IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

FIRE DETECTION AND ALERT GENERATION

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ABSTRACT-

In today's modern era, ensuring effective fire detection is imperative, particularly within industrial environments where swift response can mitigate substantial damages and save lives. Early detection serves as a crucial tool in halting the spread of fires by triggering alarms and notifying emergency responders, thereby safeguarding both property and individuals in the vicinity. However, deploying traditional fire and smoke detectors universally may not always be feasible.

Research into fire detection methods using Wireless Sensor Networks (WSNs) and video-based approaches has garnered considerable attention. Yet, WSN-based detection models often necessitate significant smoke and fire for accurate detection. Consequently, integrating fire and smoke detection capabilities into existing Closed-Circuit Television (CCTV) systems across various locations emerges as a practical solution. This integration provides timely warnings to relevant authorities, facilitating swift action to contain fires and identify individuals in high-risk areas. This also includes the number of people in the fire prone area, of which the alert is sent via message to the fire stations and their neighbours.

This study aims to develop an early fire prediction model utilizing CCTV footage images and video frames and detecting it via a live camera. Compared to conventional fire detectors, this approach may offer a more cost-effective solution. Early detection significantly contributes to fire prevention by promptly alerting emergency responders.

In this paper, we propose a fire detection method leveraging powerful deep learning algorithms, namely Haar Cascade and You Only Look Once (YOLO). We utilize data via the live camera to detect fires, count individuals, and generate alerts within the system, thereby enhancing overall fire prevention and response capabilities.

Keywords- Fire Detection, YOLO Algorithm, Haar Cascade, Alert Generation.

1. INTRODUCTION

In industrial environments, ensuring the safety and security of personnel and assets is of utmost importance. To address these concerns effectively, the integration of cutting-edge technologies into existing systems is crucial. One such advancement involves incorporating fire detection and alert generation, along with people counting capabilities, into live Closed-Circuit Television (CCTV) camera systems.

Industrial settings pose unique challenges for fire detection and emergency response due to the presence of hazardous materials, intricate machinery, and expansive infrastructure. Conventional fire detection systems, although functional, may not always deliver timely and precise results, leaving individuals and assets vulnerable to potential dangers.

By leveraging live CCTV cameras equipped with intelligent algorithms, industrial facilities can significantly enhance their fire detection capabilities. These algorithms analyze real-time video feeds, enabling early identification of smoke, flames, or other fire-related anomalies. Furthermore, through the utilization of machine learning techniques, these systems continuously refine their accuracy and reliability, minimizing the occurrence of false alarms and ensuring swift responses to genuine threats.

In addition to fire detection, the integration of people counting capabilities into CCTV camera systems provides an added layer of safety and security within industrial settings. Accurately tracking the movement and presence of personnel allows emergency responders to better evaluate the situation during fire incidents, facilitating more efficient evacuation procedures and resource allocation.

Moreover, people counting technology contributes to regulatory compliance and adherence to occupancy limits within industrial facilities. By monitoring occupancy levels in real-time, facility managers can proactively manage crowd density and enforce safety protocols, thereby reducing the risk of accidents and promoting the well-being of workers.

Overall, the integration of fire detection and alert generation with people counting capabilities in live CCTV camera systems offers a comprehensive approach to enhancing safety and security within the industrial domain. By harnessing advanced technologies and real-time data analysis, industrial facilities can mitigate risks, improve emergency response capabilities, and protect both personnel and assets from potential threats. As industrial practices evolve, the adoption of such integrated systems is poised to become indispensable for maintaining a safe and productive work environment.

2. LITERATURE SURVEY

The challenge of efficient fire detection by introducing an enhanced YOLOv4 method based on CNN. Traditional sensors struggle in specific environments and early stages of fires, leading to economic and ecological losses. The proposed model, refined using a high-quality fire dataset, employs a modified loss function and advanced post-processing techniques (Soft-NMS and DIoUNMS) for accurate small-scale flame detection and reduction of redundant bounding boxes. Experimental results demonstrate the model's outstanding real-time performance in detecting multi-scale fires [2]. The complexity of fires in diverse settings like forests, malls, and crowded areas poses significant threats, leading to massive losses yearly. Current fire safety methods are limited, emphasizing the need for early detection. It introduces an advanced fire detection model using deep learning algorithms, integrating high-end image surveillance and convolutional neural networks (CNN). The system effectively identifies fire in its early stages, surpassing existing models. The evaluation confirms its superior performance, addressing critical limitations for accurate fire detection in various environments [3].

This research paper discusses the development of an efficient and cost-effective forest fire detection method using convolutional neural networks. The goal is to prevent the devastating impact of forest fires on ecosystems and ecology by enabling early and accurate fire detection. This system aims to identify fires in real-time video streams, minimizing false alarms and reducing costs compared to traditional fire detection methods that rely on expensive sensors. The primary motivation is to enhance the protection of forests and their valuable resources through advanced computer vision technology [4]. The research paper aims to create an efficient system for forest fire detection using deep learning and machine learning. Its goal is to improve fire detection accuracy in forests, vital resources on Earth. It combines deep learning for feature extraction with machine learning algorithms like Random Forest, SVM, XGBoost, and K-Means to classify fire and non-fire images. The focus is on finding the most accurate algorithm combination, with CNN-RF and CNN-XGBOOST achieving 98.53% accuracy. This research aims to enhance early forest fire detection to prevent large-scale fires and protect our vital ecosystems [5].

The aim of this research paper is to create an affordable and effective fire detection system for surveillance videos, utilizing a CNN architecture. The objective is to harness advancements in embedded processing to identify fires in video surveillance. The system strives to find a balance between computational efficiency and detection accuracy, drawing inspiration from the GoogleNet architecture and fine-tuning it for fire detection. The primary drive behind this work is to enhance early fire detection in surveillance systems, a critical factor in minimizing losses and boosting safety by reducing response times to fire incidents [6].

3.MODEL

3.1. DESIGN OF THE PROPOSED SYSTEM

1. Video Input Processing:

The system starts by capturing live video input from cameras deployed in fire-prone areas. These cameras could be strategically placed in locations such as industrial facilities, commercial buildings where the risk of fire outbreaks is relatively high. To process these effectively, the video stream is divided into individual frames, which are essentially snapshots of the scene at different points in time. Each frame of the incoming video stream is processed in real-time to extract relevant information for fire detection and people counting.

2. Fire Detection using YOLO:

YOLO (You Only Look Once) is a state-of-the-art object detection algorithm known for its speed and accuracy in real-time applications. In this step, the YOLO algorithm is employed to analyze each frame of the video feed and identify instances of fire. The YOLO algorithm partitions the image into a grid, where it then proceeds to forecast bounding boxes and the likelihood of specific classes for objects contained within each grid cell. The trained YOLO model is capable of recognizing various objects, including fire, with high accuracy, enabling rapid detection of fire incidents in the video stream.

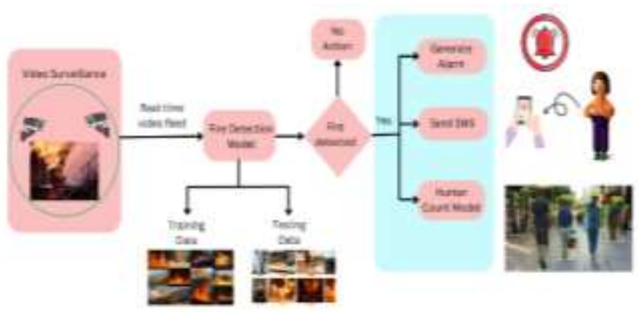


Figure 1. Design of the proposed system

3. People Counting with Haar Cascade Algorithm:

The Haar Cascade algorithm is a machine learning-based approach commonly used for object detection, particularly in detecting faces. In the context of this system, the Haar Cascade algorithm is utilized to count the number of people present in the vicinity of the fire-prone area. By detecting human faces in each frame of the video stream, the algorithm estimates the number of individuals within the camera's field of view. This provides valuable information for assessing the potential impact of the fire and planning evacuation procedures.

4. Alert Generation:

Upon the detection of fire in a frame, the system activates an alert mechanism to notify relevant parties and facilitate prompt action. Audible alarms can be activated to alert individuals in the vicinity of the fire. Text messages or notifications are sent to designated emergency contacts, providing them with information about the fire incident.

3.2. ARCHITECTURE DESIGN ANALYSIS

1. Model Backbone: Darknet-53

The backbone of YOLOv3 is called Darknet-53, which refers to a deep convolutional neural network with 53 layers. This backbone is crucial for extracting meaningful features from input images. Darknet-53 is designed to capture both low-level and high-level features through its deep architecture. Low-level features include edges, textures, and basic shapes, while high-level features encompass more complex patterns and object structures.

Darknet-53 achieves this feature extraction by employing a series of convolutional layers, followed by activation functions like ReLU (Rectified Linear Unit), and occasional pooling layers for downsampling. These layers work together to progressively learn and represent hierarchical features in the input image, making the model capable of understanding and detecting objects of varying complexities.

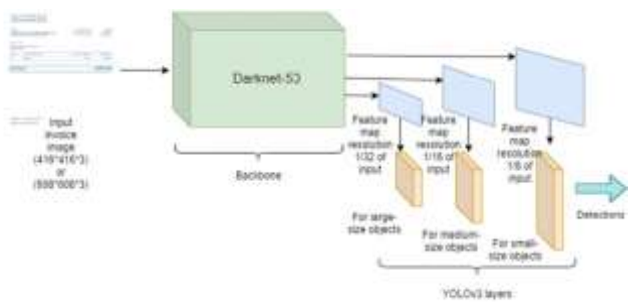


Figure 2. Architecture of the YOLOv3s network

2. Model Neck: Feature Pyramid Network (FPN)

YOLOv3 incorporates a Feature Pyramid Network (FPN) in its neck architecture. The purpose of the FPN is to address the challenge of detecting objects at different scales and sizes within an image. It achieves this by combining feature maps from multiple layers of the backbone network, creating a pyramid-like structure of features.

The FPN helps in building a robust representation of the input image, enabling the model to detect objects regardless of their scale. By integrating features from different pyramid levels, YOLOv3 becomes adept at handling objects that are small, medium, or large in relation to the image size. This scalability enhances the model's accuracy and generalization capabilities across various object sizes and complexities.

3. Model Head: Anchor Boxes and Activation Functions

In the detection head of YOLOv3, anchor boxes play a crucial role in predicting bounding boxes for objects. Anchor boxes are predefined bounding box shapes with specific aspect ratios and scales. These boxes serve as reference templates that the model uses to localize and identify objects within an image.

YOLOv3 predicts bounding box coordinates, class probabilities, and objectness scores (confidence scores) for each anchor box. The objectness score indicates the likelihood of an object being present within a given anchor box. Additionally, the model employs a sigmoid activation function in its detection layer to produce the final output vectors. This activation function scales the output values between 0 and 1, aiding in the interpretation of probabilities and confidence scores.

In summary, YOLOv3's architecture comprises a robust backbone (Darknet-53) for feature extraction, a feature pyramid network (FPN) in the neck for multi-scale object detection, and a detection head utilizing anchor boxes and activation functions for accurate object localization and classification.

4. EXPERIMENTAL RESULTS

In YOLOv3, the Model Neck is responsible for generating feature pyramids that aid in object scaling and identification across different sizes and scales. The key component here is the Feature Pyramid Network (FPN), which helps the model generalize well. The FPN combines features from different scales to create a multi-scale representation of the input image.

The first layer in YOLOv3's backbone network is typically a series of convolutional layers that extract features from the input image. Let's denote the input image as I. The output of these convolutional layers is a set of feature maps denoted as F.

$$F = \text{Conv}(I)$$

Next, the FPN takes these feature maps F and generates feature pyramids. The process involves downsampling and upsampling to create feature maps at different scales. Let's denote the feature pyramids as P.

$$P = \text{FPN}(F)$$

Now, let's move on to the Model Head in YOLOv3. The Model Head is responsible for the final detection part, where anchor boxes are applied to features to generate output vectors containing class probabilities, objectness scores, and bounding boxes.

Let's denote the features from the FPN as P. The anchor boxes are denoted as B, and the output vectors are denoted as O.

$$O = \text{ModelHead}(P, B)$$

In YOLOv3, the activation functions used depend on the specific layers. Typically, ReLU (Rectified Linear Unit) activation is used in intermediate layers for feature extraction. The Leaky ReLU activation function is a variant of ReLU that allows a small, non-zero gradient when the input is negative, which can help with training stability. It is defined as:

$$\text{LeakyReLU}(x) = \begin{cases} x, & \text{if } x > 0 \\ \text{alpha} \cdot x, & \text{otherwise} \end{cases}$$

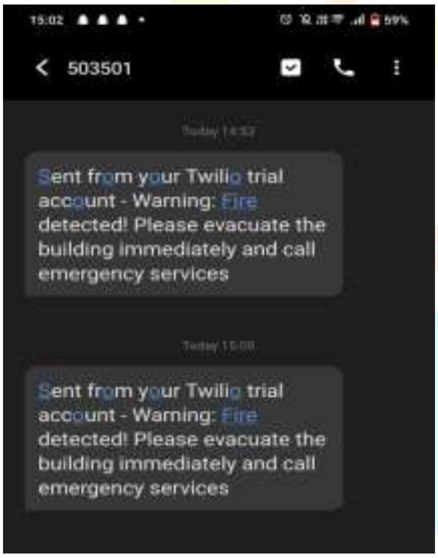
Where, alpha is a small constant. For the final detection layer in YOLOv3, a sigmoid activation function is typically used. The sigmoid function is defined as:

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

Regarding optimization, YOLOv3 commonly uses algorithms like Stochastic Gradient Descent (SGD) for training. SGD updates the weights of the network using gradients and a learning rate α, according to the formula:

$$w_{t+1} = w_t - \alpha \cdot \frac{\partial L}{\partial w_t}$$

Where, wt represents the weights at iteration t, L is the loss function, and ∂L/∂w is the gradient of the loss with respect to the weights at iteration t.



5. FUTURE SCOPE

The future scope of research in fire incident management systems includes collaboration with insurance companies to streamline claims processing and assessment through real-time data integration, which can expedite post-incident support. Additionally, incorporating location sharing features can significantly improve emergency response times by allowing individuals to share their precise locations with emergency services and loved ones, enhancing overall safety and coordination during fire incidents. Moreover, the integration of suppression systems like sprinklers or fire extinguishing drones into these systems can automate firefighting efforts, minimizing fire spread and reducing potential damage. Furthermore, exploring IoT integration for smart building solutions offers opportunities for seamless communication among fire detection systems, building infrastructure, and emergency response teams, thereby enhancing incident management efficiency. Lastly, integrating multiple sensors such as smoke detectors, heat sensors, or gas sensors can provide enhanced data for improved fire detection and situational awareness, contributing to the accuracy and reliability of these systems in mitigating fire risks.

6.CONCLUSION

The integration of real-time fire detection and people counting system using YOLO and the Haar Cascade algorithm presents a promising solution for enhancing safety measures in fire-prone areas. By leveraging advanced computer vision techniques, the system demonstrates rapid and accurate detection of fire incidents, as well as efficient estimation of the number of individuals present in the vicinity. The implementation of multiple alert mechanisms, including alarms and text messages, ensures timely notification of relevant authorities and individuals, facilitating prompt response to emergencies. Experimental results validate the effectiveness and efficiency of the proposed methodology in real-world scenarios, underscoring its potential to mitigate the impact of fire incidents and safeguard lives and properties. Future research efforts may focus on further refining the system's algorithms, optimizing its performance, and exploring additional features to enhance its functionality and robustness in fire safety applications.

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