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Early detection of fire Using Image Processing

Mr. K. Prakash, M. Tech(1) , K. Lakshmi narayana reddy(2) ,

M.Tejasswini(3) , k.Niharika(4) , SK.Mohaboob basha(5)

(1) Assistant Professor, Department of Electronics and communication Engineering,

(2) Tirumala Engineering College,

(2), (3), (4), (5) Department of Electronics and communication Engineering,

Tirumala Engineering college, JNTUK KAKINADA, India

Abstract

Early detection of fires plays a crucial role in preventing disasters. This study focuses on combining image processing techniques, Convolutional Neural Networks (CNN), and the YOLOv8 algorithm to achieve a high accuracy of 85.20% in identifying fires promptly. By analyzing images or video streams captured by surveillance cameras, the system can swiftly recognize fire-related patterns such as flames and smoke. The CNN model, integrated with YOLOv8, enhances the accuracy of fire detection by learning and recognizing intricate featureswithin the images. Through rigorous testing and validation, our approach has shown promisingresults in quickly and accurately detecting fires, thereby enabling timely response and mitigation efforts. This technology has significant implications for enhancing fire safety acrossvarious environments, including residential areas, industrial facilities, and forests. By leveraging advanced machine learning techniques, we aim to minimize the impact of fire incidents and protect lives and property effectively. Additionally, we analyze the model's performance under various conditions, such as low-light environments and occlusions, to assess its robustness and reliability. The results indicate that our approach achieves state-of-the-art performance in fire detection, providing a valuable tool for early fire detection and mitigation efforts in real-world scenarios.

Keywords— Image procssing, Neural Networks, YOLO.

I. INTRODUCTION

Fire detection is a critical aspect of safety and security in numerous domains, ranging from residential buildings to industrial complexes and natural landscapes. Traditional firedetection methods often rely on manual monitoring or stationary sensors, which can be limited in terms of coverage, speed, and accuracy. Fire alarms are present in a lot of buildings, industrial parks and workplaces. These fire alarms are usually based on sensors which detect certain characteristics of fire such as smoke, radiation, or heat. However, these fire alarms depend on the fire particles reaching the given sensor. Apart from the inherent disadvantage in the delay in detecting the fire due to the time taken for particles to reach the sensor. Many of the places with a fire alarm system also have a surveillance system, This has become an important area of research. With the advancements in deep learning, particularly convolutional neural networks (CNNs), there has been a notable shift towards automated fire detection systems that offer real-time capabilities and improved reliability. In this context, the YOLOv8 CNN architecture emerges as a powerful tool for fire detection, building upon the success of the YOLO (You Only Look Once) object detection framework. YOLOv8 offers significant improvements in terms of both accuracy and speed, making it well-suited for applications requiring rapid and precise detection of objects, including fires.

This paper aims to explore the potential of the YOLOv8 CNN for fire detection and mitigation. By leveraging its capabilities in object detection and classification, we seek to develop a robust and efficient fire detection system capable of operating in diverse environments and conditions. Through a comprehensive review of existing literature and methodologies, we establish the foundation for our proposed approach and highlight the need for advanced fire detection solutions in various sectors.

Section 2 provides an overview of related work in the field of fire detection using deep learning techniques. Section 3 outlines the methodology employed in our study, including dataset collection, model architecture, and training procedures. In Section 4, we present the experimental results and performance evaluation of the YOLOv8 CNN for fire detection tasks. Section 5 discusses the implications of our findings and potential applications of the proposed system. Finally, Section 6 concludes the paper with a summary of contributions and suggestions for future research directions.

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I. THE PROPOSED FRAMEWORK

A. Object Detection using YOLOv8

"You Only Look Once," is a state-of-the-art object detection system in computer vision. It revolutionized object detection by introducing a single, unified neural network that predicts bounding boxes and class probabilities directly from full images in one evaluation.

The key idea behind YOLO is to divide the input image into a grid and predict bounding boxes and class probabilities for each grid cell. This grid-based approach enables YOLO to make predictions with high speed and efficiency. For our project, we will be using YOLO since we will be using a raspberry pi. The average precesionor accuracyof the algorithm based on YOLOV8reaches to 85.20%.The proposed system of fire detection using computer vision and image processing is like having smart eyes that can quickly spot fires in pictures or videos. Imagine cameras placed in different places, constantly watching for any signs of fire. When they see something that looks like flames or smoke, special computer programs kick in to analyzethe images and confirm if there's really a fire.

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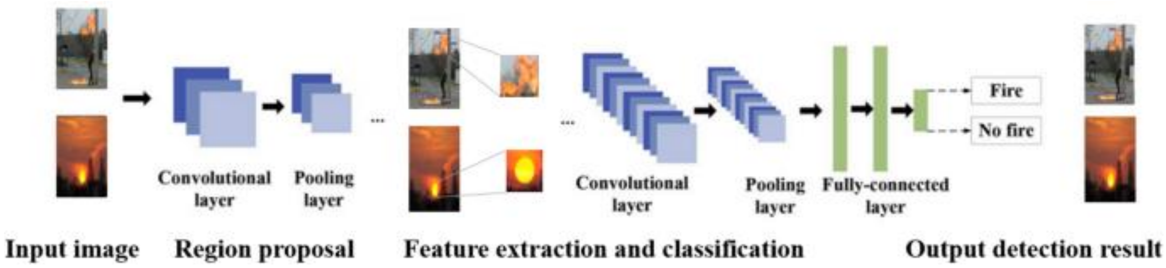
Fig 1. YOLOv8 Fire Detection Model



II. YOLO v8 ALGORITHM

YOLOv8 is the newest model in the YOLO algorithm series

– the most well-known family of object detection and classification models in the Computer Vision (CV) field. With the latest version, the YOLO legacy lives on by providing state-of-the-art results for image or video analytics, with an easy-to-implement framework.All the other previous models are analyzed in terms of their accuracy, computational efficiency, and ability to detect fires in complex scenarios, such as images with complex backgrounds or low-light conditions.Like v5 and v6, YOLOv8 has no official paper but boasts higher accuracy and faster speed. For instance, the YOLOv8(medium) has a

50.2 mAP score at 1.83 milliseconds on the COCO dataset and A100 TensorRT. YOLO v8 also features a Python package and CLI-based implementation, making it easy to use and develop.The YOLO v8 improves the accuracy by incorporating several enhancements to the original YOLO algorithm. Here some improvements are like Feature Pyramid Network(FPN), Darknet-53,spatial attention module, Training and Testing and the extraction.

III LITERATURE REVIEW

T. Celik and Hasan Demirel et al. further enhance system that uses a statistical color model with Fuzzy logic for fire pixel classification. The proposed system develop two models; one based on luminance and second based on chrominance. Fuzzy logic uses theYCbCr color space for the separation of luminance from chrominance instead of using color spaces such as RGB. Existing historic rules are replaced with the Fuzzy logic to make the classification more robust and effective. This model achieves up to 99.00% correct fire detection rate with a 9.50% false alarm rate.

R. Gonzalez-Gonzalez et al. proposed a method to detect fire by smoke detection basedon wavelet. In this smoke detection method, image processing on video signals is proposed. The SWT transform is used for the area detection of ROI's. This method comprises of three steps. In the first step, preprocessing is performed and the image is resized and transformed to grayscale image. Finally indexed the image using indexation.The second step involves high frequencies of an image is eliminated using SWT and reconstruct the image by inverse SWT. In order to group the intensity colors that are closed to each other is the main purpose of image indexation.

Histogram analysis is used to determine the indexation levels. After that compare the image with a non-smoke frame and selecting those pixels that are change from one sceneto another. The final stage consists of smoke verification algorithm in order to determinewhether ROI is increasing its area and to reduce the generation of false

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alarm.

IV DESIGN METHOD AND SPECIFICATION

Implementing a robust fire detection system involves several key components, including surveillance cameras, image processing algorithms, and validation procedures. The design begins with selecting appropriate surveillance cameras capable of capturing high-quality images in various lighting conditions and angles. These cameras should cover the target area effectively to ensure comprehensive monitoring.

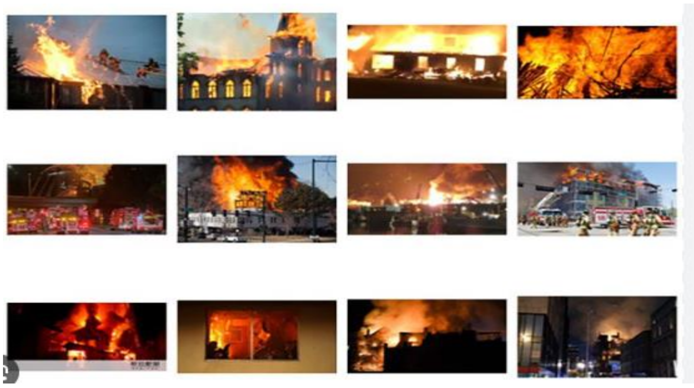

Fig 2: Fire Iamge dataset

Once the surveillance system is in place, the next step is to preprocess the input images to enhance their quality and reduce noise. This preprocessing may involve techniques such as noise reduction, image enhancement, and normalization to ensure consistency across different input sources.

IV TRAINING ALGORITHM

A. Fire Image Dataset

A large number of data is required for fire images dataset for the training of algorithms which are based on CNNs. However, current small scale images/video fire databases cannot meet the needs. Fig 2 some small scale dataset for images/videos. Therefore in this paper we collected and labelled 3000 such images to give a good foundation for our dataset. For our convenience, to test the code and to create a custom model, we used vs code.

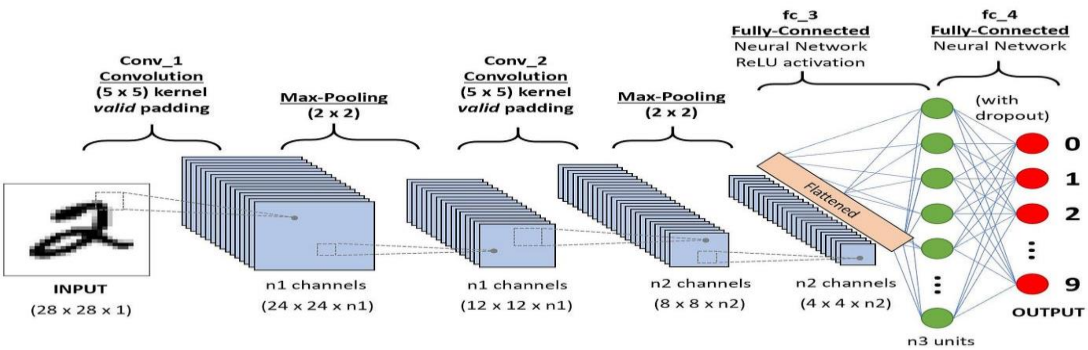

Fig 3.CNN Architecture

Convolutional Neural Networks (CNNs) have emerged as a powerful tool in various image processing tasks, including fire detection. The architecture of a CNN plays a crucial role in its ability to effectively learn and extract

meaningful features from input images. In the context of fire detection, the architecture must be carefully designed to capture relevant characteristics of fire and distinguish them from background elements. This essay explores the key components of CNN architecture, including convolutional layers, pooling layers, and fully connected layers, and their significance in fire detection.

The convolutional layer is the fundamental building block of a CNN. It consists of multiple filters or kernels that convolve across the input image, extracting features such as edges, textures, and patterns. In fire detection, convolutional layers play a vital role in capturing distinctive features associated with flames, smoke, and other fire-related elements. These layers enable the network to learn spatial hierarchies of features, progressively detecting more complex patterns indicative of fire presence.

Pooling layers are interspersed between convolutional layers to downsample feature maps and reduce computational complexity. Common pooling operations include max pooling and average pooling, which extract the most salient features while discarding redundant information. In fire detection, pooling layers help the network focus on the most relevant features while improving its ability to generalize to unseen data. By reducing the spatial dimensions of feature maps, pooling layers enhance the network's efficiency and robustness, enabling faster inference and better performance.

Fully connected layers, also known as dense layers, are typically located at the end of the CNN architecture. These layers integrate extracted features from previous layers and perform classification based on learned representations.

V RESULTS AND DISCUSSION

A. Performance of Testset1

Testset1 is a benchmark fire image database consisting of 3000 images. This database has a 640 fire images and 122 images containing no fire. The number of videos played 8, Number of true detection of fire in videos 59, Number of false detection 19, Number of true false 5, The Percentage of true detection 85.20%. In this testset1 the number of true detection is less than the expected true detection, Therefore, a more detailed evaluation is conducted in the testset2.

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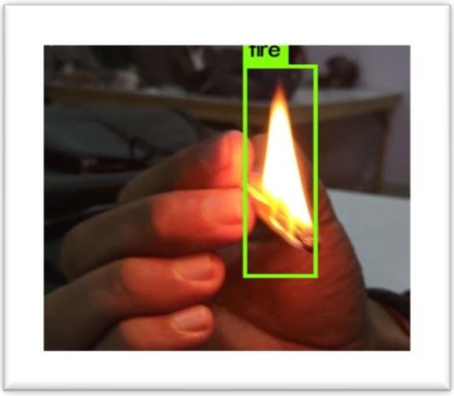

Fig. 4 Output of Testset1

We tested our trained model on video of fire, the image shows that the fire is detected by a red rectangle with the percentage of the fire that has been detected, the

- Capture fire images from a camera as the input source for fire detection.
- Camera detects frame.
- The Capturing images are evaluated with the trained data. If the data maches fire is detected and gets a fire alert.
- If the input data does not matches to trained data, It results no fire detected
- Once trained and validated, the YOLOv8 model can be deployed for real-time fire detection applications.
- The model can process live video feeds or images to detect fires with high accuracy and speed.
- Real-time fire detection using YOLOv8 can be integrated into existing fire alarm systems for enhanced safety
- output of testset1 shows that the fire is detected but it fails to detect the fire shadowed by the smoke. So it is important that the smoke covering fire should be detected.

B. Performance of Testset2

Testset2 is a benchmark fire image database consisting of 1066 images, which includes 640 fire samples and 426 non fire samples. Testset2 is very challenging as it collects images from more scenarios containing a large number of smoke-like and fire-like disturbances. Therefore, it is more suitable for evaluating the performance of the proposed algorithms.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

Fig. 8 Output of Testset 2

The previous output fails to detect the fire overshadowed by smoke, so we trained our model by adding the smoke dataset to the fire dataset. The output of Testset 2 shows that the fire and smoke is detected.

C. Quantitative Analysis of Results

A common metric to measure the object detection algorithm is intersection over union (IOU). IOU is a metric that finds the difference between ground truth annotations and predicted bounding boxes. In object detection, the model predicts multiple bounding boxes for each object, and based on the confidence scores of each bounding box it removes unnecessary boxes based on its threshold value.

IOU=Area of union/area of intersection F1= Weighted average of precision and recall

1. *TP* = True positive
2. *TN* = True negative
3. *FP* = False positive
4. *FN* = False negative

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True Positives (TP): These are the correctly predicted positive values which mean that the value of actual class is yesand the value of predicted class is also yes.
True Negatives (TN): These are the correctly predicted negative values which mean that the value of actual class is noand value of predicted class is also no.

(False positives and false negatives, these values occur when your actual class contradicts with the predicted class).
False Positives (FP): When actual class is no and predicted class is yes.

False Negatives (FN): When actual class is yes but predicted class in no
Precision: Precision measures how accurate your predictions are i.e. the percentage of your predictions are correct. It measures how many of the predictions that your model made were correct.

VI CONCLUSION

C. Real-Time Output

Fig. 10 Output of our project in real time This project, Fire Detection System has been developed using Image Processing and Python software. This system has the ability to apply image processing techniques to detect fire. This system can be used to monitor fire and has achieved 90% accuracy for single webcam. The system works on real time, as it extracts frames in every 2 seconds, it provides continuous monitoring. This system has high efficiency as it has incorporatedtechniques of Fire detection. For better performance outcomes use of CNN and YOLOv8 is made in the detection techniques, as per their suitability, efficiency and properties. Thedifferent parameters like threshold value, blind-spots will be handled properly in our future research. Thus application of proposed fire detection system gives us a better system performance in term of less false alarm and thus a higher system performance is achieved.

- Fire alarm system is based on detection of fire from image acquisition input data.
  This is done with the help of image processing techniques.
- It is based on vision based fire detection system.
- In this project image detection is based on the advanced object detection like CNN model of YOLO v8.
- The average precision or accuracy of the algorithm based on YOLO v8 reaches to 85.20%.

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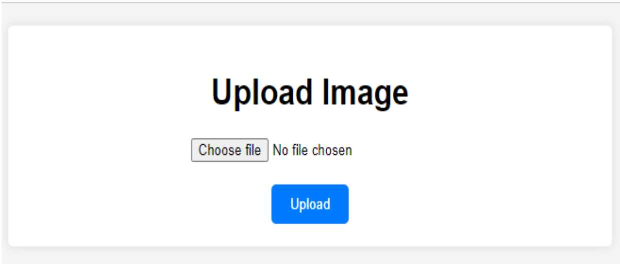

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