JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Fire Detection Using Image Processing

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Abstract : In this paper, we propose a deep CNN-based fire detection system that can accurately and efficiently detect fires in real-time. After detecting fire it goes one step further by trying to detect the presence of any fire extinguishers at one of the connected devices so that we not only quickly detect fire but also quickly control it. Our fire detection model uses a deep convolutional neural network with multiple layers of convolution and pooling to extract features from the input images. [We evaluate the performance of our system on a publicly available dataset of fire and non-fire images and achieve a high accuracy of over 98%.] Our proposed system has the potential to be used in various applications, such as fire monitoring in buildings, and can greatly improve the efficiency and effectiveness of fire detection and prevention.

***IndexTerms* - Convolutional neural networks (CNNs), Deep Learning, Fire Detection, Image Classification.**

I. Introduction

Fire detection is an important task in preventing and minimizing the damage caused by fires. Due to human activities and dry weather conditions, the incidence of forest fires has been increasing consistently. Monitoring systems that include fire detection have become essential for ensuring the safety of structures and the surrounding environment. It is crucial for these systems to detect fires at their earliest stages as part of an early warning mechanism. Extensive research and implementation have been conducted on various fire detection systems to prevent the devastating consequences of fires. For fire detection, two major sorts of approaches can be distinguished: 1) Conventional fire alarms, and 2) fire detection supplemented by vision sensors.

Traditional fire detection systems are built around proximity-activated sensors like optical and infrared ones. These are not suitable for critical situations, and in the event of an alarm, human intervention is required and a visit to the fire's location is required. Additionally, such systems typically are unable to offer details like the size, location, and level of the fire's burning. Researchers in this subject have looked into a variety of optical sensor-based technologies to get beyond these constraints; these systems have the advantages of requiring less human involvement, quicker response times, lower costs, and wider surveillance coverage. These can also confirm the presence of fire without the need for a person to travel to the scene and can provide comprehensive information on the fire, such as its degree, dimensions, etc

II. Literature Survery

The India Risk Survey Report, published by Pinkerton**[1]**, employs an attention module to extract important cues from the input image experiments conducted on their internally generated dataset. Through this approach, the method achieves a detection rate of 97.5% and an accuracy rate of 96.8%.

In their work, T. Celik, et al.**[2]** enhance a system that utilizes a statistical color model combined with Fuzzy logic to classify fire pixels. The proposed system introduces two models: one based on luminance and another based on chrominance. Instead of employing color spaces like RGB, Fuzzy logic utilizes the YCbCr color space to effectively separate luminance from chrominance. By replacing existing historical rules with Fuzzy logic, the classification becomes more robust and efficient. This model achieves an impressive fire detection rate of up to 99.00% while maintaining a false alarm rate of 9.50%.

Hidenori Maruta et al.**[3]** have presented an alternative approach for smoke detection based on support vector machine (SVM). Their proposed method introduces a robust and innovative smoke detection technique utilizing SVM. The process begins with preprocessing, which involves extracting moving objects from images. The preprocessing phase comprises five steps: image subtraction and accumulation, image binarization, morphological operations, extraction of Feret's regions, and creation of the image mask. Image subtraction is employed to isolate regions containing moving objects, while binarization and morphological operations are used to eliminate noise-like regions. Feret's regions are identified to determine the position and approximate shape of the object. Following preprocessing, texture analysis is performed to extract texture features, which are incorporated into a feature vector. This feature vector serves as the input for the support vector machine, which is responsible for classifying whether smoke is present or not. The smoke detection method encompasses a sequence of three steps: analyzing texture features, employing support vector machine to discriminate Feret's regions, and incorporating time accumulation. By applying texture analysis, this method successfully extracts feature vectors from the image, allowing the support vector machine to accurately classify smoke or non-smoke. A notable advantage of this approach is its ability to achieve more precise extraction of smoke areas in images through the utilization of SVM.

In their study, Zili Zhang et al. **[4]** introduce an approach that utilizes the YCBCR color space to distinguish between luminance and chrominance. This method employs a rule-based general color model for classifying flame pixels, resulting in a remarkable fire identification rate of up to 99%.

Surapong Surit et al.**[5]** put forth a digital image processing strategy that combines static and dynamic characteristic analysis. The proposed method involves identifying the area of change in the current input frame by comparing it to the background. It then utilizes the connected component algorithm and convex hull algorithm to locate regions of interest. The identified area of change is segmented, and static and dynamic characteristics are calculated as part of the process.

Y. Habiboglu et al.**[6]** introduced a system that utilizes covariance descriptors, color models, and an SVM classifier based on the spatio-temporal covariance matrix. This system computes covariance characteristics from video data, which is divided into temporal blocks. By employing an SVM classifier, the system effectively detects fires. It is important to note that this classification system exclusively accepts clear data and does not support hazy data. It successfully classifies fire and fire-like locations.

K. Dimitropoulos et al.**[7]** have proposed an algorithm that employs a computer vision approach for early-stage fire detection. The algorithm begins by utilizing a non-parametric model, which incorporates background subtraction and color analysis, to identify potential fire zones in a frame. Different spatio-temporal features, including color probability, flickering, spatial energy, and spatiotemporal energy, are utilized to describe the behavior of the fire. Each identified region undergoes dynamic texture analysis, employing linear dynamical systems, histograms, and medioids. The linear dynamical systems analyze the time evolution of pixel intensities to enhance the stability of the algorithm. Non-candidate locations are subsequently filtered using pre-processing techniques, contributing to the algorithm's reliability. Spatiotemporal analysis is employed to further strengthen the algorithm's accuracy and robustness.

Zhanqing Li et al.**[8]** have presented a technique that utilizes a neural network (NN) for categorizing smoke, sky, and background. The NN not only classifies these elements but also generates a continuous random output that represents a combination of them. Due to the time-consuming nature of NN processing for large areas, multi-threshold algorithms are also employed. Depending on the size of the area, these two methods can be utilized together or independently. The technique leverages a multilayer perceptron neural network as its underlying model.

Saad Albawi et al.**[9]** provided a comprehensive explanation of the individual components of Convolutional Neural Networks (CNNs) along with their major considerations. Additionally, the factors influencing the effectiveness of CNNs are listed. It is assumed in this article that the readers possess a familiarity with neural networks and machine learning.

In their study, Ganesh Samarth et al.**[10]** Investigate different Convolutional Neural Network (CNN) architectures and their variants for the purpose of non-temporal binary fire detection and localization in both video and still images. They specifically focus on experimentally defined, reduced complexity deep CNN architectures and analyze the impact of different optimization and normalization techniques across CNN architectures like Inception, ResNet, and EfficientNet. In contrast to prevailing trends in the field, their research demonstrates remarkable results. accomplish a remarkable overall accuracy of 0.96 for full frame binary fire detection and 0.94 for superpixel localization. A significant advantage of their approach is the lower false positive rate of 0.06, surpassing previous works. This demonstrates their solution's efficacy, resilience, and real- time capabilities in detecting fire regions efficiently.

Roshan Koirala **[11]** presented a system designed to detect the presence of fire in provided image data. The system employs a transfer learning approach to train a deep convolutional network, resulting in high accuracy with a score of 97% on the testing dataset. Furthermore, the system achieves recall and precision rates of 98.99% and 98.50% respectively.

Zhentian Jiao et al.**[12]** put forward the creation of a large-scale YOLOv3 network to ensure optimal detection performance. This method is subsequently employed within the framework for UAV tracking of fire (UAV- FFD), enabling real-time transmission of fire images from the UAV to the base station.

Dewi Putrie Lestari et al.**[13]** proposed an image-based detection system that utilizes the You Only Look Once (YOLO) Method and the Tiny YOLO model to detect fire hotspots in CCTV videos. The purpose of this detection system is to assist firefighters in optimizing the evacuation process. The research conducted predictions using a dataset consisting of 40 training images and 20 test images. The results obtained from testing with the YOLO method demonstrated an average accuracy of 90% and an average loss value of 0.3131451712598113<1, indicating good performance of the model.

Shuai Zhao et al.**[14]** proposed an improved video-based fire detection system that addresses the limitations of slow image-based fire detection and the restriction to static fire characteristics in the presence of electric fields. The system integrates an improved version of You Only Look Once version 4 (YOLO-v4) and the Visual Background Extractor (ViBe) algorithms. Within YOLO-v4, the feature fusion network is enhanced through the use of a weighted bi-directional Feature Pyramid Network (Bi-FPN) instead of the Path Aggregation Network (PANet). This substitution allows for the elimination of erroneously recognized frames by leveraging various dynamic fire characteristics. The ViBe algorithm has also been enhanced to account for the rapid changes in lighting caused by fire flickering. In comparison to other fire detection algorithms, the proposed method attains an impressive fire detection accuracy of 98.9% while maintaining a low false detection rate of 2.2%. Additionally, the system successfully detects fires with more dynamic characteristics compared to image-based fire detection in the presence of electric fields.

III. Objectives of the Proposed System

Proposed system will take live video input from devices like cameras , mobile phones, webcams which are connected over the internet. On detection of fire in any of the connected devices the system will raise an alarm and send notifications. We aim to provide a reliable fire detection solution that can be easily accessible to everyone.

IV. Proposed Framework

In this section, we learn about the framework of our proposed system and how it works.

Methodology

This code trains a convolutional neural network (CNN) for a binary classification problem of fire vs smoke detection.The architecture used is InceptionV3, which is a popular CNN architecture that uses multiple parallel convolutional layers with different filter sizes to capture features at multiple scales. The code uses transfer learning, where the pretrained weights of InceptionV3 are used as the initial weights for the model. The last layer of the model is replaced with a fully connected layer with 2 output nodes and softmax activation, representing the fire and smoke classes. The code also uses data augmentation with ImageDataGenerator and fine-tuning to improve the model's performance. Finally, the code prints the number of layers in the InceptionV3 model

Fire-smoke Dataset Description

The Fire-Smoke dataset is a collection of images used for binary classification of fire and non-fire images. It consists of a total of 2000 images, with 1800 images in the training set and 200 images in the validation set. The dataset is evenly divided into two classes: fire and non-fire. The images in the dataset were collected from various sources, including online image databases and personal collections. The images in the dataset are of varying sizes and resolutions, and were manually annotated to ensure accuracy in classification. The images are of varying sizes and contain different types of fire and smoke, including wildfires, house fires, and cigarette smoke. The dataset is commonly used in research and development of computer vision models for fire detection, such as the one described in the code provided.

Proposed System Algorithm

1. Import necessary libraries: Django, OpenCV, threading, IPython.display, playsound, smtplib, numpy, PIL, TensorFlow, keras, pydub, and defaultdict.
2. Load saved models for fire detection and extinguisher detection.
3. Set flag and status using defaultdict.
4. Define a class named "VideoStream" for video streaming. Initialize the video stream using OpenCV VideoCapture in the constructor.
5. Release the video stream in the "del" method of the VideoStream class.
6. Read a frame from the video stream, resize it to (224,224), pass it to the fire detection model, and draw text based on extinguisher detection in the "get_frame" method of the VideoStream class.
7. If fire is detected with high probability and the alarm sound is not playing, set the status flag to 8. True and play the alarm sound in a separate thread.
8. If fire is not detected, set the status flag to False.
9. Encode the frame to JPEG format and return it as bytes.
10. Define a function named "play_alarm_sound_function" to play the alarm sound. Set the flag to True, start playing the alarm sound using the playsound library, and when the sound finishes, set the flag to False and print "working".
11. Define a generator function named "gen" for video streaming. Continuously read frames from the video stream using the "get_frame" method and yield them as multipart/x-mixed-replace.
12. Define views for rendering HTML templates and video streaming using Django.
13. Define an API view to return the status using JsonResponse.
14. Run the Django server

Workflow of the Proposed System

1. You can use our system with the help of the website we created using Django.
2. When on the home page you can fill in the details of the devices you need to connect
3. After filling out correct ip addresses you click on start live feed button.
4. You will be directed to the live_feed page and you will be able to see the video feed of all the devices that you connected.
5. The live feed from all the connected devices is captured, converted into frames and then fed to the fire detection model
6. When fire is captured in any of the frames the CNN model detects it
7. On detection of fire the model does these three things:
   a. Raises an alarm,
   b. Sends notifications,
   c. Fire extinguisher detection starts

8. If an extinguisher is detected in any of the connected devices it informs us of the location. (In this way we can even control fire as quickly as possible)
9. If an extinguisher is not detected it simply shows that it is not detected.

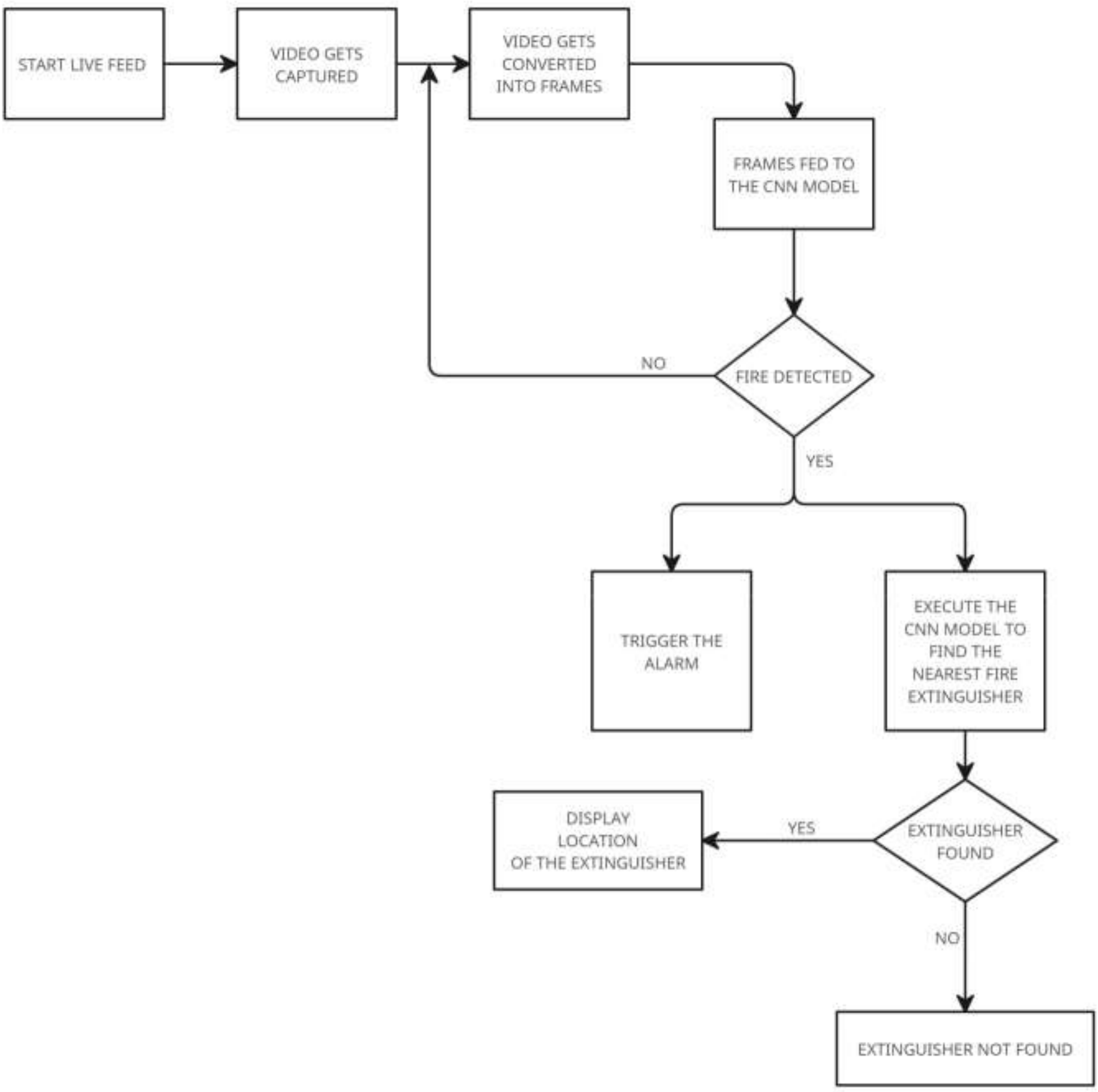

Fig.1. Proposed System Architecture

V. RESULTS AND DISCUSSION

Epoch	Loss	Acc	Val_loss	Val_acc
1	17.69	92.46	41.18	88.27
2	02.13	99.46	31.60	93.88
3	1.38	99.52	25.64	95.92
4	0.48	99.94	20.81	95.41
5	1.31	99.52	13.32	96.94
6	1.28	99.46	11.38	96.94
7	0.71	99.88	12.28	96.43
8	0.53	99.88	10.31	96.94

Table 1. Epoch Comparison

Epoch : It Represents the complete cycle of iterating through the entire training dataset to train the machine learning model.
"- loss: 0.0053 - acc: 0.9988": These values indicate the loss and accuracy achieved during the training process. A lower loss value and higher accuracy value are generally desirable. "- val_loss: 0.1031 - val_acc: 0.9694": These values indicate the loss and accuracy achieved on a separate validation dataset, which is used to evaluate the performance of the model on unseen data. Refer Figure.2 for comparison values of epoch.

Implementation Screenshots

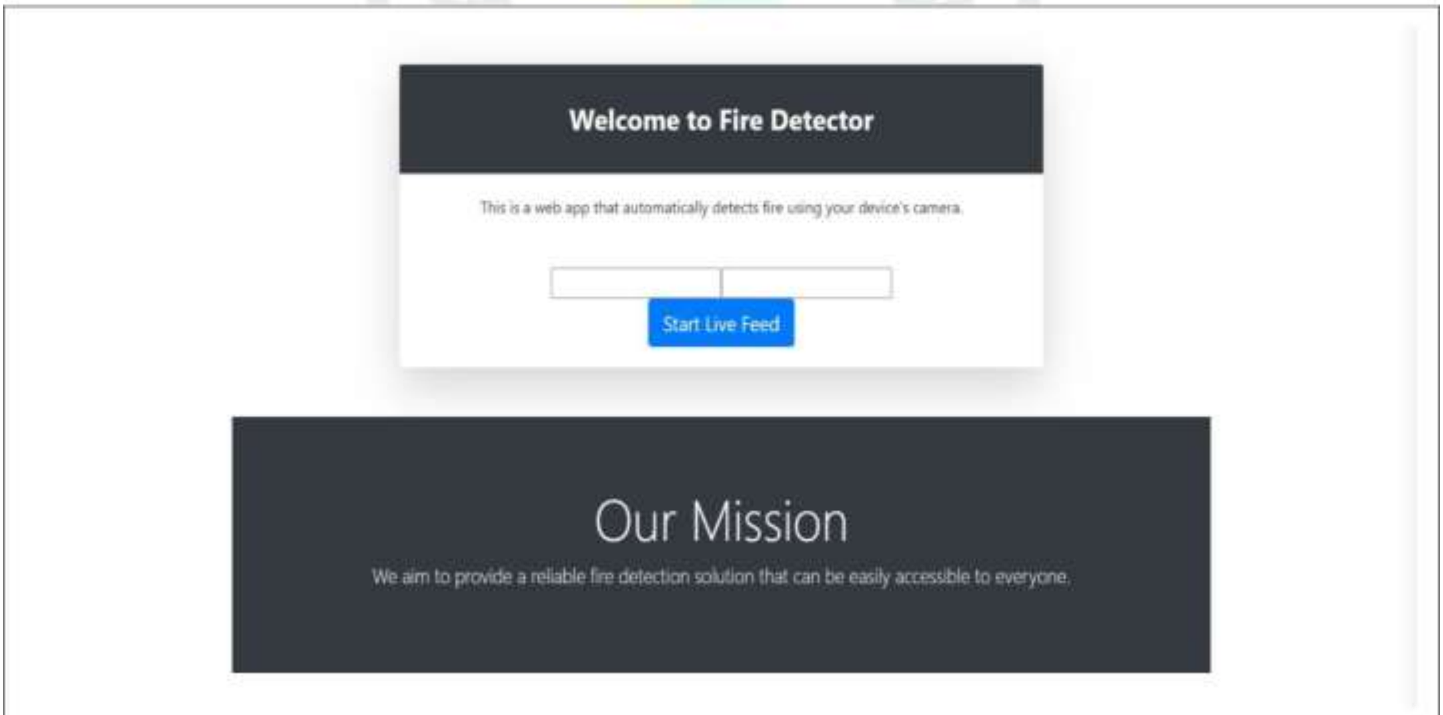

Fig.2 Homepage

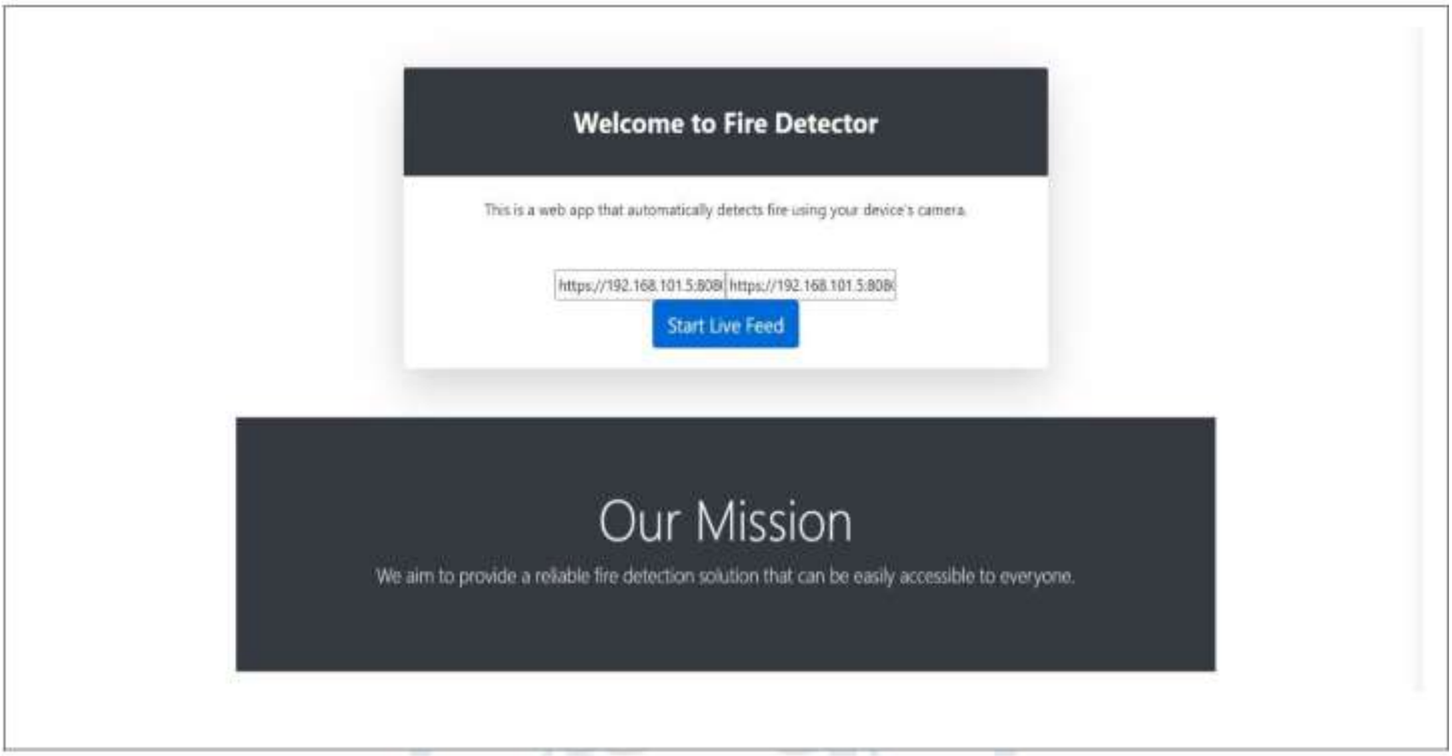

Fig.3. Entering IP Addresses

Fig.4. Live Fire Detection Feed

Fig.5 Live Fire Detected on Camera No.1

Fig.6. Live Fire Detected on Camera Feed 2

VI. Conclusion

The objective of this paper was to introduce a solution that addresses the need for rapid and dependable fire detection and thus in this paper, we have proposed a system that utilizes advanced techniques to promptly identify the occurrence of fire in any of the connected devices, triggering an immediate alarm and sending notifications to relevant parties. Furthermore, our system is equipped with the capability to detect the presence of fire extinguishers in the vicinity, leveraging the connected devices. By detecting both the presence of fire and fire extinguishers, our system enables swift response and potential control of the fire, significantly minimizing the potential for casualties. Overall, our solution aims to enhance fire safety measures by providing quick and reliable detection and facilitating prompt action to mitigate fire-related risks.

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