International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 10 Issue 7 ǁ July 2022 ǁ PP. 666-673

Detection and Prevention of Fire disasters using Image processing Techniques.

Dr. Shailaja Shastri
Department of Computer Science and Engineering
Poojya Doddappa College of Engineering
Kalaburagi, Karnataka 585102, India

Ankita. C. Kulkarni
Ananya. K
Soundarya
Department of Computer Science and Engineering
Poojya Doddappa College of Engineering
Kalaburagi, Karnataka 585102, India

ABSTRACT
Fire disasters are man-made disasters, which cause ecological, social, and economic damage. To minimize these losses, early detection of fire and an autonomous response are important and helpful to disaster management systems. Therefore, in this paper, we are implementing an early fire detection framework using fine-tuned convolutional neural networks for cameras, which can detect fire in varying indoor and outdoor environments. Convolutional neural networks (CNNs) have yielded state-of-the-art performance in image classification and other computer vision tasks. Their application in fire detection systems will substantially improve detection accuracy, which will eventually minimize fire disasters and reduce the ecological and social ramifications.
Keywords: *Fire detection, image processing, video processing, colour modelling, motion detection, image segmentation.*

Date of Submission: 08-07-2022 Date of acceptance: 22-07-2022

I. INTRODUCTION

Fire detection is crucial task for the safety of people. To prevent damages caused by fire, several fire detection systems were developed. One can find different technical solutions. Most of them are based on sensors, which is also generally limited to indoors. However, those methods have a fatal flaw where they will only work on reaching a certain condition. In the worst-case scenario, the sensors are damaged or not being configured properly can cause heavy casualty in case of real fire. Those sensors detect the particles produced by smoke and fire by ionization, which requires a close proximity to the fire. Consequently, they cannot be used for covering large area. To get over such limitations video fire detection systems are used. Due to rapid developments in digital cameras and video processing techniques, there is a significant tendency to switch to traditional fire detection methods with computer vision-based systems. Video-based fire detection techniques are well suited for detecting fire in large and open spaces. Nowadays, closed circuit television surveillance systems are installed in most of the place's monitoring indoors and outdoors. Under this circumstance, it would be an advantage to develop a video-based fire detection system, which could use these existing surveillance cameras without spending any extra cost. This type of systems offers various advantages over those standard detection methods. For example, the cost of using this type of detection is cheaper and the implementation of this type system is greatly simpler compare to those traditional methods. Secondly, fire detection system responds faster compared to any other traditional detection methods because a vision-based fire detection system does not require any type conditions to trigger the devices and it has the ability to monitor a large area.

Two broad categories of approach can be identified for fire detection: 1) Traditional fire alarms and 2) Vision sensor- assisted fire detection. Traditional fire alarm systems are based on sensors that require close proximity for activation, such as infrared and optical sensors. These sensors are not well suited to critical environments and need human involvement to confirm a fire in the case of an alarm, involving a visit to the location of the fire. Furthermore, such systems cannot usually provide information about the size, location, and burning degree of the fire. To overcome these limitations, numerous vision sensor-based methods have been explored by researchers in this field; these have the advantages of less human interference, faster response, affordable cost, and larger surveillance coverage. In addition, such systems can confirm a fire without requiring a visit to the fire's location, and can provide detailed information about the fire including its location, size, degree, etc

Fire is an abnormal event which can cause significant damage to lives and property within a very short time. Fire outbreak is the common issue happening everywhere and the damage caused by this type of incidents is tremendous towards nature and human.

Vision based fire detection system have recently gained popularity as compared to traditional sensor-based fire detection system. However, the detection process by image processing technique is very tedious. We propose a fire detection algorithm using Convolutional Neural Networks to achieve high-accuracy fire image detection.

Fire detection is the main objective of this project besides surveillance. The aim of the project is to early detection of fire apart from preventive measures to reduce the losses due to hazardous fire. The project mainly is based on image processing. In this project, at the user end, the fire images will be feed in the form of video frames.

Fire disasters are man-made disasters, which cause ecological, social, and economic damage. To minimize these losses, early detection of fire and an autonomous response are important and helpful to disaster management systems. Therefore, in this project, we implement an early fire detection framework using fine-tuned convolutional neural networks for CCTV surveillance cameras, which can detect fire in varying indoor and outdoor environments.

II. RELATED WORK

The image-based fire detection needs a number of sequential frames from original video, which consists of fire and non-fire images[1]. It consists of three main stages fire pixel detection using RGB and YCbCr colour model, moving pixel detection and analysing shape of fire-coloured pixels in frames. This method is applied on video sequences and then fire is detected.

The use Colour Segmentation technique to segment fire from its background. The properties of the HSV and YCbCr colour models are used to separate the flame colours from the background[2]. The HSV colour model is used to detect information related to colour and brightness. Then, they calculate the number of white frames by the difference of previous frames and actual frame for five frames consecutively.

The intelligent feature map selection algorithm is proposed for choose appropriate feature maps from the convolutional layers of the trained CNN, which are sensitive to fire regions[3]. These feature maps allow a more accurate segmentation of fire compared to other handcrafted methods. Using this the size of the model was reduced from 238 MB to 3 MB, thus, minimizing the cost and making its implementation Another feature of this system is the ability to identify the object which is on fire, using a pre-trained model.

A convolutional neural network and created a new small dataset of fire and smoke images to train and evaluate the model to solve the over fitting problem in training the network on a limited dataset, they improve the number of available training images using traditional data augmentation techniques[4]. They collected a new dataset, which consists of fire, and smoke images dataset that can be used to train the network and test the data and this helps the network to learn fire and smoke features under different weather and light conditions.

A small subset is used for developing and evaluating the algorithm. In [5] author have investigated two types of classifiers: linear classifier and a non-linear one due to the size of our annotated dataset is small. They changed the number of outputs in last fully connected layer into two for our binary classification. In this network, they also reduced over fitting these are trained in just several hundred iterations and reaches both training and testing accuracy as high which is surprisingly good.

The main objective of the classification in [6] is to decide whether an image contains fire or smoke. They created three subsets of training 60% of images, Validation 20% and test 20%. To optimize the detection and localization of fire on a video, we must improve our training set. The training data has been realized with a computer composed of a microprocessor Intel Xeon (frequency CPU 3,1Ghz, RAM 16Go) and a graphic card GTX 980 Ti 2816 cores, 6 GB memories). In addition to that, they compare the algorithm to conventional methods over a wider variety of video fire images like different material, sources and ventilations the classification accuracy on the test set.

In [7] , author propose a framework, which avoids the tedious and time-consuming process of feature engineering and automatically learns rich features from raw fire data. In these, several kernels of different sizes are applied on the input data to generate feature maps. These features maps are input to the next operation known as subsampling or pooling where maximum activations are selected uncontrollable increase in the computational complexity and networks' flexibility to significantly increase the number of units at each stage.

Moreover, these systems improve the high fire detection accuracy with minimum false alarms but the model size is comparatively high of around 240 MB.

III. METHODOLOGY

The methodology is proposed using CNN (Convolutional Neural Networks) model.

The image datasets are created from fire images captured by videos and converting it into frames. These images are resized as (300,300) and then reshaped as (-1,300,300,1) and stored as a linear array. This is given as a input to the convolutional layer. In these operations, several kernels of different sizes are applied on the input data to generate feature maps. The model consists of 64 convolution filters of size 3x3 each. The feature maps go through a ReLU activation function. This function updates positive portion of the feature map rapidly. These features maps are input to the next operation known as max pooling. These feature maps are subjected again to convolution layer and pooling layer which has kernel size of 3x3. Then a flatten layer which converts 2D feature maps into a vector that can be fed to fully connected layer. Among these three main operations, the convolution and fully connected layers contain neurons whose weights are learnt and adjusted for better representation of the input data during training process. A dense layer represents a matrix vector multiplication. The values in the matrix are the trainable parameters, which are updated during back propagation. Therefore, you get an m dimensional vector as output. Finally, we have an activation function such as Soft-max to classify the outputs as fire and non-fire. Soft-max function provides a probability distribution that maps output to a 0 to 1 range. That's why it is used as final layer of classifying model. the model is compiled using an Adam optimizer which provides an adaptive learning rate to find individual learning rate of each parameter. Categorical cross entropy loss function is used in this classification as only one result could be correct.

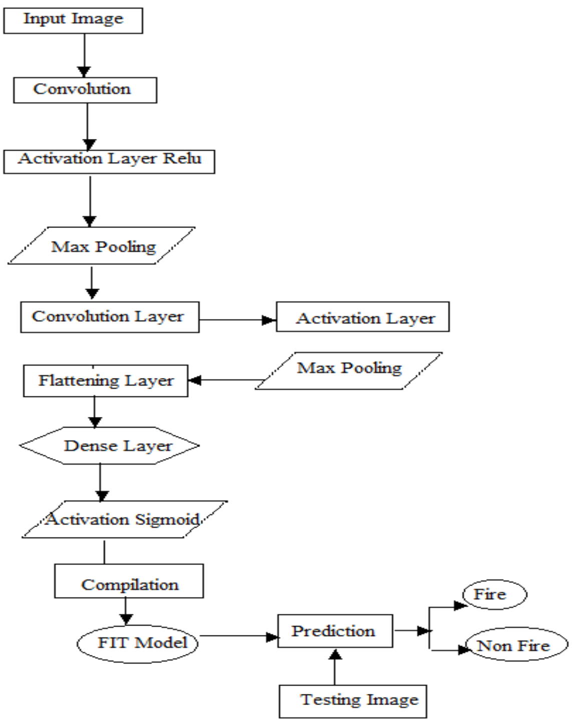


Figure 1. Data Flow Diagram

Figure 1 depicts the data flow diagram of fire detection in this the live video will be captured by our laptop web camera then converted into images in the form of frames then the input images are fed to convolution layer then the convolution layer generates feature map then the input from the feature maps are fed to activation layer, fully connected layer , pooling layer and max pooling layer then after the dense layer sigmoid activation functions are applied to predict whether our input image is consisting of fire or non fire. And in the prediction sometimes testing images are also applied to show the output.

Architecture diagram

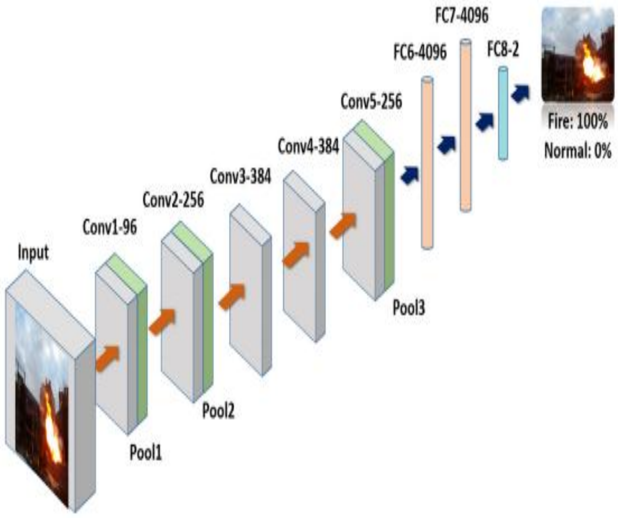


Figure 2. Architecture Diagram

Figure (2) depicts the Architecture design of our model, using convolutional neural network, which consists of convolutional layer, pooling layer and fully connected layers. Input image will be converted into frames which undergoes, several convolutional and pooling layer, finally the fully connected layer after this by using sigmoid activation function it shows whether image consist of fire or non-fire.

Design model consists of four steps:

1. Data gathering: Fire images were gathered from several images and videos uploaded to the internet. Capturing Fire accident images was taken from laptop web camera. Then the fire images were converted into JPEG format.

2. Annotation and Construction of data set 200 Fire images were gathered and selected for validation and training. 80% of the images are for the training set and for the validation set is 20%. To circumvent individualities within the Fire images, it was guaranteed that the data set comprised Fire images under various natural settings. Another 30 Fire testing images were gathered for the model evaluation for verifying the trained model stability and reliability. Generating masking images of a fire was done using the VGG Image annotation tool. Masking images were used in calculating the reverse loss in the training and model optimization. Trained model performance for instance segmentation was assessed by associating the estimated outcome of the mask with the annotated masking images.

3. Training the Model We used Mask R-CNN for Fire detection with a ResNet-101 backbone, pre- trained on the COCO dataset While training the images to undergo the process of augmentation so that there is no problem in an insufficient dataset. The training was done with 0.001 learning rate and 2 images per GPU, during10 epochs. Every after of an epoch the training loss, Mask loss, RPN loss are decreasing.

4. Mask R-CNN detection model shows that the framework of Mask R-CNN is divided into three stages. First, the extracted input Fire images feature maps to the support network. Second, the region proposal network (RPN) that produces the region of interest (ROIs) coming from the feature maps formed by the backbone. Third, the fully convolutional network (FCN) that gets the extracted corresponding target features coming from the region proposal network then performs target classification and segmentation. The outputs of this stage are generating classification scores, segmentation masks, and bounding boxes. 1. Mask RCNN Prediction Running the prediction of the model. The image is from the training images and pick randomly.

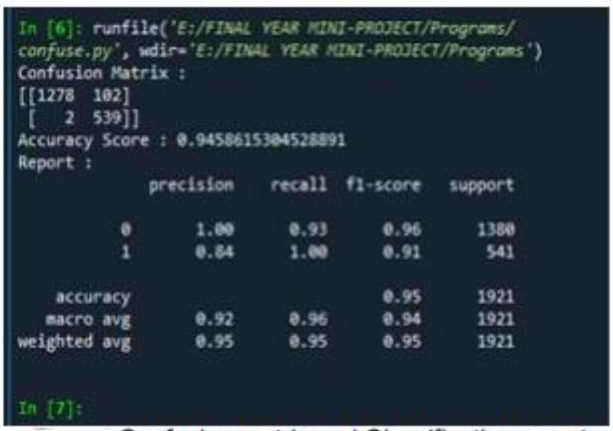
IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

Number of images in the testing dataset for fire and non-fire is 1380 and 541 respectively. Totally there are 1921 images. These images are rendered from video containing fire and certain number of images are taken from internet. Images in the dataset within the two folders ‘Fire’ and ‘Non-Fire’ are read from the folders using OpenCV. Images are in form of NumPy arrays and resized to reduce the storage size. The image array and class number are put together in a list and it is appended to a new list named ‘training data’. The ‘training data’ is shuffled. Image array and its classes are appended separately in another two new lists. The list containing image array is reshaped into a linear array. The lists ‘X’ as feature and ‘Y’ as label are saved to a pickle file. Training of model with different batch sizes and number of epochs provide different accuracy Batch size is the number of samples to work through before updating the internal model parameters. A training dataset can be divided into one or more batches. The number of epochs is the number of times that the learning algorithm will work through the entire training dataset. Here, for a batch size of 64 and 10 epochs, the loss (0.0107) is very low and the accuracy is high. This is because when the batch size is increased, the loss is decreased

Table 1.

Comparison with different batch size and epochs

BATCH SIZE	EPOCHS	ACCURACY	LOSS
32	10	0.9880	0.1220
16	10	0.9974	0.0216
64	10	0.9984	0.0107



```
In [6]: runfile('E:/FINAL YEAR MINI-PROJECT/Programs/
confuse.py', wdir='E:/FINAL YEAR MINI-PROJECT/Programs')
Confusion Matrix :
[[1278  102]
 [   2  539]]
Accuracy Score : 0.9458615304528891
Report :
              precision    recall  f1-score   support

           0       1.00      0.93      0.96      1380
           1       0.84      1.00      0.91       541

    accuracy                           0.95      1921
   macro avg       0.92      0.96      0.94      1921
weighted avg       0.95      0.95      0.95      1921


In [7]:
```

Confusion matrix and Classification report

Figure 3. Confusion matrix and classification report

Figure 4. Output showing GUI page

Figure 4. Depicts the output of our project, GUI page using tkinter, Firstly, on clicking on capture Video, it records the video by laptop web camera by using python libraries, it starts recording after that on clicking Motion detection in that it shows the motion of the fire if it detects the fire, next Shape detection in this it depicts the shape of the fire it is based on the convolutional neural network model, which consists of three layers convolutional, pooling and fully connected layer, after this on clicking Fire detection , we need to connect with a server with Gradio , in this the recorded videos which are converted into the frames are present, or we can also upload images from online it will detect the accuracy of the fire within the given the image. After this by analysis all the layers it depicts the presence of fire, and if it depicts fire or smoke then it gives alert signals by alarming to alert the user.

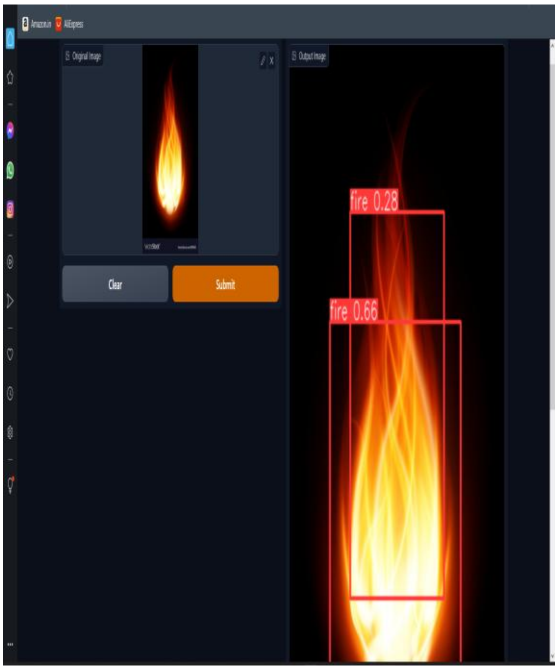


Figure 5. Fire detected

Fire images are collected from the internet and then uploaded into our output page that is in the gradio then the system predicts the accuracy of the fire that in which region the fire is detected.

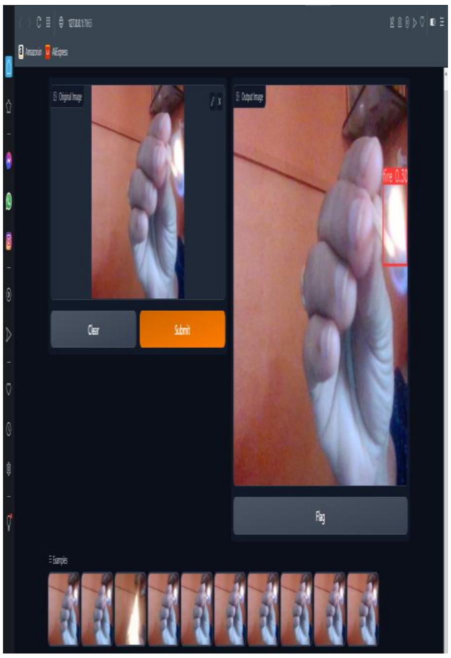


Figure 6. Fire accuracy using Gradio

These are the output images, shows the accuracy of the fire in the given area, for this we need a server.

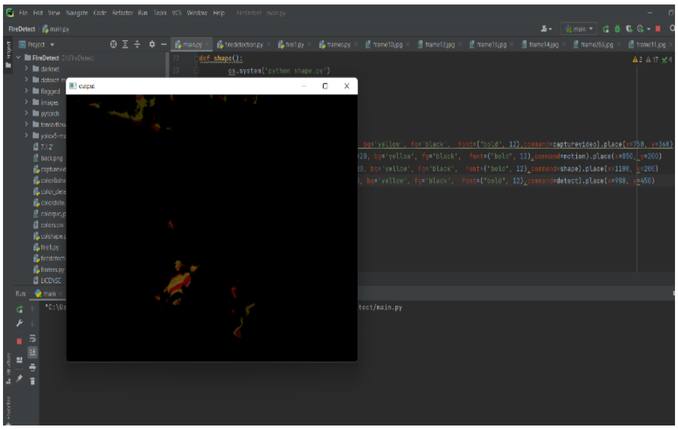


Figure 7. Output of the code

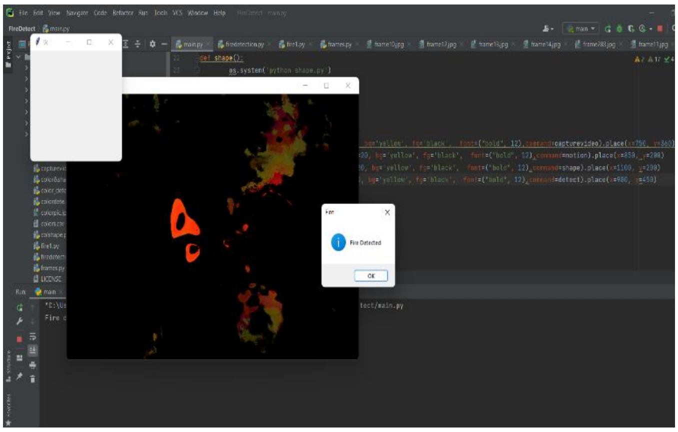


Figure 8. Fire detected

Figure 8 depicts the detection of fire using tkinter, if it detects fire then it shows the results of fire detected as a message to the user, and it alerts the user by giving alarming signal with playground sound, and it also sends the SMS to the user.

V. CONCLUSION

Fire is the most dangerous abnormal event, as failing to control it at an early stage can result in huge disasters leading to human, ecological and economic losses. Fire accidents can be detected using the cameras. So that, here we proposed a CNN approach for fire detection using cameras. Our approach can identify the fire under the camera surveillance. Furthermore, our implementing system balances the accuracy of fire detection and the size of the model using fine-tuning of datasets. We conduct experiments using datasets collected from recording of fire and verified it to our proposed system. In view of the CNN model's reasonable accuracy for fire detection, its size, and the rate of false alarms, the system can be helpful to disaster management teams in controlling fire disasters in a short time. Thus, avoiding huge losses. This work mainly focuses on the detection of fire scenes under observation.

REFERENCE

[1]. Punam Patel and Shamik Tiwari in (2016) proposed a paper entitled Flame Detection using Image Processing Techniques in International Journal of Computer Applications Volume 58– No.18.

[2]. Jareerat Seebamrungsat, Suphachai Praising, and Panomkhawn Riyamongkol in (2014) proposeda paper entitled Fire Detection in the Buildings Using Image Processing in Third ICT International Journal of IEEE Access in Department of Electrical and Computer Engineering.

[3]. Khan Muhammad and Jamil Ahmad in (2018) proposed a paper entitled Efficient deep CNN based fire detection system and localization in video surveillance system at IEEE Transactions on Systems, Man, and Cybernetics Systems.

[4]. Abdulaziz and Young Im CHO in (2018) proposed a paper entitled An Efficient Deep Learning Algorithm for Fire and Smoke Detection with Limited Data in IEEE Explore Advances in Electrical and Computer Engineering.

[5]. Qingjie Zhang, Jiaolong Xu, Liang Xu and Haifeng Guo in ([2016) proposed a paper entitled Deep Convolutional Neural Networks for Forest Fire Detection in International Forum on Management, Education and Information Technology Application by Aviation University of Air Force, Changchun.

[6]. Sebastien Frizzi1, Rabeb Kaabi, Moez Bouchouicha, Jean-Marc Ginoux in (2017) proposed a paper entitled Convolutional Neural Network for Video Fire and Smoke Detection in IEEE Transactions.
[7]. Muhammad Khan and Jamil Ahmad in (2017) proposed a paper entitled Early fire detection using convolutional neural networks during surveillance for effective disaster management.
[8]. https://github.com/cair/Fire-Detection-ImageDataset