# REAL TIME FIRE DETECTION

Sakthi Sree.V
*Computer Science and Engineering.*
*Panimalar Engineering College*
Chennai, India
sakthisreebrindha@gmail.com

Sofiya.S
*Computer Science and Engineering.*
*Panimalar Engineering College*
Chennai, India
sofiyasudha@gmail.com

Swathi.P
*Computer Science and Engineering.*
*Panimalar Engineering College*
Chennai, India
swathiprabakaran14@gmail.com

Dr. A. Hemlathadhevi, M.E.,Phd.,
*Department of CSE*
*Panimalar Engineering college*
Chennai, India
hemlathadhevi@gmail.com

***ABSTRACT***

*Fire, an hazardous incident, poses a significant risk as it can be destructive and dangerous, causing wildfires, building fires, and explosions. A fire can burn out of control, engulfing the area in heat and toxic with heavy smoke. So, it's crucial to spot and put out fire at its very beginning. The majority of fire monitoring and alarm systems now in use rely on sensors, which have drawbacks such as low sensitivity, sluggish response, limited coverage, and poor stability. This explores a way to develop a fire localization system using yolo5 network. As security technology has advanced, cctv cameras are now mounted for surveillance at the majority of buildings and traffic lights. Early fire detection and identification are possible using the camera's live footage. YOLOV5 network is used for the successful detection and warning of fire disasters. So, the moment the fire occurs, it is detected precisely and alarmed. Thus, a quick and extremely accurate fire detection could be employed day and night, regardless of size and shape was made possible by using the yolo5 algorithm.*

**Keywords**

Yolov5, fire detection, open cv, bounding boxes, labels, object detection

## I. INTRODUCTION

*The ecosystem and people's lives are seriously at risk from fires. In order to reduce the harm they inflict, it is crucial to identify fires as soon as possible. Traditionally, fire detection has been done by human observation. It is, however, a time- and labour-intensive process.*

*Since technology has advanced, sensors are now used, however sensor-based detection systems are best used in tiny indoor settings. Smoke sensors, gas sensors, temperature sensors, humidity sensors, integrated sensors, and other types of sensors are utilized for forest fire detection. However, the device's detecting range is constrained, installation costs are considerable, and it also has to deal with challenging power supply and networking issues. Additionally, the sensors are unable to deliver crucial visual information that would enable firefighters to quickly assess the situation at the fire scene. As a result, this approach might not be appropriate for big areas like forests or other spaces that differ greatly from interior settings. As hardware and software technologies advance and computer arithmetic is improved, more researchers are starting to look at using deep learning to identify forest fires in order to circumvent the limitations of sensors[11]. Methods that use visuals or images offer a number of advantages over other approaches. They can keep an eye on the forest around-the-clock and spot flames as soon as they start. These methods look for color, texture, and mobility in three different facets of forest fires. The difficulty lies in achieving accurate real-time detection, though. YOLO is a well-known real-time object detection technique. (You Only Look Once). For small objects, it is known to have lower detection accuracy.*

*Deep learning and machine vision are both crucial in the detection of fires. The YOLOv5 (You Only Look Once version 5) object detection model employs deep neural networks to identify items in real-time. It is a cutting-edge algorithm that is quicker and more precise than earlier iterations. It is feasible to create an effective and dependable fire detection system by combining YOLOv5 with computer vision and deep learning methods.*

*The system operates by reviewing pictures or movies taken by cameras placed in a specific location. The YOLOv5 model receives the images and uses them to recognize items in the scene, including fire. The deep learning algorithm then examines the items discovered and decides whether or not they are fires based on their characteristics, such as color, shape, and movement. One benefit of using YOLOv5 for fire detection is its high accuracy and speed, which enables real-time fire detection, enables quick reaction, and might even save lives. Another benefit is its capability to locate fires under different circumstances, such as in dimly lit areas or amid smoke and haze.*

*Additional methods, including thermal imaging and machine learning algorithms, may be used to increase the fire warning system's accuracy. These methods can aid in separating real fires from false alerts that may be brought on by other items in the area, such as hot steam or sunlight.*

*In summary, using YOLOv5 for fire detection in conjunction with computer vision and deep learning is a hopeful strategy for creating an effective and dependable fire detection system. High accuracy and speed are provided by YOLOv5,* *and the system's total performance can be enhanced by adding additional strategies like thermal imaging and machine learning algorithms.*

## II. RELATED WORKS

[1] Veerappampalayam Easwaramoorthy Sathishkumar, Jaehyuk Cho, Malliga Subramanian, and Obuli Sai Naren: Using AI computer vision techniques, the study "Forest fire and smoke detection using deep learning - based learning without forgetting" suggests an image-based detection method. Forests are an essential natural resource for humans, offering a wide range of direct and indirect benefits. The persistence of life on Earth and global warming are both significantly impacted by forest fires and similar natural catastrophes. In order to lessen tragedies, research into the automated detection of forest fires is essential. Early fire discovery can also help with extinguishing techniques and mitigation strategy planning. In this study, fire and smoke are recognised from photos using computer vision algorithms based on artificial intelligence. In picture classification and other computer vision problems, convolutional neural networks (CNNs), a kind of artificial intelligence (AI) approach, have been demonstrated to outperform state-of-the-art methods, although their training time may be prohibitive. A pretrained CNN may also perform badly in the absence of a big enough dataset. Transfer learning is applied to address this issue on models that have already received training. The models may, however, lose their capacity to categorise on the baseline datasets when transfer learning is utilised. To solve this problem, we employ learning without forgetting (LwF), which teaches the network a new task while preserving its pre-existing skills.

[2] Seyd Teymoor Seydi, Vahideh Saeidi, Bahareh Kalantar, Naonori Ueda and Alfian Abdul Halin: The maintenance of a robust and healthy ecosystem depends on the preservation of forests. The field of remote sensing has substantially facilitated the broad application of sensor and computer vision technologies for forest land surveillance (RS). A key area of concern is locating burning forests. Whether it starts accidentally or on purpose, a forest fire may quickly devour enormous tracts of land, wreaking havoc and even taking lives. Automatic detection of active forest fires (and burning biomass) is a vital field for research in order to avert unintentional tragedies. In addition to conducting extinguishing operations, decision-makers can employ early fire detection to plan mitigation plans. In this paper, we introduce Fire-Net, a deep learning system that can recognise burning biomass and current fires using Landsat-8 images. We carefully blend the optical (Red, Green, and Blue) and thermal modalities from the photos for a more realistic representation. The residual convolution and separable convolution blocks are also utilised by our network, enabling the extraction of more exact features from imprecise datasets. The results of the trials show a robust identification of tiny active flames and an overall accuracy of 97.35%. Images from forests in Australia, North America, the Amazon Rainforest, Central Africa, and Chernobyl (Ukraine), where reports of forest fires are common, were utilised for this study.

[3] Shuai Zhao, Boyun Liu, Zheng Chi, Taiwei Li and Shengnan Li: In order to handle slow image-based fire detection under the influence of electric fields and its restriction to static fire characteristics, this paper suggests a video-based fire detection system with improved Yolo-v4 (You Only Look Once Version 4) and visual background extractor (ViBe) algorithms. The proposed system replaces the route aggregation network in Yolo-v4 with a simpler weighted bi-directional feature pyramid network (Bi-FPN) (PANet). Many dynamic fire characteristics can be used to eliminate falsely detected frames. The ViBe algorithm has been enhanced to account for the rapid change in brightness caused by fire flickering. When compared to existing fire detection algorithms, the recommended method has a false detection rate of 2.2% and a fire detection accuracy of 98.9%. It is capable of putting out certain flames by adapting to.

[4] Byoungjun Kim and Joonwhoan LeeFire is an unusual occurrence that may gravely destroy both persons and property. In this research, we propose a deep learning-based fire detection approach based on video sequences that resembles the human fire detection process. The recommended method employs Faster Region-based Convolutional Neural Network (R-CNN) to more quickly detect suspected fire regions (SRoFs) and non-fire areas based on their spatial characteristics. In future frames, the Long Short-Term Memory (LSTM) aggregates the summary information within the bounding boxes to quickly determine whether or not there is a fire. The decisions for each succeeding short-term period are then added to the majority vote for the long-term option. The regions of flame and smoke are also estimated, and their temporal variations are provided, in order to comprehend the dynamic fire behaviour and reach the ultimate fire choice. Experiments show that the recommended long-term video-based technique may significantly improve the fire detection accuracy when compared to still image-based or short-term video-based methods by a reduction in both erroneous and inaccurate fire detections.

[5] Herminarto Nugroho: In this work, it is recommended to use a fully convolutional variational autoencoder (VAE) to extract features from a significant amount of fire picture data. The data will be used to train the deep learning system to distinguish smoke and fire. The dimensionality curse, which frequently occurs when deep learning is taught on huge datasets, is combated through features extraction. With the bulk of the dataset's essential information still preserved, features extraction aims to significantly reduce the dimension of the dataset. Variational autoencoders are powerful generative models that may be used for dimension reduction (VAEs). VAEs outperform all other methods now in use for this task because they can study variations on the data in a specific direction.

[6] Xiwen Chen, Bryce Hopkins, Hao Wang, Leo O' Neill, Fatemeh Afghah, et al: Satellite remote sensing and manned/piloted aircraft are currently used to monitor forests. The lack of comprehensive, well-annotated aerial

datasets has also hampered the development of reliable data-driven fire detection and modelling, which is in part due to the unmanned aerial vehicles' (UAVs') flight restrictions during planned burns and wildfires. Particularly in the early stages of a wildfire's growth, aircraft and observation towers leave questions regarding the fire's size, activity, and circumstances in its immediate surroundings. Rapid mapping and in-the-moment fire monitoring can guide in-the-moment management or intervention strategies to maximise good fire outcomes. In particular, in distant forests that are difficult for ground vehicles to access, drone systems' distinctive qualities of 3D mobility, low flight height, and quick and simple deployment make them an invaluable tool for early detection and assessment of wildland fires.Furthermore, research advancements in trustworthy data-driven fire detection and modelling techniques have been hampered by the lack of a wealth of well-annotated aerial datasets, which is partly a result of the flying limits placed on unmanned aerial vehicles (UAVs) during controlled burns and wildfires. While most wildland fire datasets currently available only include thermal or colour images of the fire, we present (1) a multi-modal UAV-collected dataset of dual-feed side-by-side videos featuring both RGB and thermal images of a prescribed fire in an open canopy pine forest in Northern Arizona, and (2) a deep learning-based methodology for detecting fire and smoke pixels at an accuracy much higher than the typical single-channel video feeds. Two human experts use side-by-side RGB and thermal images to determine the label for the collected photos before classifying them as "fire" or "no-fire" frames. The provided additional dataset offers a georeferenced pre-burn point cloud, an RGB orthomosaic, meteorological data, a burn plan, and other burn information in addition to the aerial footage from the main dataset. Research can create novel data-driven fire detection, fire segmentation, and fire modelling tools by utilising and expanding on this guide dataset.

[7] Xuehui Wu1, Xiaobo Lu1, and Henry Leung: The unique method for detecting fire and smoke using video pictures is suggested in this paper. To update the precise motion areas and extract a background from the full movie, the ViBe approach leverages frame-by-frame differences. Combining dynamic and static feature extraction, we can pinpoint the fire and smoke locations. Deep learning is applied to much of the fire and smoke areas identification utilising static features and a Caffemodel.
Another static trait is the level of fire and smoke irregularity. A weighted adaptive direction technique is also presented in this article. The footage is segmented into 1616 grids for each frame in order to further lower the false alert rate and aid in locating the original fire. It also keeps track of when smoke and fire incidents occur.

[8] Taha Zaman, Muhammad Hasan, Saneeha Ahmed, Shumaila Ashfaq: The technique described in the paper " Fire Detection Using Computer Vision" uses computer vision to process video data from a typical camera to recognize hazardous fires and detect fire. Despite the abundance of books on fire detection that include images, it is still difficult to tell a hazardous fire from a non-hazardous one. The suggested method locates fire by utilizing its color and movement properties. The method first identifies motion-containing areas in the video; these areas are then used to extract pixels that are colored red or orange, which are then subjected to a wavelet transform to determine whether the moving object is actually a fire. In order to differentiate between dangerous and controlled fire, the suggested method monitors the rate of growth of the fire region.

[9] Murat Muhammet Savcı, Yasin Yıldırım, Gorkem Saygılı, and Behcet Ugur Toreyin: Using macroblock types and Markov models in H.264 video, we propose a compressed domain fire detection technique using macroblock types and Markov models in H.264 video. Compressed domain approaches use a syntax parser to extract syntax components that are only present in compressed domain, as opposed to requiring decoding to the pixel domain. Our approach only extracts the macroblock type and the matching macroblock address. The Markov model with fire and the non-fire model are contrasted using offline-trained data. Our testing show that, despite just using a little amount of data, the system successfully detects and classifies fire incidents in compressed domains.

[10] Xuehui Wu, Xiaobo Lu, Henry Leung: Video pictures are presented as a brand-new method for smoke and fire detection. The ViBe approach is used to extract a background from the full movie and update the precise motion areas using frame-by-frame changes. To identify the fire and smoke zones, static and dynamic features are extracted together. Based on static characteristics and a Caffe model, we employ deep learning to identify the bulk of fire and smoke regions.Another static property is the degree of irregularity of fire and smoke. This paper also includes a presentation of an adaptive weighted direction technique.

## *III.EXISTING SYSTEM*

*Fire detection devices include smoke alarms and heat alarms. The main limitation of smoke sensor alarms and heat sensor alarms is that one module cannot monitor all of the potentially flammable areas[4].*
*A fire can only be prevented by always being cautious. It is simply not enough to consistently create an efficient output, regardless of how many of them are installed. Price will increase by a factor of multiples as the number of smoke sensors needed increases. The proposed technology can create a dependable and extremely precise alarm within seconds of an accident or a fire. Costs are decreased because the entire monitoring network just needs one piece of software to function.*

## *IV.PROPOSED SYSTEM*

*The proposed model combines both open cv and deep learning algorithm(yolo5) to efficiently detect fire. Yolov5 is faster than its earlier versions and offers improved speed and accuracy for object detection, classification and localization. It is a light weight model and it is easy to deploy that makes it suitable for real time application. Pre-trained weights and configuration files of yolo5 algorithm is loaded into the webcam for image processing and fire detection. The input obtained from webcam is resized to fit the network size of yolo5 algorithm. Then, it is fed into the*

*yolo5 network where object detection and labelling occurs .If the labelling matches with the class fire, the system alerts with an alarm sound. The advantages of this system are,*
*Accurate detection: YOLOv5 is a state-of-the-art object detection algorithm that uses deep learning to accurately detect fire in real-time. By combining this algorithm with computer vision techniques, the system can identify and locate fires with high accuracy, reducing false alarms and improving response times.*

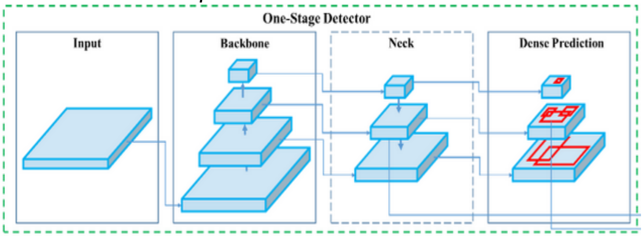
*Fast response times: The real-time detection capabilities of YOLOv5 combined with computer vision techniques enable the system to quickly detect fires and alert emergency responders, enabling them to take prompt action and potentially save lives and property.*

*Robustness to environmental conditions: Fire detection systems based on YOLOv5 and computer vision are less prone to false alarms caused by environmental conditions such as smoke, shadows, and low light levels. The deep learning algorithms can learn to distinguish between real fires and these other factors, improving the overall reliability of the system.*

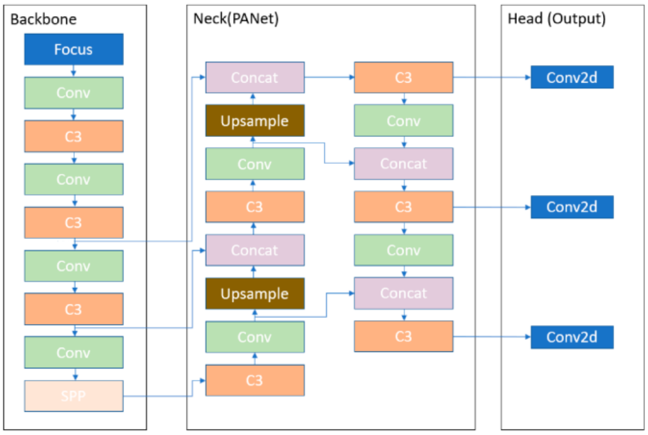
*Scalability: YOLOv5 and computer vision techniques can be easily scaled up to cover large areas such as warehouses, factories, and other industrial facilities. This makes them suitable for use in a wide range of applications where traditional fire detection systems may be less effective.*

*Cost-effectiveness: YOLOv5 and computer vision techniques can be implemented using off-the-shelf hardware, reducing the cost of deploying fire detection systems. Additionally, the accuracy of these systems reduces false alarms, potentially saving costs associated with unnecessary emergency responses.*

YOLO ALGORITHM:
*Yolo is a cutting-edge, in-the-moment item detector. It now performs at the very top of two certified object detection datasets: Microsoft COCO and Pascal VOC (visual object classes) (common objects in context). We selected Yolov5 as our initial learner for three reasons.*




*Initially, Yolov5 built CSPDarknet, the backbone of Darknet, by integrating cross stage partial network (CSPNet) into Darknet. By integrating the gradient changes into the feature map and resolving the issues with repeated gradient information in large-scale backbones, CSPNet reduces the model's parameters and FLOPS (floating-point operations per second), ensuring inference speed and accuracy while also shrinking the model's size. Speed and accuracy of detection are essential in fire detection tasks, and the efficiency of inference on edge devices with limited resources is also determined by the compact model size.In order to improve information flow, the Yolov5 used the path aggregation network (PANet) as its neck. The transmission of low-level features is boosted by the use of a novel feature pyramid network (FPN) structure by PANet with an improved bottom-up path. In addition, adaptive feature pooling, which connects feature grid and all feature levels, is employed to enable each feature level's important information to spread instantly to the subsequent subnetwork. At lower layers, PANet enhances the use of precise localization signals, which can obviously increase the object's position accuracy.*
*Finally, the Yolo layer, which is the head of Yolov5, creates feature maps in three distinct sizes (18 18, 36 36, and 72 72) to provide multi-scale prediction, allowing the model to handle tiny, medium, and large objects.*



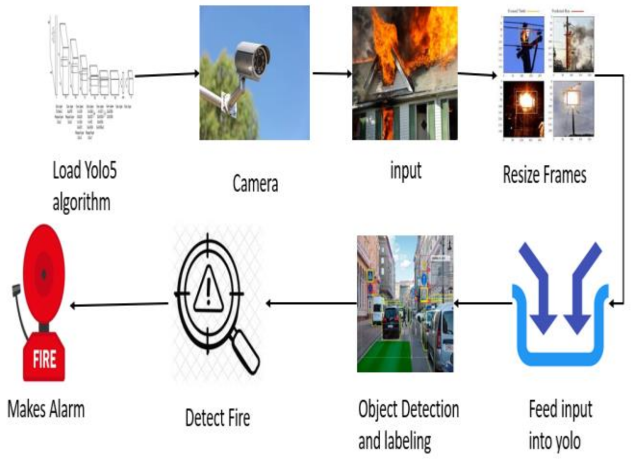

## SOFTWARE DESCRIPTION

OPEN CV:
A well-known open-source library for computer vision and machine learning techniques is called OpenCV (Open Source Computer Vision). It is developed in C++ and offers a wide range of tools and methods for processing images and videos, detecting objects, recognising faces, and many more uses. Several operating systems, including Windows, Linux, macOS, Android, and iOS, are supported by OpenCV.
In both academia and business, OpenCV is often used for research and development. It is utilised in several real-world applications, including augmented reality, driverless cars, and security camera systems. The library is developed and maintained by a significant community of users and developers.
ANACONDA PROMPT
Anaconda Prompt is a command-line interface for managing and working with environments created by the Anaconda distribution of Python. Anaconda is a popular distribution of the Python programming language, which includes a package manager, a collection of pre-built packages, and other tools for scientific computing and data analysis.
Anaconda Prompt provides a command-line interface that allows users to manage environments, install packages, and execute Python code. It includes a set of pre-defined commands that can be used to manage environments and packages, such as creating new environments, activating and

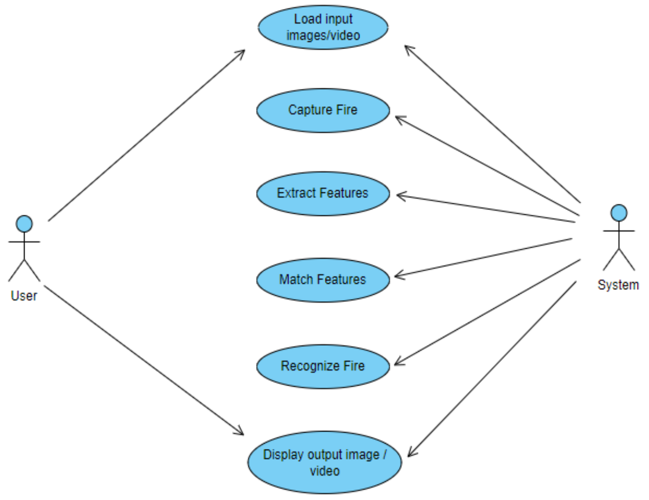
deactivating environments, installing and updating packages, and listing installed packages.
In addition to managing environments and packages, Anaconda Prompt can also be used to run Python scripts and execute Python code. It includes the Python interpreter, as well as other tools and libraries for scientific computing and data analysis, such as NumPy, SciPy, and pandas. Overall, Anaconda Prompt is a powerful and flexible tool for managing environments, installing packages, and running Python code.

VS CODE:
Visual Studio Code is a sophisticated integrated development environment that boasts an extensive suite of powerful functionalities and features, including advanced debugging tools, customizable user interface, code editing capabilities, syntax highlighting, and a vast array of extensions and plugins that augment its extensive range of capabilities. Moreover, its adaptable and flexible design enables it to accommodate various programming languages and frameworks, thereby enabling developers to undertake complex development projects with a high degree of precision and efficiency. Additionally, its ability to integrate seamlessly with various software development life cycle tools and package managers make it a highly sought-after tool among developers and software engineers.

**SYSTEM ARCHITECTURE**




**USECASE DIAGRAM**




**V.WORKING OF PROPOSED TECHNOLOGY**

1. LOAD YOLO.
- Download Pre-trained Weights: The pre-trained weights for the many YOLO iterations are accessible on the official website. Fill a folder with the weight files after downloading them.
- Load the configuration and weight files: In OpenCV, you can load the configuration and weight files using the cv2.dnn.readNetFromDarknet() function. This function takes two arguments: the path to the configuration file and the path to the weight file.
- The YOLO algorithm is trained to recognize a specific set of objects. The class names can be loaded by reading a text file that contains one class name per line.
- The input image needs to be preprocessed before feeding it to the YOLO network. Resizing the image to the same size as the input size of the network must be done.
- Once the input image is preprocessed, set it as the input to the YOLO network using the net.setInput() function.
- In the network's forward pass, a list of bounding boxes and class probabilities for each object in the image will be produced.
- The final set of bounding boxes and class probabilities must be obtained after filtering out the weak detections and non-maximum suppression from the network outputs.

2. START WEBCAM.
To start the webcam in OpenCV, you can use the cv2.VideoCapture() function. This creates a Video Capture object with a device index of 0, which represents the default webcam. It sets the width and height of the frame to 640 and 480, respectively, and starts a while loop to read frames

from the webcam, display them, and exit the loop when the 'q' key is pressed.

## 3. IMAGE PROCESSING

Image processing is an essential component of YOLO, as it involves preparing and pre-processing the input images for object detection.

The important steps in image processing involves:

Set Input and Output Layers: To set the input and output layers, use the "blobFromImage()" function to pre-process the input image for the network.
Resizing the input image to a fixed size: The YOLO model expects a fixed input size. Therefore, the input images are resized to a fixed size before being fed to the model.

Converting the image to a format suitable for the model: The YOLO model expects the input image to be in RGB colour format. Therefore, if the input image is in a different format, it is converted to RGB.

Normalization: The pixel values in the input image are normalized to a range between 0 and 1. This step helps improve the accuracy and stability of the object detection model.

## 4.OBJECT DETECTION

A key problem in computer vision called object detection includes locating and classifying items in an image or video. Due to its speed and precision, the cutting-edge object identification algorithm YOLOv5 has become very popular.

Real-time predictions of bounding boxes, object classifications, and confidence levels for each identified object are made using the YOLOv5 algorithm using a deep neural network. The algorithm computes the likelihood that an object will be present in each cell by dividing the input image into a grid of cells. Then, for every cell that surpasses a predetermined threshold, bounding boxes are forecast.

The speed of YOLOv5 is one of its key advantages. Real-time applications like robots, surveillance cameras, and autonomous vehicles can benefit from its ability to process up to 155 frames per second on a single GPU. YOLOv5 also performs at the cutting edge on a variety of benchmark datasets, making it a solid option for object detection tasks

Overall, YOLOv5 has revolutionized object detection and inspired various applications across different industries. Its speed, accuracy, and ease of use make it a popular choice for developers and researchers alike.

## 5.POST PROCESSING

Post-processing is an essential step in computer vision (CV) that involves analysing and refining the output of a computer vision algorithm. Post-processing is particularly important in CV applications that involve object detection and recognition, as the output of these algorithms may contain errors or inaccuracies.

Some of the common techniques used in post-processing for CV include:

Non-maximum suppression: This method is used to get rid of repeated detections of the same object. Selecting the bounding box with the highest confidence score entails locating overlapping bounding boxes.

Bounding box refinement: Bounding box refinement involves moving and enlarging bounding boxes to better match the detected object. In doing so, object detection and recognition accuracy may be enhanced.

Post-classification analysis entails looking at the results of a classification algorithm to find patterns or trends. The accuracy of object detection and recognition may be enhanced as a result.

## 6. ALERTING

Alerting in OpenCV (Open-Source Computer Vision Library) is a technique used to notify users of specific events or occurrences detected in a video stream or image. Alerting is a crucial component of many computer vision applications, such as security systems, where alerts need to be triggered if an intruder is detected.
Overall, alerting in OpenCV is an essential feature for many computer vision applications. The ability to trigger alerts based on specific events detected in a video stream or image is critical in applications such as surveillance, security, and monitoring systems.

**PERFORMANCE ANALYSIS**

| S.NO | TEST CASE | INPUT | STEPS | OUTPUT |
|---|---|---|---|---|
| 1 | Fire detection accuracy | Different types of fires and non-fire images. | a. Create a dataset of images and videos containing different types of fires and non-fire objects<br>b. Use the YOLOv5 algorithm to detect the presence of fire in the images and videos in the dataset<br>c. Record the number of true positive, false positive, true negative, and false negative detections<br>d. Calculate the precision, recall, and F1 score to evaluate the accuracy of fire detection using YOLOv5. | Correct prediction of images. |
| 2 | YOLOv5 performance on different types of fires | Images resembling different types of fires. | a. Create a dataset of images and videos containing different types of fires such as campfires, wildfires, and house fires<br>b. Use the YOLOv5 algorithm to detect the presence of fire in the images and videos in the dataset<br>c. Compare the performance of YOLOv5 in detecting different types of fires by analyzing the accuracy and detection time. | Correct prediction of images even the location, size, and type of fire changes. The prediction is accurate |
| 3 | Impact of environmental factors on YOLOv5's fire detection accuracy | Live video in different lighting conditions through web cam or images with different lighting conditions. | a. Test YOLOv5's fire detection performance under different lighting conditions such as daylight, low light, and darkness<br>b. Observe how the algorithm performs in detecting fires under different weather conditions, such as haze or smoke.<br>c. Measure how well YOLOv5 works in detecting fires at varying distances. | The system predicts the fire accurately. |
| 4 | YOLOv5's ability to detect false positives | Images and videos containing objects that resemble fire. | a. Create a dataset of images and videos containing objects that resemble fire, such as bright lights, reflections, and sunsets.<br>b. Run YOLOv5 algorithm to detect the presence of a fire in the images and videos in the dataset.<br>c. Analyze the number of false positives generated by YOLOv5 by examining the images and videos in the dataset. | Detects only fire and not images that resemble fire. |
| 5 | YOLOv5's ability to detect fires in crowded scenes | Fire images/video occurring in a crowded location. | a. Create a dataset of images containing crowds of people in which a fire occurs<br>b. Run YOLOv5 algorithm to detect the presence of a fire in the images in the dataset.<br>c. Measure how well the algorithm works in detecting fires when there is a crowd of people and other obstacles in the scene. | Detect fire even in a crowded place and produce alarm sound. |

## *VI.FUTURE ENHANCEMENT*

*Future study will address concerns with blurring in low-light conditions and enhance the accuracy of our approach. Our long-term goal is to develop a compact model with reliable detection performance that enables the configuration of embedded devices with limited computational resources. Future research will be based on employing geostationary satellite imagery to quickly monitor active fires on a greater scale and to give high temporal resolution.*

## *VII. CONCLUSION*

*When used correctly in reality, the real-time object detection algorithm YOLOV5 has many benefits. The main credit goes to straightforward loss function, it is a unified object detection model that is easy to build and train. It can also be parallel-trained, which accelerates compared to other models. In addition, YOLOV5 is superior to other models at generalizing object representation, which makes it the best option for real-time object recognition. Since it uses the most recent fire detection technology, it is excellent for real-time fire monitoring.*

*There is significant potential for future growth in the area of fire detection. Changing the algorithm (or model size) and the dataset can rapidly and accurately detect a real-time fire, according to experiments. This implies that YOLOV5 can be used in a variety of fire detection apps and optimized to produce good results based on the requirements of the user. YOLOV5 has a wide range of possible uses, from detecting fires in open areas like buildings to spotting wildfires in sizable outdoor areas. These applications can be tailored and customized with YOLOV5 in order to suit various contexts and environments. In the end, YOLOV5 is a useful instrument for ensuring that fires are discovered and put out before they do much damage.*

## REFERENCES


[1] Veerappampalayam Easwaramoorthy Sathishkumar, Jaehyuk Cho, Malliga Subramanian, and Obuli Sai Naren, “Forest fre and smoke detection using deep learning-based learning without forgetting,”2023.

[2] Seyd Teymoor Seydi, Vahideh Saeidi, Bahareh Kalantar, Naonori Ueda and Alfian Abdul Halin, "Fire-Net: A Deep Learning Framework for Active Forest Fire Detection" , Feb 2022

[3] Shuai Zhao, Boyun Liu, Zheng Chi, Taiwei Li and Shengnan Li, "Characteristics Based Fire Detection System,Under the Effect of Electric Fields With Improved Yolo-v4 and ViBe", August 2022.

[4] Byoungjun Kim and Joonwhoan Lee,” A Video-Based Fire Detection Using Deep Learning Models,”July 2019.

[5] Herminarto Nugroho, "Fully Convolutional Variational Autoencoder For Feature Extraction Of Fire Detection System", March 2020.

[6] Xiwen Chen, Bryce Hopkins, Hao Wang, Leo O' Neill, Fatemeh Afghah, et al, "Wildland Fire Detection and Monitoring Using a Drone-Collected RGB/IR Image Dataset" , Nov 2022.

[7] Xuehui Wu1, Xiaobo Lu1, and Henry Leung,” An Adaptive Threshold Deep Learning Method for Fire and Smoke Detection,” Oct 2017

[8] Taha Zaman, Muhammad Hasan, Saneeha Ahmed, Shumaila Ashfaq, "Fire Detection Using Computer Vision" ,2019

[9] Murat Muhammet Savcı, Yasin Yıldırım, Gorkem Saygılı, and Behcet Ugur Toreyin,” Fire Detection in H.264 Compressed Video,” 2019.

[10] Xuehui Wu, Xiaobo Lu, Henry Leung,"An Adaptive Threshold Deep Learning Method for Fire and Smoke Detection", Oct 2017.

[11] Zhenyang Xue, Haifeng Lin, and Fang Wang,” A Small target forest fire detection model based on yolov v5 improvement,”Aug 2022.