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RESEARCH ARTICLE

FP-BEN: IOT-BASED VISION SENSOR FOR FIRE PIXEL DETECTION IN BUILDING ENVIRONMENTS

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Abstract – Smart building that detects fire using advanced technologies such as artificial intelligence (AI), the Internet of Things (IoT), and computer vision can improve safety and enhance emergency response. However, factors like smoke dispersion, varying lighting conditions, and sensor placement can significantly impact detection accuracy. To address these challenges, this study proposes a novel deep learning-based FP-BEN model for computer vision-inspired fire detection strategy using a vision sensor. The proposed technique consists of three stages to enhance detection reliability. The first stage applies a Gaussian probability distribution to identify potential fire pixels, reducing false positives. The second stage incorporates a hybrid background subtraction method to differentiate fire from dynamic background changes. Finally, the third stage utilizes temporal variation analysis to refine fire detection by considering frame-to-frame variations. This three-step approach effectively mitigates challenges such as Gaussian noise, varying video resolutions, and false alarms caused by environmental factors. Experimental results demonstrate high detection accuracy across different lighting conditions, ensuring robust and noise-resistant fire detection, even in the presence of smoke and environmental disturbances.

Keywords *– Artificial Intelligence, Internet of Things, infrared sensor, fire detection, Gaussian noise, environmental factors.*

1. INTRODUCTION

One of the most destructive natural disasters that can result in death, significant financial losses, and damage to the environment is fire [1,2]. Accidental fires may occur for many different reasons, including faulty electrical and gas devices, electrical problems, incendiary ignitions, and climate change [3]. The degradation of forest regions is thought to be exacerbated by human activities such as intentionally starting fires to clear fields and feeding animals in forests [4,5]. As a result of human intervention in forests to produce products, dense forests are transformed into dry grasslands and scrublands, which are much more prone to fires [6]. Fire detection using sensors involves the use of specialized devices to monitor environmental changes such as smoke, temperature, and gas levels [7,8]. These sensors trigger alerts when fire or smoke is detected, enabling early intervention to prevent damage [9,10]. After wildfire events, the soil temporarily resembles a concrete surface. When it rains, healthy plants and roots typically absorb the water, but after a wildfire, the water has nowhere to go. The landscape may completely alter over time as shrubs and grasses take the place of trees [11].

The US National Fire Protection Association reports that from 2009 to 2013, 1.18 fire fatalities per 100 occurred without a smoke sensor, while 0.53 fire deaths per 100 occurred in homes with sensors installed [12]. Hospitals, schools, forests, supermarkets, and parking lots, among other places, now have fire detection devices installed. Since the turn of the twenty-first century, 75000 people have died annually as a consequence of fire, according to the Centre for CTIF [13,14]. Modern smoke sensors were created thanks to a transducer accidentally discovered by Swiss physicist Walter Jaeger in the 1930s that could sense smoke [15]. Factors like changing lighting conditions, fog, humidity, and background noise can reduce the accuracy of vision-based fire detection systems, foremost to false positives or missed detections. In this paper, a novel computer vision-inspired fire detection strategy using a vision sensor. The key contributions of this work are summarized as,

- A thermal camera and infrared sensor are used to capture real-time environmental data, ensuring continuous monitoring. The system records a video of the monitored area. Frames are extracted from video input to facilitate further processing and analysis.
- Gaussian Probability Distribution is applied to detect potential fire pixels in each frame while minimizing false positives.
- Hybrid background subtraction differentiates fire from dynamic background changes, while temporal variation analysis refines detection by considering frame-to-frame variations. The luminance variance helps refine fire detection by analysing intensity variations.

- After luminance-based filtering, the final fire regions are extracted and highlighted. The output is a binary mask where white pixels represent fire, and black pixels indicate the background.

The structure of the paper is organized as follows, section-2 describes the literature survey, the proposed FP-BEN was explained in section-3, the performance outcomes and their comparison analysis were provided in section-4 and section-5 encloses with conclusion and future work.

2. LITERATURE SURVEY

The fundamental purpose of conducting a literature review is to gather basic information about existing approaches and research subjects. The numerous deep learning (DL) strategies used to diagnose the condition are described in this research.

In 2020, Xie et al. [16] suggested a technique for video fire detection that makes use of both deep static features and dynamic features based on motion flicker. It is suggested to extract the deep static properties of flames using a lightweight adaptive convolutional neural network (ALCNN). Lastly, by combining static and dynamic fire characteristics, a more accurate and efficient runtime technique for detecting fire in movies is developed. The suggested approach is state-of-the-art and suitable for difficult video scenarios in terms of accuracy and false alarm rate.

In 2022, Muhammad et al. [17] suggested a CNN architecture for reliable and affordable fire detection for video surveillance. The Google Net architecture, which is less computationally expensive than networks like AlexNet and better suited for the intended issue, served as the model's inspiration. The fire datasets demonstrate the effectiveness of the proposed technique and demonstrate that it is a good fit for fire detection in CCTV scrutiny systems.

In 2022, Xue et al. [18] suggested a model built on YOLOv5 for small-target detection of forest fires. In real-world applications, cameras must serve as sensors for spotting forest fires. In YOLOv5, the Spatial Pyramid Pooling-Fast-Plus module replaces the original Spatial Pyramid Pooling-Fast module to better focus on small forest fire data. According to statistics for small-target forest fires, the enhanced structure increases the mAP of 0.5 by 10.1%.

In 2022, Zheng et al. [19] suggested a deep CNN could achieve real-time forest fire smoke tracking. Various deep CNN-based object detection methods have been evaluated, including SSD (Single Shot Multi-Box Detector), the advanced CNN model, Faster R-CNN, YOLOv3, and EfficientDet. Among these, the EfficientDet algorithm achieved the highest average accuracy of 95.7% for real-time forest fire smoke detection.

In 2020, Pan et al. [20] presented a highly effective way for detecting wildfires using video that is based on the AddNet additive DNN. This AddNet is a vector function that can only handle addition and signs; it's unable to multiply the situation. Comparing AddNet to a comparable regular CNN, time savings of 12.4% can be obtained. Additionally, AddNet outperforms binary-weight neural networks and regular CNNs in terms of smoke recognition ability.

In 2023, Abdusalomov et al. [21] proposed a DL technique to classify flames and enhances the detection of forest fires. A unique dataset was required for the training model, which was more accurate than the other models. The experimental outcomes confirmed that the developed method for forest fire detection effectively identified fires with an enhanced precision of 99.3%.

In 2022, Zhou et al. [22] proposed a DL-based instance segmentation method for automatically detecting indoor fire loads using computer vision. First, the materials that make up various types of indoor components are what distinguish them. This strategy is based on methods like categorization and training. The method's high efficiency is demonstrated by the fact that it can identify fire loads 1200 times quicker than humans can when compared to manual detection.

In 2022, Mukhiddinov et al. [23] suggested a fire detection and notification system for blind and visually impaired individuals that uses DL. The use of technology makes it possible to identify flames before they spread inside buildings. The smart glasses system uses audio signals to take pictures and alert residents of the BVI to fires and other nearby objects. The big fire image dataset includes interior fire images to identify fires.

In this chapter, the literature review shows that the early detection of fires is difficult to implement, and expensive sensor components are one of the main challenges in construction. One of the main sources of fire accidents is smoking, faulty wiring, lighting, chemical fires, and heaters. To overcome these problems, a novel FP-BEN was introduced fire detection by collecting semantic data from sensors in real time.

3. PROPOSED FP-BEN

Fire pixel has a commonly high-intensity value than nearby pixel values for both outdoor and indoor environments furthermore, fire shape varies irregularly based on fuel type or airflow. Probabilistic fire pixel detection is required in the first phase. Second, modified hybrid background subtraction is used to identify the fire, and third, luminance mapping is used to enlarge the fire area. Figure 1 depicts the suggested FP-BEN model's architecture. This strategy includes several techniques, which are described in more depth in the following sections.

3.1. Fire pixel detection by Gaussian probability distribution

On videos, it employed a mechanism for early fire detection. This technique uses a red plane threshold to locate the pixels that represent flames and determine saturation limits. Although this method needs certain criteria to identify fire pixels, it is limited in its ability to detect changes in burning material or fluctuations in the lighting of the fire environment. As a result, the proposed approach uses the RGB probability distribution to identify potential fire pixels. Different picture distributions are used by each station. The following description of this distribution's fit to each channel's individually calculated Gaussian probability distribution follows:

$$p_c = \frac{1}{\sqrt{2\pi\sigma_c}} exp - \left(\frac{(I_c(x,y)-\mu_c)^2}{2\sigma_c^2}\right), c\epsilon\{R,G,B\} \quad (1)$$

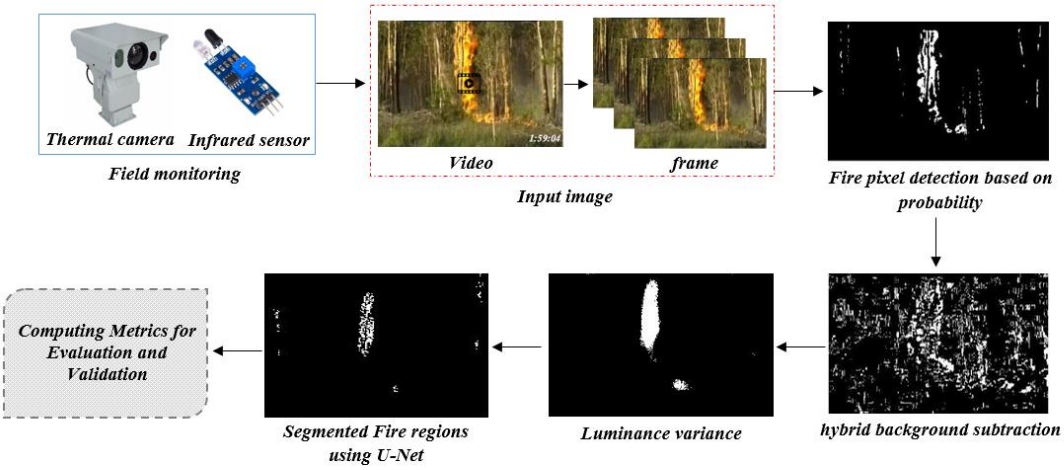


Figure 1. Proposed FP-BEN methodology

Where I_c (x, y) shows the amount of channel C pixels in a frame, μ_c is the average color space value, and σ_c is the normal distribution's fire area standard deviation. Figure 2 displays the probability distribution function value for the red channel. The computed pdf for the blue and green channels is done identically.

$$p\big(I(x,y)\big) = \Pi_{c\in\{R,G,B\}} p_c(\mathrm{I(x,y)})$$
$$\begin{cases} if\ p\big(I(x,y)\big) > \tau & fire\ pixel \\ else & non-fire\ pixel \end{cases} \quad (2)$$

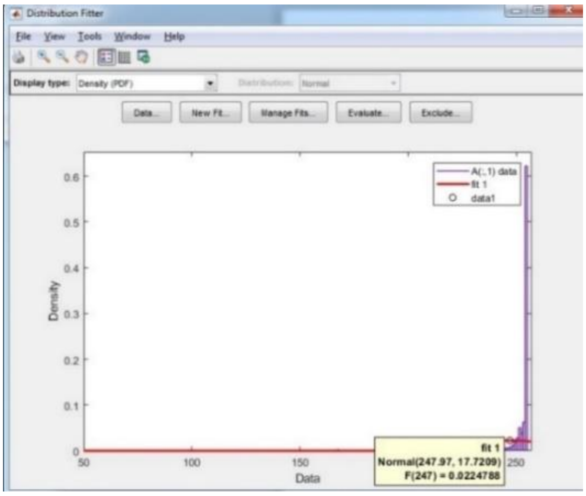


Figure 2. Graph showing the red channel fire pixel distribution

3.2 Hybrid Background Subtraction for Moving Pixel Detection

The background subtraction method is used to eliminate the non-fire pixel possibilities after the delineation of the fire pixels using the Gaussian probability model. Fire travels according to the wind and the material that is burning. The threshold for the background subtraction technique in the videos is the difference between two adjacent frames. A different technique for background subtraction is the double-difference method, but it cannot be applied in real-time. They must become familiar with a background using a hybrid background subtraction technique to prevent aperture and ghosting effects. The solution illustrates in (3)

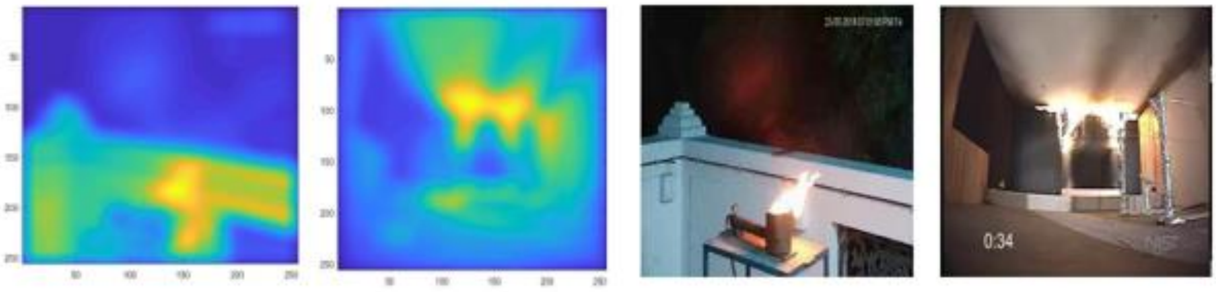
$$background[x,y]_{n+1^{th}frame} = \begin{cases} I\ [x,y]_{n+1^{th}frame} \\ \quad if\ frame\ no = 1 \\ |(1-alpha)^{*} I[x+y]_{n+1^{th}frame} - \big(alpha * I[x+y]_{n^{th}frame}\big)| \quad else \end{cases}$$

$$moving\ pixel\ detection = \begin{cases} \quad firepixel \\ if\ I^{th}_{n+1}frame\ [x,y] - uint8\big(background[x,y]_{n+1\ th\ frame}\big) > \tau \\ \quad non\ fire\ pixel \quad else \end{cases} \quad (3)$$

In this method, the background is learned and updated frame by frame to detect the moving object (fire) with fewer false positives. Alpha numbers range from 0 to 1 in equation (3). This suggested method selects an alpha value of 0.8 and a cut-off value that ranges from 2 to 4. For the test video dataset, these values are established experimentally. According to observations, setting the threshold number to 2 yields the best detection results.

3.3 Temporal-luminance Filter for removal of non-Flame pixel

Despite that a few non-flame pixels could be removed using the first two steps, it is still challenging to discriminate the moving fire region and moving fire color region, and false positions by using these conditions. The creation of the luminance feature map (L) in a frame using the 7x7 and 13x13 filter settings. The image is down-sampled by two before these two filters are applied. The filter will substitute the absolute difference between the window size w's center pixel and its surrounding pixels. The result of the filter is referred to as brightness mapping. Equation (4) L represents the luminance resulting from combining the output from two filters of different sizes. This featured image is up-sampled by 2, and the noise is then removed using a Gaussian filter. Figure 3 displays the result of the luminance map.



(A) (B) (C) (D)

Figure 3. (A, B) Luminance map, (C, D) original frame of our dataset.

$$\tilde{L} = \frac{1}{2}\left(\sum_{we(7\times7,13\times13)} \otimes\, w\right) \tag{4}$$

After creating a luminance feature map, the luminance variance of pixels at (x, y) positions for ten additional frames is determined. Real-time flame detection is noise-insensitive, meaning that it is irrelevant if we consider more than 10 sequential frames. If considering fewer than 10 frames, however, it fails to detect fires. The flame pixel variance in this work is substantial due to the disorganized nature of the succeeding frames. After reviewing several video datasets, the variance threshold is set to L, which denotes the fire pixel. The following formulae are used to determine the feature map image's mean and variance:

$$\mu_{x,y\;L(r)} = \frac{1}{\sum_{r=1}^{N} H_{xy\;L(r)}} \sum_{r=1}^{N} r H_{xy\;L(r)} \tag{5}$$

Where r is the vector that represents the various intensities of the ten successive luminosity images. The probability density function of the 10 successive Luminance images is represented by the pixel-by-pixel histogram H_{xyL}, where L is the luminance map.

$$\sigma_{x,y\;L} = \frac{1}{\sum_{i=1}^{N} H_{x,y\;L(u)}} \sum_{i=1}^{N} (r - \mu_{x,y\;L})^2\, H_{x,y\;L(u)} \tag{6}$$

$$\begin{cases} if\ \sigma_{x,y\;L} > L_\tau : fire\ pixel\ candidate \\ \quad else \quad : non\ fire\ pixel\ candidate \end{cases} \tag{7}$$

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3.4 Segmented Fire regions using U-Net

The fire regions are segmented using u-net, it performs encoding and decoding operation. The encoder contains of series of convolutional layers tracked by max-pooling layers. Each convolutional layer applies a convolution operation with filters of size $k \times k$, using optional padding to preserve the spatial dimensions. Mathematically, the output of a convolutional layer can be stated as:

$$Y = \sigma(W * X + b) \tag{8}$$

where $X \in \mathbb{R}^{H\times W\times C}$ denote the input image, where H, W, and C signify the height, width, and no. of channels. W represents the convolutional kernel, b is the bias, $*$ denotes the convolution operation, and σ is ReLU/GeLU. After each convolution, a $m \times m$ max-pooling operation is applied to decrease the spatial resolution by a factor of m. The bottleneck, or bridge, connects the encoder and decoder. It consists of cl, $k \times k$ convolutions, surveyed by a ReLU/GeLU activation function. This layer captures the deepest level of feature representations with the smallest spatial dimension.

The decoder is structurally symmetric to the encoder and comprises up sampling operations followed by convolutional layers. The up-sampling operation doubles the spatial resolution, achieved through either transposed convolution (also known as deconvolution) or interpolation techniques. This can be represented as:

$$Z = W^T * Y \quad (9)$$

where W^T is the transposed convolution kernel, and Y is the input from the previous layer. After up sampling, the corresponding feature map from the encoder is connect to the decoder feature map to preserve spatial information. This is known as a skip connection and is crucial for retaining fine details. Following concatenation, each feature map is refined by passing it through activation function, cl, and $k \times k$ convolutions, which gradually reconstitute the spatial resolution. A 1 × 1 convolution, the last layer of the U-Net architecture, lowers the number of channels to the required number of output classes. In segmentation tasks, the softmax function provides a probability distribution over the classes for each pixel.

$$P(c_i|X) = \frac{exp\,(S_i)}{\sum_{j=1}^{C} exp\,(S_j)} \quad (10)$$

where s_i is the score for class i, and C is the total no. of classes. For binary segmentation tasks, U-Net uses the binary cross-entropy (BCE) loss:

$$L_{BCE} = -\frac{1}{N} y_i\, log(\hat{y_i}) + (1 - y_i) log(1 - \hat{y_i}) \quad (11)$$

where y_i represents the true label, $\hat{y_i}$ represents the predicted probability, and N represents the total number of pixels.

where y_i is the true label, $\hat{y_i}$ is the predicted probability, and N is the total number of pixels. For multi-class segmentation, CE loss is generalized as:

$$L_{CE} = -\sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y_i}, c) \quad (12)$$

where, c is the predicted probability for class c and $y_{i,C}$ is the one-hot encoded label for class c and $\hat{y_i}$

4. RESULTS AND DISCUSSIONS

An algorithm fire detection approach has been implemented for different resolutions of videos. This technique has been used to identify flames in live fires that are spreading slowly. For testing purposes, the frame rate was adjusted to 3–10 frames per second.

The suggested fire detection method and Amin Khatami method have both been put through their paces on the same set of test videos that present a variety of difficulties, including frame flipping, Gaussian noise, objects that resemble fire, different illumination, and different resolution. These videos are distinct from the training videos used to teach the model patterns and features during the training phase as shown in Table 1. Table 2 lists the recommended technique for the test videos and outcomes, along with a comparison to Amin Khatami's approach. Total detection accuracy and true positive rate for fire segmentation using this technique are both acceptable at 91.66% and 92.43%, respectively. Since fire and objects that resemble fire have a greater degree of color similarity, Amin Khatami et al.'s [22] approach produces a high percentage of false positives for test video 2.

Table 1. Test videos description

Testing Videos	Number of Frames	Description
Test Video 1	100	Fire-Accident set-up (Smart Space LAB)
Test Video 2	100	Fire-Accident set-up (Smart Space LAB)
Test Video 3	100	Night Club fire (Dataset from NIST)
Test Video 4	100	Christmas tree fire in living room
Test Video 5	100	Forest fire (Dataset from Visifire)
Test Video 6	100	Forest fire (Dataset from media)

Table 2. Accuracy of detection in test videos

Testing Videos	Detection Accuracy	True Positive Rate	False Positive rate
	Amin Khatami Method [22]		
Test Video 1	88	88.89	20
Test Video 2	87	91.10	50
Test Video 3	80	82.68	40
Test Video 4	85	84.32	20
Test Video 5	83	86.67	20
Test Video 6	81	84.58	30
Average	84.66	86.37	30
	Proposed Method		
Test Video 1	96	96.67	10
Test Video 2	99	98.89	0
Test Video 3	93	95.56	30
Test Video 4	93	94.44	20
Test Video 5	86	84.63	20
Test Video 6	83	84.40	10
Average	91.66	92.43	15

This proposed colour model approach yields a high false positive rate. The proposed investigation reduces the false positive rate by using temporal analysis, background subtraction, and colour model probability. Results have been contrasted with the Amin Khatami strategy because, according to the literature review, it has the best TPR and detection accuracy. The performance of our suggested technique has surpassed that of the already published algorithms.

Table 3. Comparison between various filter

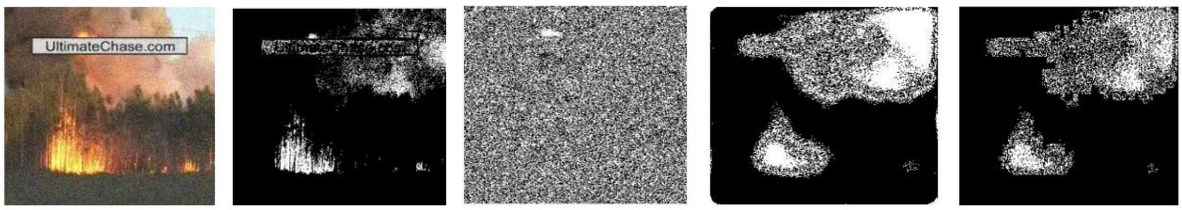
Filter	Detection Accuracy	True Positive Rate	False Positive rate
Adaptive probability distribution	78.95	82.14	20
Threshold probability distribution	83.47	88.29	20
Gaussian probability distribution (proposed)	91.83	92.77	16.66

Table 3 shows the comparsion between various filter like Adaptive probability distribution, Threshold probability distribution and Gaussian probability distribution. The step-by-step method for the fire segmentation process is shown in Figure 4. The amount of false alarms produced by each step varies, but when all the steps are taken into account, the resulting frame is confident in locating the fire area. A few real-time tasks, including flipping the frame, fire-like objects, Gaussian noise, variable brightness, and various dataset resolutions, will be used to gauge the effectiveness of the proposed work.

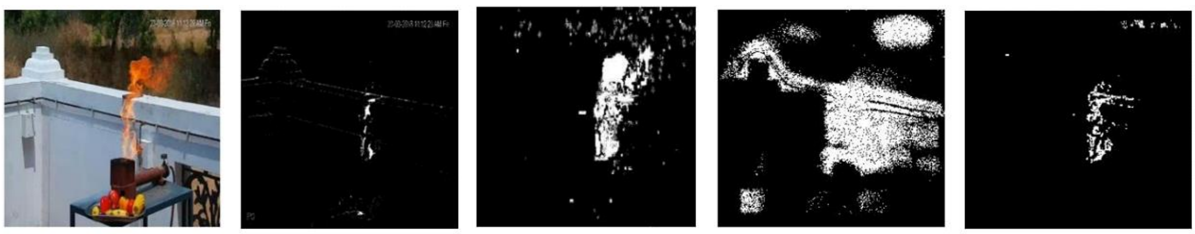
Various challenges are applied to the input frame

FLIP THE FRAME

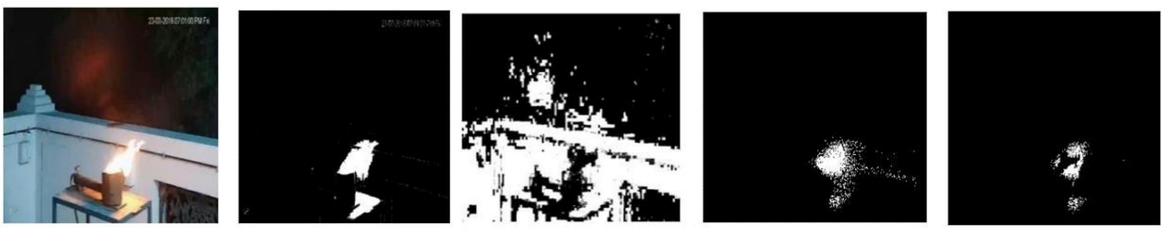
ADD Gaussian Noise with variance -0.001



FIRE-LIKE Objects



Night Vision



No Fire Frame

(a) (b) (c) (d) (e)

Figure 4. The input frame is in column (a). The burning pixel is located using the Gaussian pdf function in column (b). utilizing the hybrid background subtraction algorithm, identify the moving fire pixel in column (c). d) Column.

Table 4. Test frames with varying resolutions and their corresponding outputs

S. No	Different Resolution of Input Frames	Corresponding Output
1	492x360 	
2	512x288 	
3	640x360 	
4	1280x720 	
5	1920x1080 	

Table 4 presents a comparison of fire detection across different video resolutions, showing input frames alongside their corresponding processed outputs. The outputs highlight detected fire regions, demonstrating the robustness of the suggested fire detection technique across various resolutions.

5. CONCLUSION

In this research, a novel FP-BEN model for detecting fire in images or videos. This study used a mix of probabilistic, hybrid background subtraction, and temporal Luminance variance methods to identify fire pixels. The Gaussian probability density model was used to calculate the colour probability of the fire pixel. The fast-moving fire object is isolated by the hybrid background technique, which updates the background of the current frame. Utilizing a luminance filter to increase the fire region's magnitude and a variance threshold to reliably identify fire pixels from a temporal viewpoint, the temporal luminance method. This method has been tried on many difficult video datasets. The proposed model uses colour channel probability, fast-moving object tracking, and temporal analysis of pixels facing different challenges as well. This method also proved to be effective at detecting fire areas in images or videos that contain background noise. High recognition precision and true positive rates are shown by the experiment's results. It can try to speed up computation times for real-time fire detection systems by using the temporal luminance method in this research, which has longer computation times. The trials' findings show outstanding identification accuracy for video frames in several illumination scenarios and resilience to noise, such as smoke. The fire spreading direction can also be predicted in future work based on the wind and spreading speed of the fire.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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