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Early Fire Detection Alarm Using Deep Learning

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ABSTRACT: Fires pose a big danger to each of the surroundings and human lives, needing the development of an efficient detection gadget to mitigate their effect. Using pc vision and device mastering techniques, this paper introduces a new device for detection of fireplace in infrared images. The machine leverages brightness classification, photograph processing, and histogram based totally segmentation to decorate accuracy and allow real time implementation. Deep Learning (DL) techniques, particularly YOLO V3 as a classifier, are employed to reap excessive accuracy in hearth detection. The device is evaluated towards the backdrop of growing wildfire occurrences globally, highlighting the urgency of an effective detection answer. Feasibility research, danger evaluation, and software development phases are mentioned, emphasizing rigorous trying out and optimization to ensure reliability. The proposed device proves promising effects, presenting a robust and green method to early and exact fireplace detection, thereby mitigating the damages because of wildfires. Collaboration with stakeholders and continuous refinement will in addition beautify the gadget's effectiveness and impact.

KEYWORDS: Fire accidents, CNN, YOLOv3, Deep Learning.

I.INTRODUCTION

The challenge of forest fires persists as a significant threat to our planet's health, disrupting ecosystems, biodiversity, and crucial natural resources. Detecting these fires early and accurately is essential, and our proposed vision-based fire detection system, powered by deep learning, presents a groundbreaking solution tailored for large-scale outdoor environments. During dry summer months, vegetation becomes highly flammable, escalating the risk of forest fires [1]. Regions like the Garhwal Himalayas experience frequent and devastating fires due to prolonged dry spells, leading to ecological damage and loss of vegetation cover [2]. The repercussions extend beyond immediate destruction, impacting wildlife habitats, contributing to soil erosion, and affecting air quality. Forest fires result from natural phenomena and human activities [1]. While lightning strikes can ignite trees, human actions significantly contribute to wildfires [2]. In the United States, human-related causes account for a staggering 90% of wildfires, stemming from negligence or deliberate arson [3]. Forest fires categorize into natural, negligent, and intentional types [3]. Understanding seasonal fire occurrence patterns underscores the need for preventive measures, especially during dry periods [3]. Historically, forest management involved creating fire lines to contain outbreaks, emphasizing the importance of early detection and swift responses. Sensor-based fire detection systems, primarily used indoors, face challenges in vast outdoor settings like forests [1]. Their reliance on fire proximity and susceptibility to heat damage hinder early wildfire detection effectiveness [2]. Vision-based fire detection offers a potent alternative for large-scale environments [1, 2]. Utilizing cameras and advanced algorithms, these systems provide immediate fire detection, proving cost-effective and robust compared to sensor-based methods [1, 2]. Vision-based systems detect fires from a distance, enabling timely intervention and minimizing damage extent. Deep learning, notably techniques like YOLOv3, revolutionize fire detection [3, 4]. Unlike traditional methods, YOLOv3 autonomously learns complex fire patterns, accurately distinguishing fires from other objects even in challenging environments [3]. This adaptability is crucial in forests where background complexities can obscure fire visibility. Our vision-based fire detection integrates seamlessly with various camera types, including UAVs, facilitating comprehensive forest monitoring [5]. Leveraging deep learning, it overcomes background subtraction method limitations, reliably detecting fires against dynamic backgrounds [6]. YOLOv3's superior performance ensures a highly accurate and robust system [3]. Early detection is pivotal in combating forest fires. Our proposed vision-based system, driven by deep learning, significantly enhances fire detection,

minimizing their devastating impact. Integrating this technology into forest management protects ecosystems, biodiversity, and promotes woodland health.

II.LITERATURE SURVEY

Fire accidents pose a significant threat to forest lands and residential areas. Various measures, including prevention, detection, and extinguishing, are vital in fighting fires. The use of advanced records generation, like Geographic Information Systems (GIS), was explored to enhance strategic and tactical planning, along firefighting operations. GIS has the capacity to revolutionize firefighting operations with the aid of supplying real-time records and strategic insights. However, notwithstanding its capability, the effectiveness of GIS became drastically low and didn't make a sizable effect on reducing fire harm. This suggests that whilst era can aid in firefighting efforts, it isn't a silver bullet and have to be complemented with effective floor operations[6].The random forest model turned into proposed to predict hearth injuries the use of satellite information and climatic variables from affected regions. This method leverages the strength of system learning to predict fire incidents, aiming to limit the results of future fires. Although this model better the accuracy of fire detection in tropical regions, it lacked efficiency and precision in detecting woodland fires. This highlights the demanding situations of applying gadget gaining knowledge of models in complicated, actual-world situations where in several variables can have an effect on the final results[7].Unmanned Aerial Vehicles (UAVs) have been utilized to examine fire accidents. They offer a chook's eye view for quicker response in great affected areas. The fireplace detection version the usage of UAVs performed an accuracy of 93.97%, but the alarm rate and error rate stood at 7.08% and 6.86%, respectively. The thick layer of smoke masking maximum of the fire place became the main reason for misidentifications. To enhance fire detection in such situations, a further step to locate smoke became delivered. Segmenting smoke pixels primarily based on color and movement capabilities proved useful in finding the hearth in smoky situations. However, this approach nonetheless faces challenges in differentiating between smoke and different comparable-looking phenomena[8].A fire incident detection method leveraging optical pix for smoke detection and infrared images for fireplace detection was proposed. This technique combines special styles of data to improve detection accuracy. However, this model become confined to looking at large landscapes plentiful in wooden resources. This dilemma indicates that even as the model may be powerful in sure scenarios, it can no longer be universally applicable[9].The proposed framework introduces novel mechanisms for flame motion analysis in fire incidents primarily based on spatiotemporal functions the usage of videos. This approach goals to triumph over the constraints of static photo analysis via leveraging the temporal records available in videos. However, assessing fireplace movement/motion inside woodland zones with static pics gives a venture. This highlights the want for more superior video analysis techniques in fireplace detection[10].The E-EFNet model, which uses the lightweight EfficientNetB0 as a primary function extractor, become designed to reduce false alarms and enhance accuracy. It exceeded prior latest fashions in each accuracy and false alarm rate. However, it needs to be examined on resilient systems and useful resource-confined part devices for actual-time fireplace detection in numerous IoT packages. This shows that at the same time as the model performs nicely in managed environments, its performance in real-global scenarios remains to be seen[11].The paper proposes a easy, rapid, and correct electronic discovery method using deep mastering. This method filters the picture into pixels based on properties which includes color, tone, and flame and their mirrored image as thresholds. The results obtained display more than 97% accuracy while applied to greater than seven hundred photographs for schooling and checking out functions. However, a comparative evaluation of the proposed device and some operational records shows that the set of rules proposed on this paper outperforms different algorithms in phrases of accuracy, precision, and recall. This shows that while the proposed method shows promise, it nevertheless has room for development, specifically in phrases of precision and recall[12].

III.PROPOSED SYSTEM

The proposed system for real-time wildfire detection using a YOLOv3 deep learning model deployed on a portable Neural Network compute stick. The system leverages a UAV (Unmanned Aerial Vehicle) for image acquisition and leverages geospatial tagging to pinpoint fire locations.

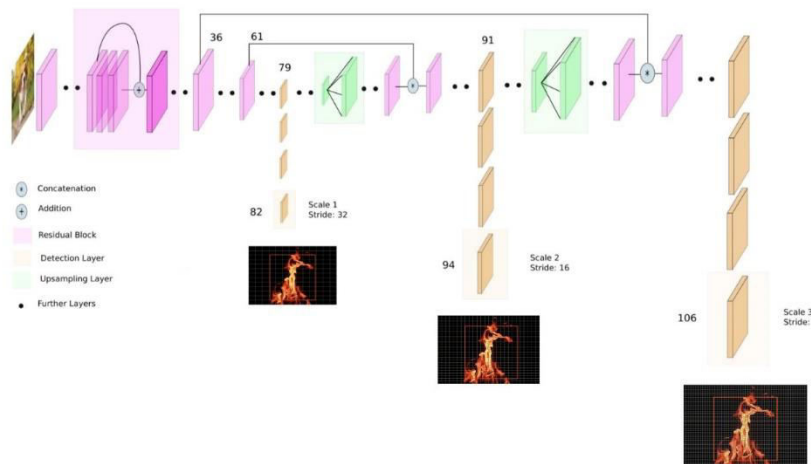


Fig. 1: YOLOv3 Network Architecture

The core of the system is the YOLOv3 deep learning model, renowned for its object detection capabilities. As illustrated in Figure 1, YOLOv3 follows a multi-stage architecture designed for efficiency and accuracy. The model can be broken down into the following key stages:

- **Preprocessing:** Input image resized to a standard size (e.g., 416x416 pixels). Possible data augmentation techniques applied (random scaling, cropping) to enrich the dataset and prevent overfitting on fire-specific details.
- **Feature Extraction:** A series of convolutional techniques with batch normalization and Leaky ReLU enable further enhancement of fire-related features. The First layers capture low-level features like edges and texture. Later layers combine these features to form higher-level representations crucial for fire detection (e.g., identifying smoke patterns, and analyzing color variations typical of wildfires).
- **Object Detection:** YOLOv3 uses multiple detection layers to predict bounding boxes and class values for different objects. Each layer focuses on a specific size range (large, medium, and small fires). The network predicts offsets to predefined anchor boxes to obtain final fire-bounding boxes. Class probabilities indicate the likelihood of fire being present in the bounding box.

The YOLOv3 predicts an objectness score for each bounding box using logistic regression. This should be 1 if the bounding box prior overlaps a ground truth object by more than any other bounding box prior. If the bounding box prior is not the best but does overlap a ground truth object by more than some threshold we ignore the prediction, following Redmon et al., 2016. We use a threshold of .5. If the bounding box prior does not overlap any ground truth object we use "no object" loss.

The YOLOv3 network predicts 4 coordinates for each bounding box t_x, t_y, t_w, t_h . If the cell is offset from the top left corner of the image by (c_x, c_y) and the bounding box prior has width and height p_w, p_h then the predictions correspond to:

$$\begin{aligned} b_x &= \sigma(t_x) + c_x \\ b_y &= \sigma(t_y) + c_y \\ b_w &= p_w e^{t_w} \\ b_h &= p_h e^{t_h} \end{aligned}$$

Where $\sigma(x)$ is the sigmoid function. The sigmoid function is defined as:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

The network also predicts a confidence score for each bounding box. This score reflects how likely the box contains an object (objectness) and how accurate is the box. The score is in scale 0 to 1. The loss function also accounts for this score.

The YOLOv3 model, which is used in our proposed system for real-time wildfire detection, employs a specific loss function during its training phase. This loss function plays a pivotal role in adjusting the model's internal parameters for optimal performance. It quantifies the discrepancy between the model's predictions and the actual data, providing a measure that the model aims to minimize.

In the context of fire detection, the YOLOv3 loss function is a composite of three distinct components:

1. Localization Loss: This component of the loss function ensures the accuracy of the bounding box predictions for detected fires. It computes the sum of squared differences between the predicted and actual bounding box parameters, which include the center coordinates (x, y), and the width and height of the bounding box.
2. Confidence Loss: This component measures the error in the objectness prediction for each bounding box. The model predicts a confidence score that indicates the likelihood of the bounding box containing a fire. The confidence loss is the squared difference between this predicted confidence score and the actual label (1 if the box contains a fire, 0 otherwise).
3. Classification Loss: While this component is more relevant in multi-class detection scenarios, in the binary classification context of fire detection, it ensures that the model correctly identifies whether a detected object is a fire.

The overall loss function can be represented as:

$$\begin{aligned} Loss = & \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^B 1_{ij}^{obj} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \\ & + \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^B 1_{ij}^{obj} [(\sqrt{w_i} - \sqrt{\hat{w}_i})^2 \\ & + (\sqrt{h_i} - \sqrt{\hat{h}_i})^2] \\ & + \sum_{i=0}^{S^2} \sum_{j=0}^B 1_{ij}^{obj} (C_i - \hat{C}_i)^2 \\ & + \lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^B 1_{ij}^{noobj} (C_i - \hat{C}_i)^2 \\ & + \sum_{i=0}^{S^2} 1_i^{obj} \sum_{c \in classes} (p_i(c) - \hat{p}_i(c))^2 \end{aligned}$$

Where:

1_{ij}^{obj} denotes if an object appears in cell i

1_{ij}^{obj} denotes that the jth bounding box predictor in cell i is "responsible" for that prediction

λ_{coord} and λ_{noobj} are weights for the localization loss and no objectness loss, respectively

This loss function is used during the training process to update the model's parameters and improve its performance. It helps the model to learn to detect fires accurately and reliably.

In the YOLOv3 model, lambda constants are utilized to differentially weight the components of the loss function, thereby improving model stability. The highest penalty is assigned for coordinate prediction with $\lambda = 5$, while the lowest penalty is assigned when no fire is detected, with $\lambda = 0.5$.

The model employs a binary cross-entropy error function. In this context, the squared error terms typically used in regression problems are replaced by cross-entropy error terms. As a result, class predictions and object confidence are predicted through logistic regression.

$$CE(p, y) = \begin{cases} \log(p), & \text{if } y = 1 \\ \log(1 - p), & \text{if } y = 0 \end{cases}$$

Where CE is the cross-entropy, p is the predicted probability, and y is the true label (1 for fire, 0 for no fire).

Non-Maximal Suppression (NMS) is employed to select the best bounding box. It first discards predicted bounding boxes that have a detection probability less than a given NMS threshold. Then, it eliminates all the bounding boxes whose Intersection Over Union (IOU) value is higher than a given IOU threshold. IOU is an evaluation metric used to measure the accuracy of an object detector on the task of fire detection.

$$IOU = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

This step ensures that all boxes that have a large overlap with the selected boxes are removed. Only the “best” boxes, which are those that accurately encapsulate the region of the fire, remain.

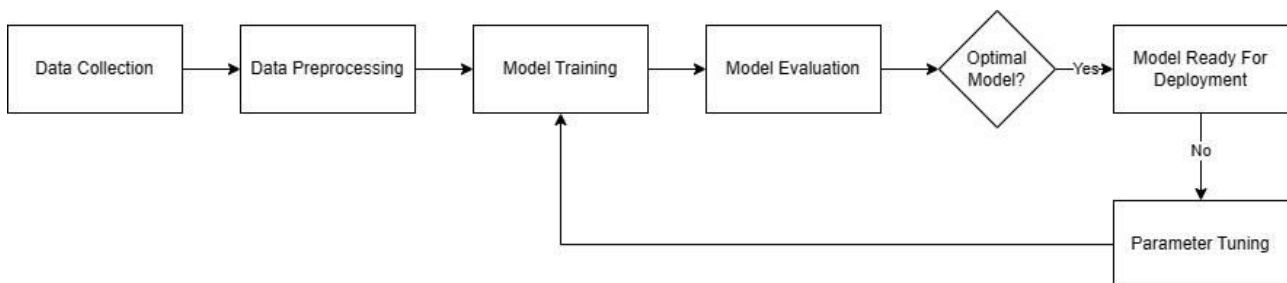


Fig.2: Model Training Flow Chart

The success of the YOLOv3 model hinges on effective training. The flow chart shown in Figure 2 illustrates this process. The main steps are divided as follows:

- **Data Preparation:** A dataset of wildfire images is collected and undergoes preprocessing. This may involve tasks like resizing, labelling fire instances, and potentially data augmentation techniques to enrich the dataset and prevent overfitting. The entire data is divided into a training set and a testing set.
- **Model Training:** The YOLOv3 model architecture is loaded, and the training set is fed into the model. An optimizer function (e.g., RMSprop) guides the model to adjust its internal parameters to minimize the loss function (often binary cross-entropy) and improve its ability to distinguish fire from non-fire images.
- **Evaluation and Refinement:** The performance of the model is evaluated on the testing set. Measures such as accuracy are used to evaluate the model's performance in classifying fire and non-fire images. Based on the evaluation results, the model's hyperparameters or training process may be refined to achieve optimal performance. Real-time Fire Detection Flowchart The system transitions into real-time operation once a well-trained YOLOv3 model is obtained.

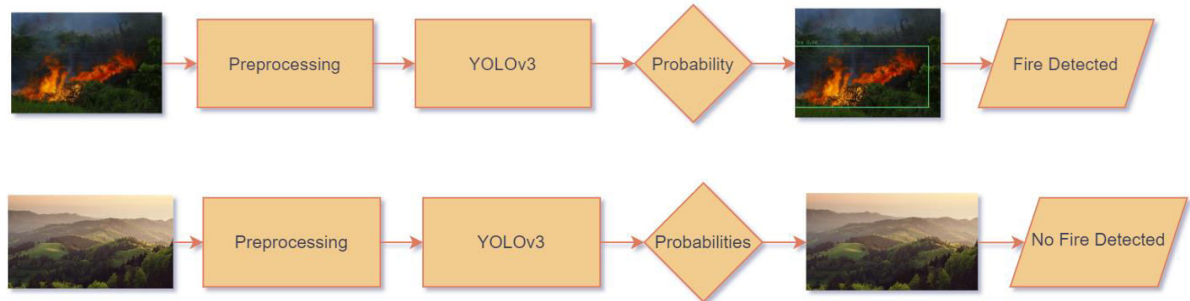


Fig.3: Real-time Fire Detection with Probability Determination and Classification

The real-time fire detection with probability determination and classification involves in the following sequence of steps:

- Image Acquisition and Preprocessing: The UAV captures real-time video footage. Frames are extracted from the video feed at a designated rate of 1 frame every 4 seconds using OpenCV, an open-source computer vision library. Each extracted frame undergoes preprocessing to ensure compatibility with the trained YOLOv3 model. This may involve tasks like resizing and normalization.
- YOLOv3 Model Inference: The preprocessed frame is fed into the trained YOLOv3 model. The model performs inference, analyzing the frame and predicting the presence or absence of fire.
- Probability Determination and Classification: If the model predicts fire, it assigns a probability score indicating the model's confidence level in this prediction. A pre-defined threshold is used to determine if the predicted fire probability is high enough to be considered a true positive fire detection. Frames exceeding the threshold are classified as "fire," while those below the threshold are classified as "no fire." The class probabilities are calculated using a softmax function:

$$P(\text{Class } i \mid \text{Object}) = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

Where x_i is the score for class i before softmax.

The final output of YOLOv3 is the multiplication of the class probabilities and the bounding box objectness scores:

$$Pr(\text{Class}_i) * Pr(\text{Object}) * IOU_{pred}^{truth} = Pr(\text{Class}_i \mid \text{Object}) * Pr(\text{Object})$$

This gives us the final detection scores across all classes and we can filter out the ones below a certain threshold.

- Alert System and Geospatial Tagging: If a frame is classified as "fire," the system triggers an alert mechanism. This may involve sending notifications to designated personnel or triggering automated responses. The geospatial tagging functionality, while not explicitly covered in this paper, would leverage the UAV's GPS data to pinpoint the exact location of the detected fire, enabling a swifter response. The proposed system is designed for deployment on a portable Neural Network compute stick, leveraging its computational power for real-time inference. This allows for on-site wildfire detection without relying on remote servers or high-powered computing resources.

IV. EXPERIMENTAL RESULTS

Spectrum Our model has been trained on Google Colab, a platform that provides free access to a T4 GPU for training machine learning models. We used a custom dataset of about 500 images containing fire, which were downloaded from Google and annotated using LabelImg, a graphical image annotation tool. The dataset is also annotated in ($\langle x_{min} \rangle \langle y_{min} \rangle \langle x_{max} \rangle \langle y_{max} \rangle$) format which were converted into the format suitable for YOLO ($\langle object_class \rangle \langle x_center \rangle \langle y_center \rangle \langle width \rangle \langle height \rangle$) The images were annotated in a format suitable for YOLO, which includes the object class and the centre, width, and height of the bounding box for each object in the image.



For testing our model's performance, we used the images in the FireNet Dataset. We also made a custom dataset of 100 images downloaded from Google, which contains images of wildfires from various perspectives and angles.

The model was trained with the parameters of YOLO as shown in Table I. Fires are represented by label 0. The training parameters were as follows:

TABLE I
TRAINING PARAMETERS

Parameter	Value
Max Batches	2000
Steps	1600, 1800
Filters	18
Classes	1

The YOLOv3 model achieved exceptional results, demonstrating its effectiveness in fire detection. It attained a remarkable mean Average Precision (mAP) of 98.98%, signifying a high degree of accuracy in predicting fire across diverse conditions. This is further corroborated by the high precision (96%) and recall (96%) achieved by YOLOv3. Precision indicates the model's ability to minimize false positives (non-fires identified as fires), while recall reflects its success in capturing all actual fire instances. Both metrics being at 96% highlight YOLOv3's proficiency in accurate fire detection with minimal false alarms.

TABLE II
PERFORMANCE COMPARISON OF YOLOV3 AND CNN FOR FIRE DETECTION

Metrics	YOLOv3 Model	CNN Model
Precision	96%	84.5%
F1-score	96%	84.5%
Recall	96%	84.5%
Mean Average Precision (mAP)	98.98%	86.6%

Table 2 provides a quantitative comparison of the YOLOv3 and CNN models across various performance metrics. As evident from the table, YOLOv3 significantly outperforms the CNN model in all aspects. The CNN model achieved a lower mAP of 86.6%, suggesting a less robust performance in identifying fires under varying conditions. Additionally, its precision and recall were both at 84.5%, indicating a higher likelihood of both false positives and missed fire detections.

TABLE III
CONFUSION MATRIX FOR FIRE DETECTION

	Predicted Fire(+ve)	Predicted non-fire (-ve)
Actual Fire	True Positive (TP)=484	False Negative (FN)=18
Actual non-fire	False Positive (FP)=21	True Negative (TN)

Table 3 presents a detailed confusion matrix for the YOLOv3 model's fire detection performance. The table breaks down the predictions into True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Based on this data, we can calculate the F1-score, which combines precision and recall, further solidifying the model's effectiveness (F1-score \approx 0.96). The Intersection over Union (IoU) metric, which measures the overlap between the prediction and the accuracy of the box, also confirms the accuracy of YOLOv3, with an average IoU of 76.03%.

TABLE IV
CONFUSION MATRIX FOR FIRE DETECTION

	Predicted Fire(+ve)	Predicted non-fire (-ve)
Actual Fire	True Positive (TP)=422	False Negative (FN)=78
Actual non-fire	False Positive (FP)=78	True Negative (TN)

For reference, Table 4 displays the confusion matrix for the CNN model. The table reveals a significant number of misclassifications compared to YOLOv3. The CNN model identified only 422 actual fire instances (True Positives), resulting in a lower recall of 84.5%. Additionally, it produced 78 false positives, leading to a precision of 84.5%. The calculated F1-score 84.5% and mAP (86.6%) further emphasize the limitations of the CNN model compared to YOLOv3.

The comparative results demonstrably showcase the clear advantage of YOLOv3 for real-time fire detection. Its superior performance translates to a more reliable and accurate fire detection system, crucial for real-world applications. Early and precise fire detection plays a vital role in minimizing damage and ensuring safety in fire-prone environments. YOLOv3's exceptional performance metrics make it a compelling choice for developing robust fire detection systems.

V.CONCLUSION

Using image analysis technology, this paper presents a new method for forest fire detection. Forest area photographs are captured and fed into the system, where a computational method extracts and processes the information. The approach involves image preprocessing to focus on specific colour components, followed by image segmentation and data classification. The RMSprop optimization algorithm is employed to train the classifier, enabling it to predict the presence of forest fires. Our evaluation demonstrates the effectiveness of the proposed procedures, achieving a high detection accuracy of approximately 98% with a low false detection rate of around 2%. This promising performance suggests the system's potential for integration into forest fire monitoring systems, enabling real-time fire detection and improved response times.

VI.FUTURE SCOPE

The effectiveness of the fireplace view may be in addition accelerated by putting off smoke within the early ranges of the fireplace. However, smoke detection is a difficult mission and results in inaccurate readings because of climate situations, herbal lighting fixtures adjustments and other external factors. This high false detection can be stated by inspecting everywhere, together with smoke. However, this creates a excessive computational workload. Additionally, if we pick out video, we will calculate the unfold of the hearth over time with out the use of a digicam. Additionally, a far-advanced model such as YOLOv9 can be used to reduce false alarm rates.

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