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# Real Tıme AI, Computer Vısıon Based Framework To Detect And Prevent Lıquıd Metal Fıre Hazards

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***Abstract***

*Fire hazards are common while handling combustible fluids. It frequently brings human deaths and loss of properties. Research on proficient fire identification and stifling discovery frameworks has become a hotly debated issue in industries. In any case, shows frameworks are either PLC or microcontroller or computer-vision frameworks based frameworks. The yield prompts a higher bogus caution rate or the framework will a rule-based. In this paper, we propose an AI with conventional sensor-based ways to deal with identifying a fire in indoor and open-air situations. Various topologies of data from the video gained by the cameras and sensors are consolidated and investigated by the proposed framework to expand the general unwavering quality of the approach and decrease the bogus positives distinguished by the framework*

***Index Terms:*** *Convolutional Neural Networks, Fire Detection, Internet of Things (IoT), Neural Networks, Smoke Detection*

## 1 Introduction:

Fire represents a significant danger in a modern system. In chemical industries and nuclear reactors, the usage of fluid metals will be higher. Fire accidents are the most regular happening catastrophes these days. To prevent the fire accidents the security systems stay the essential structures in industries.

When fluid metals combine with air or oxygen chemical reactions happens and now and again blast may occur. Spillage detection, fire detection, and amendment are significant difficulties in a mechanical situation. Ordinary fire counteraction systems use smoke recognition, fireplace, heat discovery sensors. Leakages checked by various sorts of sensors. Aside from the issue of early fire discovery, present alarm frameworks additionally end up being wasteful as far as the bogus activating of the alert frameworks. Present fire recognition strategies typically have sensors like thermal, smoke, and fire. In any event, these sensors-based recognition frameworks are not truly solid for fire identification. At times, smoke sensors trigger bogus alerts. It doesn't differentiate fire and smoke. Then again, the other two identification frameworks need an adequate degree of fire inspection for a reasonable discovery, which prompts the right identification and reduces severe damage.

Vision-based smoke detection methods face several difficulties. Video preparing strategies for the most part chip away at the standard of perusing pixel estimations of the shading. In this way, progressively, it gets hard recognizing the actual smoke to be identified and the grayish hued data present in the picture. Characteristics of the camera make it tough to detect smoke in a dim situation [3]. Henceforth, for better by and large execution, typically a smoke sensor incorporated in the structure to identify smoke, subsequently expelling the requirement for introducing separate fire and smoke alarms. Sometimes, the bogus warnings happen with smoke alarms utilized as fire identifiers in regular alarm frameworks. Smoke and additionally financially reasonable sensors can recognize smoke proficiently.Wireless transmission system is also used to alert the end customers. This kind of quick-fire and smoke identification unit can be

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used for an extensive extent of employments, for instance, an early warning of fire dangers can get the firemen to distinguish the site of the fire at the soonest, setting off the modified fire disguise systems, etc.

On account of fast progressions in electronic camera development and image processing methodologies, there is a critical tendency to displace standard fire distinguishing procedures with PC vision-based algorithm. Video-based fire identification strategies are appropriate to separate fire in indoor and outdoor spaces Likewise, CCTV perception frameworks are nowadays presented in various spots checking inside and outside. In this circumstance, it is gainful to develop a video fire identification structure that could utilize current surveillance frameworks. The investigation around there has started since the nineties. There are a couple of video-based flames and fire detection calculations in the composition. Most of these calculations centers around the shading and the shape qualities together consolidated to the fleeting conduct of smoke and flares [2]. A short time later, the goal is to build a rule-based calculation or a combination of traditional algorithms with multi-dimensional machine learning algorithms (SVM, Neural Network, and so forth)

Consequently, ordinary video fire discovery techniques address the issue by depending on master information to build feature extraction. Specialists required to make the rule-based models and decision-based models. An alternate method for this issue is to use a machine-learning algorithm to classify the valuable information as opposed to utilizing a specialist to build them. Deep-learning calculations can learn such valuable highlights to find fire and smoke in the video. CNN, a deep-learning algorithm that can separate topological attributes from a picture. Accordingly, the proposed method is thoughtfully straightforward. CNN used as a fire and smoke identifier. CNN uses a raw RGB outline without the need for the element extraction stage. CNN learns a lot of visual highlights from the training dataset.

As per the object classification algorithm, video-based fire identification strategies detects fire and smoke. Irregularly, the smoke comes before the blazes. Video smoke discovery considered for the early warning in fire security buildings. Detection techniques predominantly focus on the mix of static and dynamic properties of smoke. The general properties of smoke contain shading, surface, movement, direction, and so on. Shading attributes of smoke considered in YUV space [1].

In recent years, innovations in computer vision and machine learning algorithms are rapid. Deep-learning algorithms perform better on

a) Picture characterization,

b) Object recognition,

c) Current estimation

d) Semantic division.

As opposed to conventional computer-vision draws near, deep learning calculations keep away from hand-created configuration and can take in complex portrayals from a lot of pictures dataset. Along these lines, it is sensible to accept that CNN can likewise advance the improvement of video smoke discovery.

Next section summarizes

- The list of associated works,
- An overview of the proposed approach, and algorithms.

## 2 Related Works

Identifying fire is a big challenge, present-day development is in urgent demand for distinguishing and diminishing fire hazards [3]. Researchers have endeavored to use CNN in fire detection [1]. Fire or smoke detected from video recordings using a CNN framework [1]. A full picture CNN classifier model proposed [1] to detect fire. Faster R-CNN is an amazingly compelling framework for unstructured data recognition. Upgrading the present technique represents a significant step to improve control and minimize error rates.

Below are the lists of fire and smoke detection methods

- Four stages [1] of the video-based identification system used.
- Automatic edge detection for fire [3],
- Static and dynamic properties of the fire.
- Fire detected from the smoke using two diverse color spaces, RGB color space technique, and YCbCr shading space. Past drawbacks of fire detection decreased by applying some dynamically traditional standards with YCbCr. However, the high false-positive recognition rate and failure of detection were the related downsides. In certain works, color and movement have been taken as the measure to detect the fire.
- The dynamic properties of the fire used for fire recognition, yet this strategy additionally fizzled with pictures having pseudo fire like images.
- Multi-sensor framework to recognize smoke and fire. System is expensive. Inefficient in higher data volume.

Diverse deep-learning ways to detect the fire have been proposed. CNN for finding the fire patches on forest fire identification,

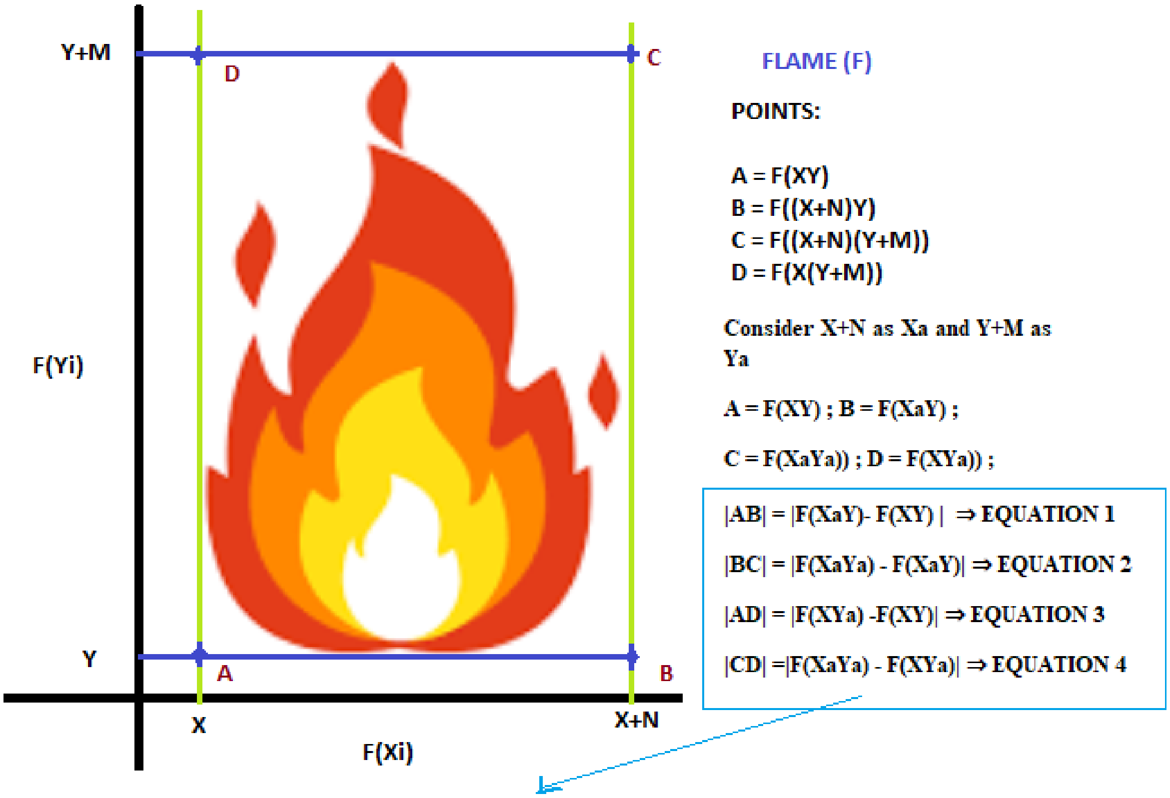
- CNN-based fire detection methodology with VGG16 and Resnet50 as pattern design. Not suitable for outdoor fire detection application.
- Variations of CNN like AlexNet, SqueezeNet, GoogleNet, and MobileNetV2.

To develop a robust system for detecting fire this paper suggests the mix of sensors and artificial intelligent frameworks.

### System Overview:

This area contains the detail of fire and smoke location strategies[12]. Intense smoke and fire can be seen during the occasion of a fire. The beginning time of the fire recognized utilizing the phenomenal properties of the fire. Shape, color, and movement of the fire are used to recognize the occurrence of fire.

### Edge detection:




Perimeter of flame is (PF)= |AB| + |BC| + |AC| + |CD| substitute equation 1,2,3,4.

Consider ABCD as a rectangular surface, then area of the surface can be obtained by the formula Area = half of (Perimeter of a Rectangle * Length of a Rectangle) - square of length of a rectangle.

A = ½(PF*|AB|) - (|AB|)^2 ⇒ ½(PF* |F(XaY) - F(XY) |) - (|F(XaY) - F(XY) |)^2

## Color Shade Detection:

The picture caught by the camera produces an RGB format[6-7]. In a shading band, RED > GREEN > BLUE. Fire or Fire lies in the RED - GREEN range.

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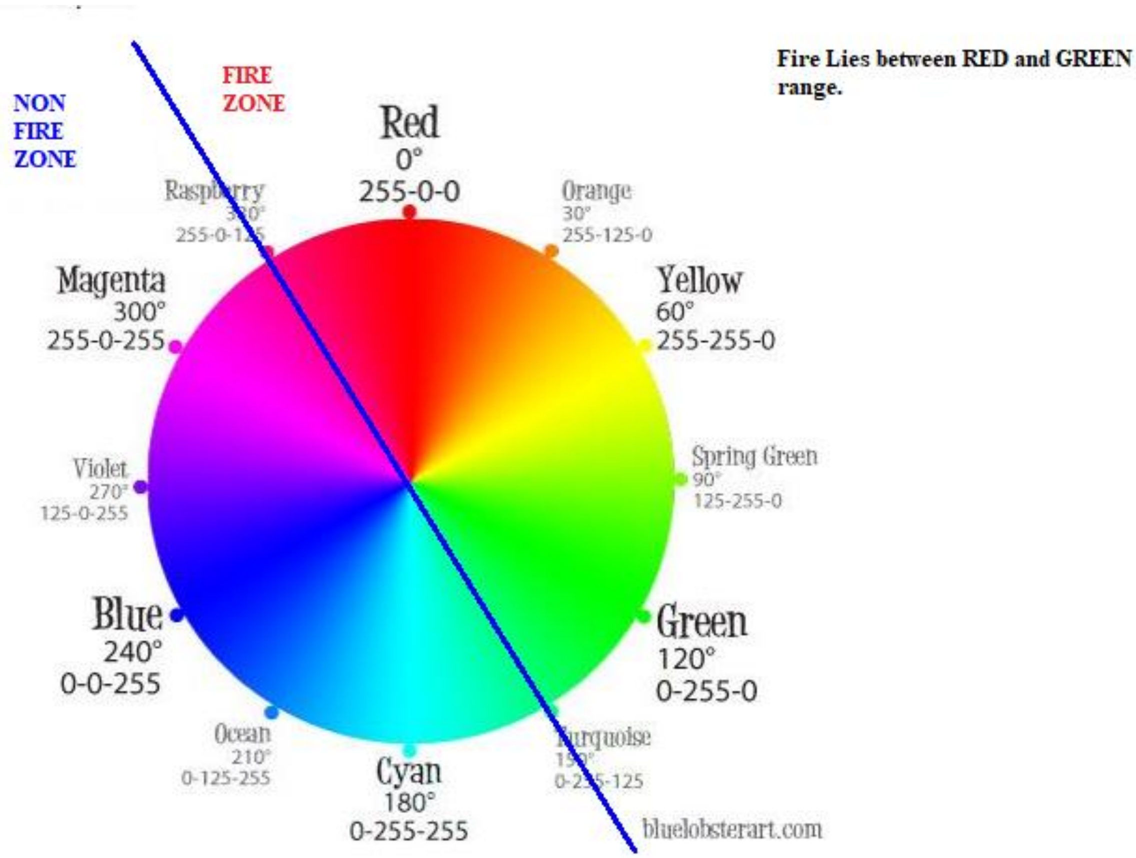
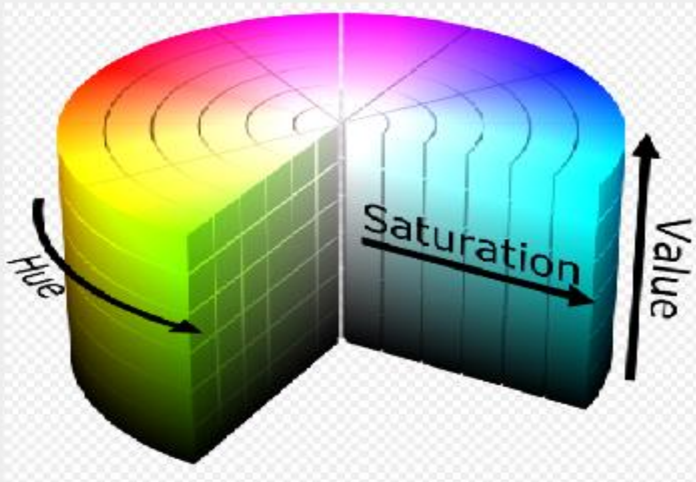
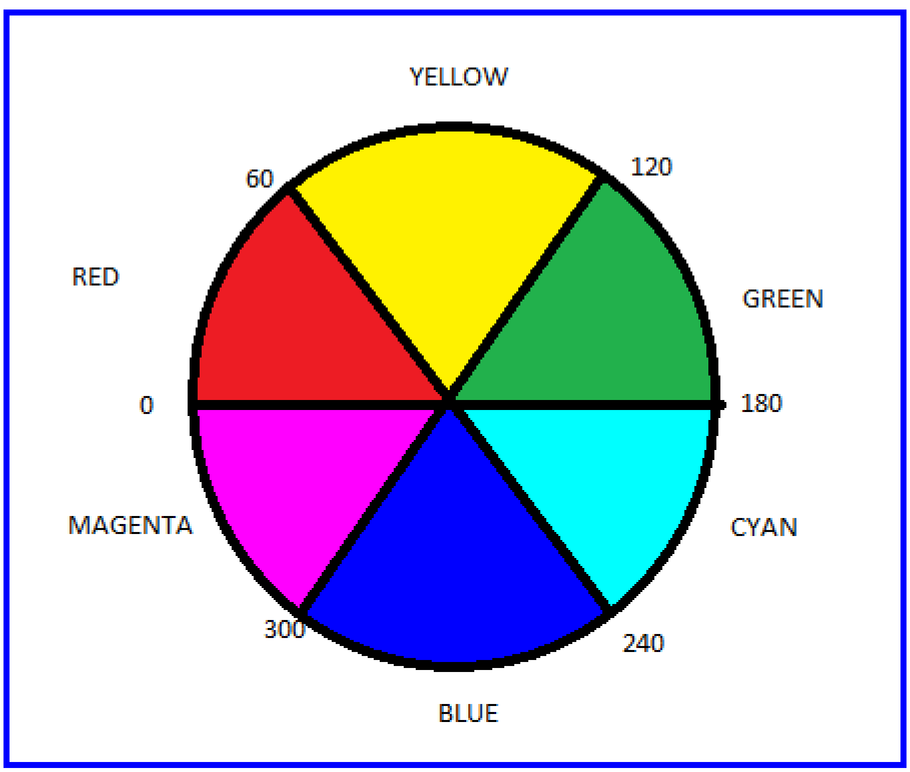



The relationship between RED & GREEN gives a theory ablaze. In a range of shading, RED is a commanding shading and it is given more significance than other shadings. On the off chance that a casing is taken and changed over as pixels, the thickness of RED will be high on a focal point of the fire-influenced zone and low on the edge of the fire-influenced zone. Subsequently, the RED estimation of the picture won't be consistent. In this way, an edge esteem REDThre is determined. The range among RED and REDThre will be viewed as a fire/fire influenced zone. Our past condition will be changed as RED > REDThre > GREEN > BLUE The range among RED and REDThre can be called as Saturation Spectrum(SS) or Target Spectrum. Consequently, the last condition will be (max fire pixel esteem - RED) * proportion of SS and REDThre. ⇒ (255-R) * ST/REDThre. Normally REDThre would be between 40-60 and SS would be between 170-190. Smoke pixels in an edge are distinguished utilizing the grayscale pixel discovery strategy. RGB methodology has some drawbacks. RGB data is transformed to HSV color model. The explanation we use HSV shading space for shading location/thresholding over RGB/BGR is that HSV is progressively strong towards outer lighting changes.




- **Hue is color, expressed between 0 and 360 degrees.**
- **Saturation portrays the measure of darkness in a specific shading, from 0 to 100 percent. Reducing this segment toward zero presents progressively dim and creates a blurred impact. Now and again, saturation shows up as a range from only 0-1, where 0 is dark, and 1 is an essential shading.**
- **Value works related to saturation and portrays the brightness or force of the shading, from 0-100 percent, where 0 is dark, and 100 is the most splendid and uncovers the most shading.**



**Area, Edge, and Movement (AEM) Detection:**

The zone of a fire/fire is recognized by identifying the movement and edge of the fire, fire, and smoke. Video is changing over as casings and in each casing shading between the foreground (smoke/fire/fire) and the foundation is distinguished this recognizes the edge of the objective property. Sequential edges are taken and changed over as twofold pixel regions of closer view property between the pictures and foundation property of the pictures are determined. The contrast between the foundation property of back to back casings and the distinction between the closer view property of the successive edges is distinguished. This gives the movement and area covered by the fire/fire/smoke.

**Neural Networks:**

3 Group and 5 Group CNN architecture is discussed in the below mentioned table.

- AlexNet [12] with 8 layers is the best example for 3 group technique.
- VGG-13 layer & VGG-16 layer technique are the best examples of 5 group techniques

CNN 8 LAYER & 16 LAYER TECHNIQUE

| GROUP | 3 Group Technique | 5 Group Technique |
|---|---|---|
| 1 | • 11 part size convolution layer<br>• 5 part size convolution layer<br>• Max Pool and Standardization Layer | • 2x64-channel convolution layer of 3-part size. |
| 2 | • 3*3 part size convolution layer<br>• Max Pool and Standardization Layer | • 2x128-channel convolution layer of 3-part size. |
| 3 | • Fully connected output layers | • 3x256-channel convolution layer of 3-part size. |
| 4 | | • 2x512-channel convolution layer of 3-part size. |
| 5 | | • Fully connected output convolution layers |

## 3 Proposed Methodology

Wide sensor networks can be used to monitor fire hazards. But at times the installation of sensors might not be possible at the place and there can be installation difficulties also there might be a chance of a false trigger. The proposed methodology should work both in indoor and open spaces. This paper aims to detect the occurrence of fire by combining an array of technologies. Imagine a decorator and builder design pattern in the computer programming language. Weighted results from various modules decide the action. The first module contains sensors (like temperature sensors, smoke detectors, fire detectors). In the article "Effective Handling of Fluids and Liquid Metals using IoT" [5] detailed sensing techniques are discussed. Subsequent modules use the Computer Vision and Deep Neural Neural Network modules. Computer Vision Module uses the HSV Color Space and Motion Detection Algorithm. The Deep Neural Networks module uses Fire Detection Module using OpenCV, DNN, Tensor Flow, Image AI, Keras, CNN, trained FireNet dataset, and a Fast RCNN Smoke detection module.

**Simple Fire Detection Module**

The HSV color space (hue, saturation, value) The model describes colors similar to the human eye to sensitive color [4]. Where the human color vision reflected better than the RGB, YUV, and YIQ models, which are targeted for electronic devices. RGB Color in the relation of a mixture of basic colors, where, HSV describes the color using more comparisons are familiar with color, saturation, and brightness[1]. The figure below describes the edge detection algorithm. This method has 99% fire detection rate and 31.5 % false alarm rate.

For experimentation, this module was written using Python, OpenCV, and Numpy.

$V = max\{R,G,B\}$ (1)
$S = max - min$ (2)
$H=\{ \quad G-B6(max-min)16(2+B-Rmax-min)16(4+R-Gmax-min)$ (3)

where $max$=max $(R,G,B)$ and $min$=min $(R,G,B)$.

**ALGORITHM**

1) Capture the video and extract frames from it.
2) Set Gaussian parameters and blur the frame
   a) source image(src) ,
   b) destination image (dst),
   c) The size of the kernel (Size(w, h)) to be used (the neighbors to be considered). w and h have to be odd and positive numbers otherwise the size will be calculated using the \sigma_{x} and \sigma_{y} arguments.
   d) \sigma_{x}: The standard deviation in x. Writing 0 implies that \sigma_{x} is calculated using kernel size.
   e) \sigma_{y}: The standard deviation in y. Writing 0 implies that \sigma_{y} is calculated using kernel size.
3) Convert the GaussianBlurredImage to HSV plane.
4) Initialize a Range value to identify the fire object in an image. In this experimentation we have applied lower and upper value of BGR as {18,50,50} and {35,255,255}
5) Perform a bitwise "and" operation on the frame with hsv space value and the mask.

This algorithm when enhanced with HSV, YCbCr[43-44] color pattern, 93 and 99% of accuracy is obtained.

## Area, Edge, Movement (AEM) Detector Module:

Color, Grayscale methods are used to identify the edge, movement, and area of the fire affected a given source video. The Algorithm to detect the Area, Edge, and Movement are mentioned below.

**ALGORITHM**

1) Convert video(V) as Frames{FRAMEi} and assign a frame identifier {FRAME0-FRAMEn}
2) Initialize Previous Frame(PREV-FRAME) as null
3) Iterate the FRAME{0-N}
    a) Calculate width and height of the FRAME as {WT & HT}
    b) Let initial value of WIDTH AND HEIGHT starts from {X,Y} (as mentioned in earlier section)
    c) Get hexadecimal value of a pixel at given {X,Y}
    d) Get the average of RGB is $\frac{1}{3}(R+G+B)$
        i) If average is greater than threshold value, set pixel as FIRE.
        ii) Else the pixel does not contain a fire element.
    e) Repeat the previous two steps till the width and height reaches its end.{X+N,Y+N}
    f) Find the ratio of sum of pixels for the total width WT
    g) Find the ratio of sum of pixels for the total height HT
    h) Save Current Frame (CURR-FRAME) with the calculated value of the previous two steps.
    i) Calculate absolute difference value of CURR-FAME and PREV-FRAME. If greater than threshold then it has fire label the pixel as fire.
    j) Assign CURR-FRAME → PREF-FRAME
4) The entire operation is identifying fire data in a given pixel. Hence, it can be marked as a boolean/binary value(0,1). At this step, calculate the average of the boolean/binary value calculated in step 3. If the average is of <20%, we can mark it as LOW FIRE,> 80% HIGH FIRE, rest of the range can be marked between LOW, MEDIUM and HIGH

**Smoke Detector:**

The smoke delivered by burning chemical parts like tires is practically near dark. It implies that the RED, GREEN, BLUE parts of forest & chemical smokes are exceptionally close in RGB shading space.

- In the region without smoke, the GREEN segment >> (RED + BLUE) (approx. 30 – 40 times).
- In the territory with smoke, the GREEN ~= (RED and BLUE) with the expanding smokey area.

Fast convolutional neural systems (CNNs) have overwhelmed numerous assignments of computer vision. Utilizing Faster R-CNN [1] to identify smoke has numerous points of interest. There is no compelling reason to physically separate features. The first picture is utilized as the entire system contribution without preprocessing or square division. The handling speed is quicker than in the past two ages. At the point when we utilize Faster R-CNN to distinguish smoke in the genuine scene, smoke pictures acquired from backwoods fire scenes can be utilized to build the rich training data set. To improve efficiency, [8-12] consolidates the technique with customary sensors and different calculations.

**Real-time AI Module:**

Constant fire location venture containing a clarified informational index, pre-prepared module. This module utilizes a mix of structures like OpenCV, DNN, Tensor Flow, Image AI, Keras, CNN, and prepared FireNet dataset. FireNet nearly 500 or more pictures are part of 80% and 20% for preparing and testing. This prepared AI calculation sees, comprehends, and acts appropriately in taking care of any issue they are sent. Real-time AI Module is a system architecture made for the most part out of a solitary rehashing initiation module component comprising four equal parts of the calculation, each contains various layers. The Real-Time AI Module offers a differentiating 22 layer deep system architecture to 8 layer AlexNet.

## 4 Results of the work:

Results show that the framework execution for fire discovery involving just crude recognition is 81%, containing both shading and movement identification is 83%. At the point when these strategies are joined with grayscale recognition the framework execution is 87% and when containing territory scattering the framework execution is 93%. At long last when the proposed fire identification framework procedure applied with the above strategy in a combinational way, the framework execution is 92%. At the point when joined with reduced complexity CNN, can accomplish 93 percent precision for the twofold order assignment of fire identification. The proposed fire identification framework gives us a superior framework execution in terms of less bogus alert and in this manner a higher framework execution is accomplished. Exactness can likewise be additionally expanded by applying diverse effective calculations in each period of location. All the more ever the framework has been progressively dependable in reefing the outcome comes out from existing location strategies

The deep-learning-based algorithms have the advantage of customized extraction. As such, making the procedures extensively more successful and reliable than the regular image extraction framework. Regardless, these deep-learning approaches need HPC (High-performance Computing) power, while training the data set as well as doing a specific task.

## 5 Conclusion:

In this paper, the Proposed framework identified fire in indoor and open-air situations. Various topologies of data from the video gained by the cameras and sensors were consolidated and investigated by the proposed framework to expand the general unwavering quality of the approach and decreased the bogus positives distinguished by the framework. A combination of Faster R-CNN based, Generic Color Model-based, vision-based fire, and smoke detection were presented. The color module is better at discriminating fire images from on fire images. The performance of the system was tested with a set of random fire and non-fire images. The proposed model achieved 99% accuracy in the flame detection rate. The proposed approach provides good accuracy for detecting the fire tests. The inclusion of the Faster R-CNN method detects the smoke and it improves the overall accuracy of the system**.**

## References

1. Qi-xing Zhang, Gao-hua Lin, Yong-ming Zhang, Gao Xu, Jin-jun Wang. "Wildland Forest Fire Smoke Detection Based on Faster R-CNN using Synthetic Smoke Images" , Procedia Engineering, 2018
2. Sebastien Frizzi, Rabeb Kaabi, Moez Bouchouicha, Jean-Marc Ginoux, Eric Moreau, Farhat Fnaiech "Convolution Neural Network for Video Fire and Smoke Detection", IEEE, 2016
3. Arpit Jadon, Mohd. Omama, Akshay Varshney, Mohammed Samar Ansari, Rishab Sharma, "FireNet: A specalized lightweight Fire and smoke detection model for Real-Time IoT Applications", arXiv:1905.11922v2 2019
4. Hazim Gati' Dway, Ahmed Fakhir Mutar, "Study Fire Detection Based On Color Spaces",Al-Mustansiriyah Journal of Science, Volume 29,Issue 4,2018 ISSN: 1814-635X (print), ISSN:2521-3520 (online)
5. Praveen Sankarasubramanian, “Effective Handling of Fluids and Liquid Metals using IoT” International Journal of Institution of Safety Engineers (India), Published by ZJEW Trust, Govt. Reg. No. 5240 Volume 3, Issue 1, Jan-March 20
6. CELIK, T., DEMIREL, H.: Fire detection in video sequences using a generic color model. In: Fire Safety Journal, 2008, 44.2: 147-158.

7. Turgay Celik, Hasan Demirel, "Fire detection in video sequences using a generic color model", Fire Safety Journal, 2008
8. Gaurav Yadav et al ,"OPTIMIZED FLAME DETECTION USING IMAGE PROCESSING BASED TECHNIQUES ",Indian Journal of Computer Science and Engineering,Vol. 3 No. 2 Apr-May 2012
9. Rohini Ravindra Jadhav et al,"Enhancing Fire Detection for indoor and outdoor locations via video surveillance",(IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 7 (4) , 2016, 1902-1906
10. Gope, Hira Lal et al. "Fire Detection in Still Image Using Color Model." Indonesian Journal of Electrical Engineering and Computer Science 3 (2016): 618-625.
11. A. J. Dunnings and T. P. Breckon, "Experimentally Defined Convolutional Neural Network Architecture Variants for Non-Temporal Real-Time Fire Detection," 2018 25th IEEE International Conference on Image Processing (ICIP), Athens, 2018, pp. 1558-1562, doi: 10.1109/ICIP.2018.8451657.