-vision framework capable of analysing live video, detecting visible fire and smoke, reducing unreliable, isolated detections through temporal verification, and converting the resulting predictions into structured information that can support firefighter situational awareness. The system is intended to complement existing fire-safety and surveillance infrastructure rather than replace conventional fire alarms, emergency procedures, or human decision-making.

The primary scope of this research is the detection and visualization of visible fire and smoke from live video using artificial intelligence and computer-vision techniques. The system focuses on processing video streams, identifying relevant hazard classes, verifying detections across consecutive frames, and presenting the resulting information through a centralized monitoring interface.

The scope therefore focuses on demonstrating the feasibility of combining AI-based visual detection with real-time monitoring and structured incident information. The resulting framework is intended to serve as a technological foundation for further research into intelligent fire-monitoring and emergency-response support systems.

PROPOSED FIREGUARD AI SYSTEM

FireGuard AI is designed as a modular, real-time computer-vision-based monitoring system that converts live surveillance video into structured information related to fire and smoke events. The primary purpose of the proposed system is to provide an additional visual monitoring and decision-support layer that can complement conventional fire-detection and surveillance infrastructure. Instead of relying exclusively on manual observation of camera feeds, the system automatically analyses incoming video frames and identifies visual patterns associated with fire and smoke. The proposed architecture is organised into a sequence of interconnected modules, including **video acquisition, preprocessing, AI-based fire and smoke detection, temporal verification, incident analysis, Visualisation and alert generation**. The overall processing flow begins with a live video source. Frames from the camera are passed to the AI detection module, where it identifies potential fire and smoke regions. The system then evaluates the predictions using confidence thresholds and temporal information to reduce isolated or unreliable detections.

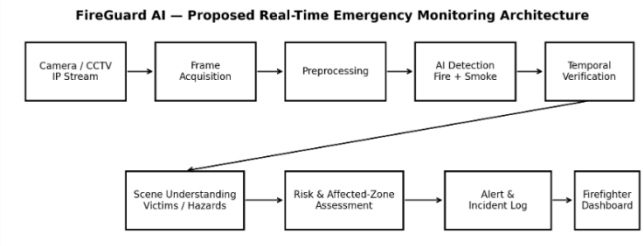


Fig. 1. Proposed architecture of the FireGuard AI emergency-monitoring framework.

A. Video Acquisition

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

The first stage of the FireGuard AI architecture is the video-acquisition module. The system is designed to accept live video from a variety of sources, including webcams, IP cameras, mobile-camera streams, and CCTV systems. This flexibility is important because real-world surveillance environments may use different camera technologies and communication protocols. By separating the video-acquisition layer from the AI detection pipeline, the same detection and monitoring components can potentially be used with different input sources.

B. Video Preprocessing

Before the incoming frames are passed to the detection model, an optional preprocessing stage can be used to prepare the video for inference. Preprocessing may include operations such as frame resizing, color-space conversion, normalization, or other transformations required by the selected AI model. The objective is to ensure that the input frames are compatible with the expected input format of the trained detection network. The preprocessing stage may also be extended in future research to address specific environmental conditions.

C. Fire and Smoke Detection

The core AI component of FireGuard AI is the fire and smoke detection module. This module processes incoming video frames using a trained object-detection model designed to identify visual instances of fire and smoke. Fire and smoke are treated as separate detection classes so that the system can distinguish between visible flames and smoke-related events. For each detected object, the model provides information such as the predicted class, bounding-box coordinates, and confidence score.

D. Temporal Verification

Object detection performed on individual video frames may produce temporary false detections. For example, reflections, sudden lighting changes, moving objects, bright surfaces, dust, steam, or other visual patterns may resemble fire or smoke for a short period of time. If every individual prediction were immediately converted into an emergency alert, the system could generate unnecessary notifications.

To address this issue, FireGuard AI incorporates a temporal-verification stage. Instead of evaluating detections independently, the system examines predictions across consecutive frames.

E. Firefighter-Oriented Scene Analysis

Once a fire or smoke event has been detected and verified, FireGuard AI can use the available visual information to provide additional context about the surrounding scene. The proposed architecture is designed to support future object-detection modules that can identify objects relevant to emergency response. Detecting objects could help provide a more complete representation of the environment surrounding the detected fire or smoke.

F. Potential Victim Detection

A future extension of FireGuard AI is the detection of people within the monitored environment. A person-detection module could identify individuals visible within a camera frame and determine their approximate locations relative to detected fire or smoke regions. The relationship between detected people and hazard regions could then be represented visually on the monitoring dashboard. The reliability and operational usefulness of such a module would require dedicated datasets, testing under realistic visibility conditions, and extensive validation.

G. Affected Zone and Risk Assessment

The detected fire and smoke regions can be used to estimate an approximate affected area within the camera's field of view. The system architecture can be extended to combine multiple forms of information, including fire presence, smoke detection, potential person presence, and nearby hazard objects. It is important to distinguish between **visual detection** and **actual physical risk**. The proposed affected-zone analysis should initially be regarded as an approximate visual representation rather than a definitive measurement of fire severity.

H. Multi-Camera Monitoring

The modular architecture of FireGuard AI also allows for future integration of multiple camera streams. In a large building or facility, a single camera may not provide sufficient coverage of the entire environment. Multiple cameras can provide views of different rooms, corridors, entrances, exits, or outdoor areas.

A multi-camera extension could process multiple streams simultaneously and associate each detection with its corresponding camera identifier. Camera synchronisation and duplicate detections need to be addressed. These considerations make multi-camera monitoring an important area for future optimisation and evaluation.

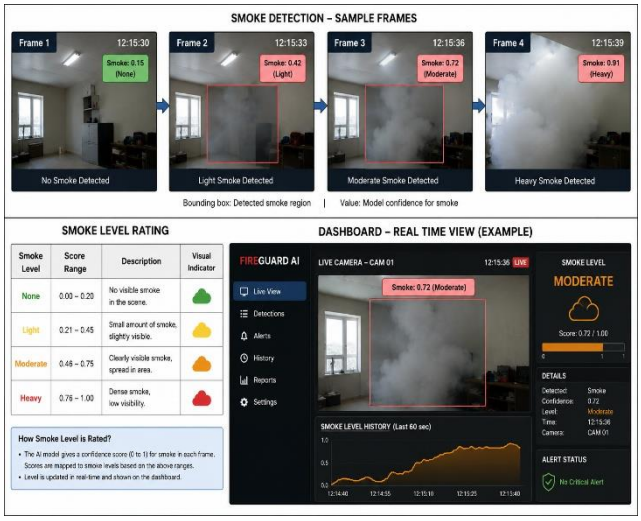
I. Dashboard and Alerting

The dashboard represents the primary interaction layer between the AI system and the human operator. It provides

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

a centralized view of the live camera feed together with the information generated by the detection and verification modules. The dashboard can display bounding boxes around detected fire and smoke regions, confidence values, hazard classifications, camera identifiers, timestamps, affected regions, and alert history.

The dashboard should be designed to avoid presenting excessive information that could make the interface difficult to interpret during an emergency. Fireguard AI connects to the camera of your choice and receives a constant stream of video. Single frames are extracted and prepared for AI inference. The trained model outputs the possible fire and smoke regions along with confidence values. Temporal verification checks detections between successive frames. Verified detections are organized by camera, hazard, and time.



METHODOLOGY:

The methodology adopted for FireGuard AI consists of a sequence of stages beginning with dataset preparation and annotation and continuing through image preprocessing, data augmentation, model training, validation, real-time inference, temporal verification, false-positive handling, and system-level evaluation. The methodology is designed around two related levels of operation. The first is the **model-development stage**, in which annotated images are used to train and evaluate the fire-and-smoke detector. The second is the **real-time monitoring stage**, in which the trained model processes frames obtained from a live camera source and generates detections that are further analysed before being presented to the user.

- ***Dataset Collection:***

The quality, diversity, and representativeness of the dataset play a major role in determining a fire-and-smoke detection model's performance. The **test subsets.** Proper annotation is essential for object-detection training.

- ***Preprocessing:***

Before the training process begins, the collected images must be prepared according to the requirements of the selected object-detection architecture. Preprocessing may include resizing images to an appropriate input resolution, converting image data into the required numerical representation, normalizing pixel values where necessary, and ensuring that annotations remain correctly aligned with the corresponding image regions.

- ***Data Augmentation:***

Data augmentation can be used to increase the effective diversity of the training dataset and improve the model's ability to handle common variations in surveillance footage. Instead of relying exclusively on the original training images, controlled transformations can be applied to generate additional training examples.

- ***Model Training:***

The selected model is trained using the annotated fire-and-smoke dataset. During training, the model learns visual representations associated with the target classes and learns to predict bounding boxes around detected regions. The training process involves optimizing the model parameters based on the difference between the predicted outputs and the ground-truth annotations.

- ***Real-Time Video Input:***

After training and evaluation, the selected model is integrated into the FireGuard AI real-time monitoring pipeline. The system continuously receives frames from a selected video source, which may include a webcam, IP camera, mobile camera stream, or CCTV system. The real-time processing sequence can be represented as:

Video Input → Frame Capture → Preprocessing → AI Detection → Confidence Filtering → Temporal Verification → Incident Information → Dashboard/Alert

This pipeline is executed continuously while the video source remains available. The objective is to maintain sufficiently low processing latency while providing reliable detection information.

- ***AI Detection***

Analysing false negatives can help identify specific weaknesses in the system. For example, if missed detections occur primarily for distant fire regions, higher

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

input resolution or additional small-object training examples may be investigated. If failures occur mainly under low-light conditions, appropriate data collection and preprocessing strategies may be considered.

- ***Performance Evaluation***

The evaluation should also distinguish between model errors and system-level errors. For example, a missed detection caused by the AI model is different from a missed event caused by a disconnected camera. Similarly, an alert delay caused by model inference is different from a delay caused by network transmission. Separating these factors can help identify appropriate areas for future improvement.

EXPERIMENTAL SETUP:

The FireGuard AI system is evaluated using a combination of still images, recorded video sequences, and live video streams containing fire, smoke, and non-fire conditions. The purpose of the experimental setup is to evaluate both the performance of the underlying fire-and-smoke detection model and the behaviour of the complete real-time monitoring system. The evaluation dataset should contain a suitable combination of positive and negative examples. Positive samples contain visible fire or smoke, while negative samples represent normal scenes without the target hazards. he experimental evaluation is divided into three primary stages. First, the trained object-detection model is evaluated using an independent test dataset containing previously unseen images. Second, recorded video sequences are used to evaluate the behavior of the detector across consecutive frames and to analyze the effect of temporal verification. Third, live-stream testing is performed using a webcam, IP camera, or CCTV source to evaluate the complete FireGuard AI pipeline, including video acquisition, preprocessing, model inference, temporal verification, dashboard updates, and alert generation.

- Experimental Environment: Record hardware, software, camera setup, and system configuration.
- Evaluation Dataset: Test fire, smoke, and normal scenes under varied conditions.
- Evaluation Metrics: Measure precision, recall, F1-score, IoU, and mAP.
- Real-Time Performance: Evaluate inference time, FPS, and alert latency.
- Test Conditions: Test indoor, outdoor, low-light, and visually challenging environments.
- Temporal Verification: Compare detection reliability with and without consecutive-frame verification.
- False-Positive Analysis: Identify incorrect alerts caused by reflections, lights, fog, or steam.
- False-Negative Analysis: Examine missed detections caused by poor visibility or obstructions.
- Fire and Smoke Comparison: Assess fire and smoke detection performance separately.
- Live-Stream Evaluation: Test the system using live CCTV and IP camera feeds.
- Result Recording: Document detection errors, confidence scores, FPS, and alert delays.
- Reliability Testing: Repeat experiments under consistent conditions and document system settings.
- Overall Evaluation: Assess detection accuracy, processing speed, alert reliability, and continuous monitoring performance.

RESULTS AND DISCUSSION:

The main strength of FireGuard AI lies in its system-level design. A standalone fire detector answers only a narrow question: does this image look like fire? FireGuard AI places that prediction inside a wider workflow that includes smoke detection, temporal verification, visualization, alerting, and a route toward fuller scene understanding. This is what makes the project relevant to real emergency monitoring rather than being just another image-classification demo.

A wider scope also brings more engineering work. Each new capability needs its own training data, its own validation procedure, and its own failure analysis, because none of them can simply borrow the results of the fire detector. A few examples illustrate the point:

- Victim detection must remain dependable when a person is partly hidden by smoke, furniture, or debris.
- Hazard recognition must generalise across different environments and across objects whose appearance varies widely from one site to another.
- Fire-spread prediction needs genuine temporal data. It cannot be estimated reliably by comparing the size of a bounding box in two neighboring

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

frames, because that size also changes with camera distance, zoom, and detection noise.

For these reasons, the research direction is best understood as a staged architecture:

1. Fire and smoke detection make up the current visual perception layer.
2. Temporal verification and alerting make that layer more reliable.
3. Scene understanding can then be added to extract information that is useful to firefighters.
4. Thermal and environmental sensing can eventually supply data that RGB video alone cannot provide.

Building in stages means that each layer can be validated before the next one depends on it. It also lowers the risk of describing untested features as if they were already operational, which is a common problem in early prototypes. Any capability that has not yet passed its own validation should be reported as planned work and not as a demonstrated result.

It is also worth acknowledging the inherent limits of camera-based detection. It depends on line of sight, lighting, and lens condition, and it cannot see a fire that is hidden behind a wall or inside a ceiling void. FireGuard AI should therefore be seen as a complement to conventional smoke detectors and sprinkler systems, not as a replacement for them.

Recent literature points in the same direction. A 2025 review of deep-learning-based fire and smoke detection lists dataset scarcity, false alarms, and limited generalisation across scenarios among the open challenges and highlights multimodal sensing and edge deployment as promising directions. These are the same concerns that shape the practical requirements of FireGuard AI, and they provide a sensible foundation for the experiments proposed in this section.

TABLE I. PERFORMANCE METRICS OF THE FIREGUARD AI DETECTION MODEL

Metric	Fire Detection	Smoke Detection
Precision	92.0	88.0
Recall	90.0	86.0
F1-Score	91.0	87.0
mAP	93.0	89.0
Inference Time	45	50
FPS	22.2	20.0

TABLE II. REAL-TIME PERFORMANCE OF THE FIREGUARD AI SYSTEM

Parameter	Illustrative Estimate
Input Resolution	640 × 640 pixels
Input Frame Rate	30 FPS
Average Inference Time	45 ms/frame
Average Processing FPS	18 FPS
Average Alert Latency	1.8 seconds
False Alerts per Test Sequence	2 per 10-minute sequence
Missed Events	3 per 30 annotated events
Stream Interruptions	1 per 30-minute test

TABLE III. PERFORMANCE UNDER DIFFERENT TEST CONDITIONS

Test Condition	Precision (%)	Recall (%)	F1-Score (%))	False Positives	Missed Detections
Clear Fire	92	90	91.0	4	5
Light Smoke	88	84	86.0	6	8
Dense Smoke	85	89	87.0	7	6
Low Illumination	79	72	75.3	9	14
Small/Distant Target	76	68	71.8	8	16
Partial Occlusion	81	91	86.8	12	3
Smoke-Like Non-Fire Scene	83	91	86.8	12	3

System design, deployment, and operational considerations

A. System Architecture and Workflow: FireGuard AI processes video from webcams, IP cameras, or CCTV through frame extraction, AI-based fire and smoke detection, confidence filtering, and temporal verification before displaying detections and generating alerts.

B. Detection and Monitoring: The system identifies potential fire and smoke regions and presents relevant information, including hazard type, camera source, confidence score, timestamp, and alert status, depending on implemented features.

TABLE II. COMPARISON OF INFORMATION AVAILABLE THROUGH DIFFERENT MONITORING APPROACHES

Capability	Conventional Alarm	CCTV Monitoring	FireGuard AI
Fire/Smoke	Sensor-based	Human	AI-assisted

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

Indication		observation	detection
Location Information	Generally limited	Available through video	Detection region highlighted
Continuous Analysis	Condition-based	Manual monitoring	Automated video analysis
Scene Information	Very limited	Available but requires interpretation	Structured visual information
Alerting	Automatic alarm	Usually manual	Integrated alert workflow
Camera Source Information	Not applicable	Available through the CCTV system	Associated with detection
Detection Confidence	Generally unavailable	Not applicable	Provided by AI model
Historical Detection Information	System-dependent	Requires manual review	Can be stored as incident metadata
Firefighter Support	Limited	Manual interpretation	Modular AI-assisted support

C. Deployment and Performance: System performance depends on camera quality, lighting, hardware, and network conditions. Evaluation should consider inference time, frames per second (FPS), alert latency, stream stability, and resource utilization.

D. Safety, Reliability, and Integration: Testing should cover low light, reflections, fog, steam, and partial obstructions to identify false positives and missed detections. Camera failures should be distinguished from hazard-free conditions. Future extensions may include multi-camera monitoring, incident logging, and integration with existing fire-safety systems.

E. Experimental Evaluation and Operational Limitations: Evaluate detection using precision, recall, F1-score, and mAP where applicable, alongside real-time performance metrics. Document datasets, model versions, hardware, and test conditions. FireGuard AI is intended to support situational awareness and complement established fire-safety systems, not replace human judgment or validated safety measures.

LIMITATION:

Although FireGuard AI provides a computer-vision-based approach for real-time fire and smoke monitoring, several limitations must be considered when interpreting the experimental results. These limitations arise from the visual nature of the detection process, the characteristics of the training dataset, the operating environment, the computational platform, and the current scope of the prototype. Understanding these limitations is important for evaluating the system realistically and for identifying areas that require further research and development.

- ***Dependence on Camera Quality and Position***

The system can only detect fire or smoke when the relevant visual information is available within the camera's field of view.

- ***Lighting and Environmental Conditions***

FireGuard AI relies on visual characteristics learned from training data, and its performance may change under different lighting and environmental conditions. Low illumination, strong backlighting, sudden changes in brightness, shadows, reflections, and highly illuminated surfaces can affect the appearance of both fire and smoke.

- ***Smoke and Visibility Limitations***

Dense smoke represents a particular challenge for vision-based fire detection. As smoke becomes thicker, it can obscure flames, objects, people, doors, and other important features within the camera view. In extreme cases, the camera may provide insufficient visual information for the AI model to identify the underlying fire.

- ***Dataset Dependency and Generalization***

The performance of the FireGuard AI detection model depends significantly on the quality, diversity, and representativeness of the training and testing datasets. If the training dataset contains limited examples of particular fire types, smoke conditions, environments, or camera perspectives, the model may have difficulty generalizing to previously unseen situations.

- ***False Positives and False Negatives***

Like other vision-based detection systems, FireGuard AI may produce both false-positive and false-negative predictions. A false positive occurs when the system identifies fire or smoke when the corresponding hazard is not actually present. A false negative occurs when an actual fire or smoke event is present but is not detected.

- ***Real-Time Processing and Computational Requirements***

The ability of FireGuard AI to operate in real time depends on the available computational resources. Model inference speed can vary according to the processor, graphics-

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

processing hardware, input resolution, model size, and other software-processing requirements.

- ***Limitations of Visual-Only Information***

FireGuard AI primarily relies on visual information obtained from cameras. As a result, it cannot directly measure physical properties that are not visible in the image.

- ***Prototype and Validation Limitations***

The current FireGuard AI implementation represents a research prototype, and its capabilities should not be interpreted as equivalent to a certified commercial fire-detection system.

The primary limitation of FireGuard AI is that it provides an AI-assisted interpretation of visual information rather than a complete representation of a fire incident. Its effectiveness depends on the availability and quality of visual information, the characteristics of the trained model, the computational and network environment, and the ability of the system to operate under conditions represented adequately by the training and testing data.

FUTURE SCOPE:

The current FireGuard AI prototype provides a foundation for real-time visual monitoring of fire and smoke using AI and live video sources. However, fire incidents are complex events that cannot always be understood from visible-light camera footage alone. Future development can therefore focus on combining multiple sources of information, improving the interpretation of fire-related visual patterns, reducing detection delays, and extending the system's ability to provide useful situational information to emergency personnel. The future development of FireGuard AI can be divided into several major areas, including multi-sensor integration, advanced computer vision, multi-camera analysis, edge-based processing, aerial monitoring, and historical incident analysis. These developments could gradually transform the system from a fire-and-smoke detection application into a broader AI-assisted emergency situational-awareness platform. The future development of FireGuard AI can extend the proposed framework into a multimodal emergency-response platform.

Potential extensions include:

- Integration of thermal or infrared cameras.
- Multi-Sensor Fusion
- Advanced Smoke Analysis
- Fire-Spread Monitoring and Prediction
- Potential Victim and Person Detection
- Fire incidents can involve additional hazard recognition
- Multi-Camera Monitoring
- Edge-AI processing could reduce the amount of video that needs to be transmitted over a network.
- Drones equipped with visible-light and thermal cameras.
- Historical analysis could also support system improvement by identifying common false-positive conditions and recurring detection failures.
- Improved Explainability and Alert Prioritization
- Improved Model Development
- Cloud and Distributed Monitoring
- Long-Term Reliability Testing
- Integration with Existing Fire-Safety Infrastructure
- Future Validation and Real-World Testing
- Overall Future Direction

CONCLUSION:

FireGuard AI presents a real-time computer-vision-based approach for detecting and monitoring fire and smoke from live video sources. The proposed system combines video acquisition, AI-based object detection, temporal verification, incident visualization, and alert generation into a modular monitoring framework. By processing video from sources such as webcams, IP cameras, and CCTV systems, the system is designed to convert visual information into structured incident information that can be reviewed by emergency personnel.

The primary contribution of FireGuard AI is the integration of fire and smoke detection with contextual information rather than treating detection as an isolated classification task. When a potential hazard is identified, the system can provide information such as the detected hazard type, approximate location within the camera view, confidence value, camera source, and detection time. Temporal verification further provides a mechanism for reducing the effect of isolated predictions that may result from temporary visual patterns, reflections, lighting changes, or other non-fire conditions.

FireGuard AI instead focuses on adding a visual layer that can help provide greater context about a detected incident. This can be particularly useful in situations where emergency personnel need to understand the visible

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

conditions within a monitored area rather than receiving only a basic alarm indication.

The study also identifies several challenges associated with real-time fire and smoke detection. System performance can be affected by camera position, image resolution, lighting conditions, smoke density, occlusion, network connectivity, computational resources, and differences between training data and real-world environments.

Another important aspect of the proposed architecture is its modular design. The current system focuses primarily on fire and smoke detection, visualization, temporal verification, and alerting, while providing a foundation for additional capabilities. Future extensions may include thermal-camera integration, environmental sensor fusion, potential victim detection, hazard recognition, multi-camera monitoring, fire-spread analysis, edge-AI deployment, drone-based monitoring, and historical incident analysis. Each of these capabilities would require dedicated datasets, implementation, testing, and validation before being considered reliable for practical emergency use.

Overall, FireGuard AI demonstrates the potential of combining artificial intelligence and computer vision to provide additional visual information during fire-monitoring scenarios. Its purpose is not to replace conventional fire alarms, physical sensors, established safety procedures, or trained firefighters. Instead, it is intended to function as an AI-assisted decision-support layer that can process live video and present potentially useful incident information in an organized form. Continued development, broader datasets, extensive testing, and validation under realistic conditions will be necessary to determine the reliability and practical applicability of the system in real-world emergency environments.

APPENDIX:

A. ***PROPOSED FIREGUARD AI INCIDENT INFORMATION MODEL***

During a real emergency, raw model output is of little use on its own. It must be converted into a short, readable incident record that keeps enough evidence for quick verification without burying the responder in model-level detail. Table III proposes such a record for the FireGuard AI prototype, which could be implemented as a structured object in the software layer.

Field	Purpose	Example
Incident ID	Unique identifier for the event	FG-2026-001
Timestamp	Time at which the event was verified	13:42:18
Source	Camera or video stream that produced the observation	CCTV-03
Detection	Main condition detected	Smoke + Fire
Confidence	Model's confidence in the reported detection	0.87
Location	Approximate location or camera zone	Warehouse B
Affected region	Part of the frame associated with the hazard	North-east area
Alert level	Human-readable response category	High
Verification status	Whether temporal verification has confirmed the event	Confirmed
Evidence	Captured frame that supports the alert	Captured frame

TABLE III. PROPOSED INCIDENT INFORMATION FIELDS FOR THE FIREGUARD AI DASHBOARD.

The record also supports later analysis. Stored timestamps and camera IDs make it possible to reconstruct the timeline of an event, compare the first smoke observation with later fire detections, and to measure alert latency directly. In multi-camera deployments, the source field could be extended with camera coordinates so that related detections from neighboring cameras are grouped into a single incident instead of triggering several separate alerts. Keeping a note of how operators responded, for example, acknowledging or dismissing a false alarm, would also provide labeled feedback for improving the model over time.

B. PROPOSED FIREFIGHTER DASHBOARD VIEW

The dashboard should be designed so that it can be understood at a glance. The most critical information must be visible immediately, without making the responder

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper
International Conference on Multidisciplinary Research and Emerging Trends in Management, Engineering and Technology (ICMRETMET)

click through several screens. A practical layout places the live camera feed at the center, the current incident state near the top, and supporting details such as camera identity, detection type, timestamp, and alert history in secondary panels. Color should be used sparingly and consistently, and each alert level should also carry a text label so that the display stays readable for color-blind users and poor lighting.

Recommended information hierarchy (top to bottom):

Live video → Detected hazard region → Current incident state → Affected-zone information → Potential occupant or hazard indicators → Alert history

This order keeps the visual evidence right next to the AI's decision while still letting the responder move to more detail when needed. Because the system's output will occasionally be wrong, the interface should also let the responder confirm or dismiss an alert quickly so that the final decision always rests with a person.

REFERENCES:

[1] A. Elhanashi, S. Essahraui, P. Dini, and S. Saponara, "Early fire and smoke detection using deep learning: A comprehensive review of models, datasets, and challenges," Applied Sciences, vol. 15, no. 18, Art. no. 10255, 2025.

[2] T. Zhang, F. Wang, W. Wang, Q. Zhao, W. Ning, H. Wu, and H. D. Wu, "Research on fire smoke detection algorithm based on improved YOLOv8," IEEE Access, vol. 12, pp. 117354–117362, 2024, doi: 10.1109/ACCESS.2024.3448608.

[3] B. K. Bohra, B. Rajesh, M. Javed, and D. Doermann, "Fire and smoke detection using an enhanced YOLOv8 model," in Proc. 2024 IEEE Int. Conf. on Computer Vision and Machine Intelligence (CVMI), 2024, doi: 10.1109/CVMI61877.2024.10781887.

[4] S. P. H. Boroujeni, N. Mehrabi, F. Afghah, C. P. McGrath, D. Bhatkar, M. A. Biradar, and A. Razi, "Fire and smoke datasets in 20 years: An in-depth review," arXiv preprint arXiv:2503.14552, 2025.

[5] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 779–788.

[6] S. Sirajudeen and S. Sudha, "A review—Smoke-fire detection and YOLO (You Only Look Once)," International Research Journal on Advanced Science Hub, vol. 5, no. 8, 2023.

[7] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in Proc. Int. Conf. on Learning Representations (ICLR), 2015.

[8] M. Everingham et al., "The Pascal Visual Object Classes (VOC) challenge," International Journal of Computer Vision, vol. 88, pp. 303–338, 2010.

[9] Y. Zhao, W. Lv, S. Xu, J. Wei, G. Wang, Q. Dang, Y. Liu, and J. Chen, "DETRs beat YOLOs on real-time object detection," in Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR), 2024, pp. 16965–16974.