Early Fire Detection System

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***Abstract*: Fire disasters can be both manufactured and naturally occurred, but most of them are man-made disasters. Fire disasters result in huge losses both economically and ecologically. We need an early fire detection system, that produces an autonomous response and helps in the early detection of disaster occurrence. Therefore, we propose an early fire detection framework using convolutional neural networks (CNN) for cameras, which detect fire in varying indoor and outdoor environments. In such cases, if the surveillance area is too large such as large buildings, complex spaces, or it would be tough to feature recognition. Applying the convolutional neural network (CNN) technology to image recognition can avoid randomness to a large extent in the feature extraction process. To ensure the autonomous response, we propose an efficient mechanism for cameras in the surveillance system.**

KeyWords:Images, deep learning, disaster management, Fire detection.

Introduction

The project Early fire detection system is important as it helps to achieve the fire as soon as possible that can be applicable in real life. Failure to control fire at an early stage can lead to large disasters. Our proposed model shows a CNN model for fire detection is assistance to disaster management teams for managing disasters that can prevent losses. For detecting fire images and videos at an early stage, the potential CNNs can be used. Our proposed model will start with the input image layer with the size of size160*160*3 for the proposed model. Then we used layers that contain batch normalization, ReLu(rectifier linear unit), Conv2d, Max-pooling layer, and dense layer, Where Conv2d layer used for mapping features for the input images with a filter size of [3*3]. Usually, this size is for the CNN architecture. Max-pooling used for selecting the maximum elements from the region map covered by the filter, Width, and Height of the input could be defined by the Filter size. We have used sigmoid for the binary classification, as our model gives theoutput in the form of binary values such as '0' and '1' represent fire, and non-fire respectively. Adamoptimizer had used. In thisproject, there is no separate code for the execution as internally tests the validation. The batch size is 32. It gives the accuracy with 96% as we have reduced the batch size to 32%lost, and the error rate is 0.01. When we get the error rate as 0.01 then it gives 96% accuracy.

1. Literature Survey

In this project, we have critically discuss the fire detection methods of the current literature along with its strengths and weakness. Later, we briefly highlight our approach of solving the problems of some of the early fire detection methods. Finally, we have discussed that how early fire detection can be used in effective disaster management systems. The advancements in technology have resulted in a wide variety of sensors for different applications like wireless capsule sensors for visualization of interior of a human body, vehicle sensors for obstacle detection, and fire alarming sensors. The current fire alarming sensors such as infrared, ion, and optical sensors need close proximity of the heat, fire, radiation or smoke for activation. As an alternate to these sensors, the vision-based sensors are widely used, which provide many advantages compared to the traditional sensors such as lower cost, fast response time, larger coverage of surveillance area, and less human intervention, avoiding the need of visiting the location from where the fire alert has been triggered.

Liu et al. [10] investigated three differentmodels including spectral,spatial and temporal for fire regions in images. However, their method is based onassumption considering irregularshape of fire, whichis not always the case as moving objects canalso change theirshape. Another firedetection approach ispresented in[22] for forests using contours based on wavelet analysis and FFT. Authors in [23] investigated YCbCrcolor model and devised new rules for effective separation of luminance and chrominance components, which leaded them to rule based pixels classification of flame. Another color model YUV along with motionwas explored by authors in [24] for classification into candidate pixels for fire or non-fire. Besides the investigation of color models, specific low level features of fire regions such as skewness, color, roughness, area size etc., have also been used for determining the frame-to-frame changes, which in combination with Bayes classifier can recognize fire [17]. Anothermethod is presented in [25] considering lookup table for detection of fireregions and their confirmation using temporal variation. This method is based on heuristic features, decreasing the surety ofgetting the same results while changing the input data.

In our model the images are captured using a PC Cam and were able to get an accuracy of 96%. The proposed model was evaluated based on fire detectiondataset.

By considering the aforementioned fire detection methods, it can be observed that some of the methods are too naïve, whose execution time is fast but such methods compromise on accuracy, producing a large number of false alarms. Some methods have achieved good fire detection accuracies but their execution time is too much, hence they cannot be applied in the real-world environments especially in critical areas where minor delay can lead to huge disasters. Hence, for more accurate and early detection of fire, we need a robust mechanism, which can detect fire during varying conditions andcansend the important keyframes and alertimmediately to disaster management systems.

2. Methodology

A. *System Architecture*

System Architecture describes how we have approached or achieved our project i.e: early fire detection system. The way we have approached to our aim can be explained clearly with the system architecture

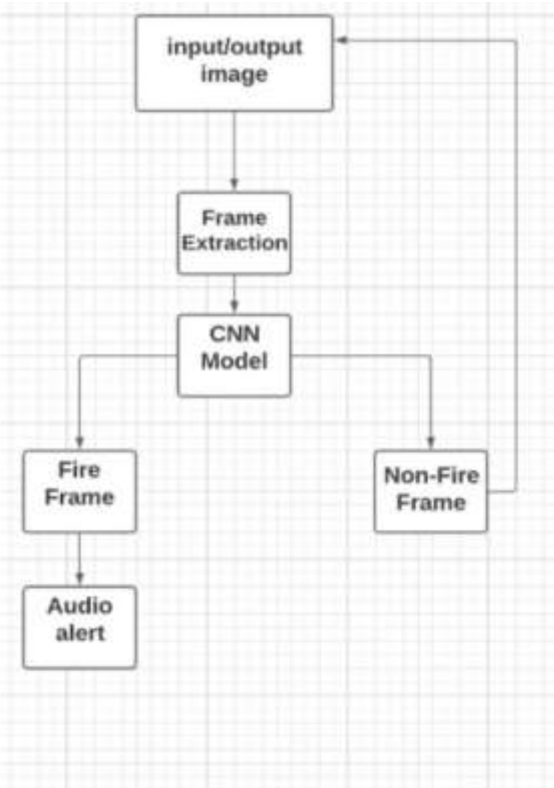

Fig. 1.: System Architecture

In this project, an early fire detection system was built with the help of deep learning, which uses vision-based systems to detect fire using Convolutional Neural Network architecture. By using CNN architecture, we are training our model and dataset. At the time of training a dataset, it takes the surveillance videos and gives the output by detecting the images and videos. Firstly, we will be given the input and output images. After, that we process the images and then extract the images. The sigmoid layer will classify the images as Fire frame and Non-Fire Frame. Sigmoid is used for binary classification. At the time of training a model, it shows as '0' for non-fire and '1' for fire. Our CNN model is implemented for cost-effective fire detection.

B. *CNN Architecture*

We have three stages in our CNN architecture. They are as follows 1. Image pre-processing, 2. Feature extraction, and 3. Fire detection.

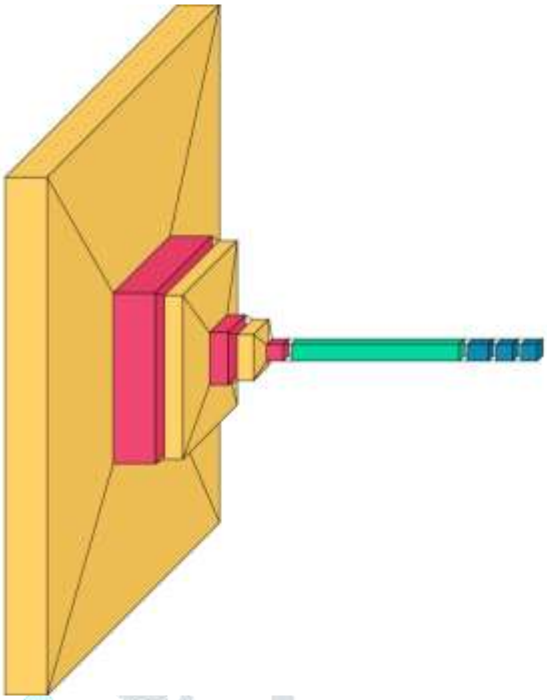

Fig.2: CNN Architecture

At stage1, it processes the image data from a camera, at stage2, feature extraction is the main part of algorithms, it extracts the features of smoke and flame. The input image or video is processed through the convolution layer and pooling layer for detecting appropriately without producing any false results. After flattening, the process trains as mentioned in the above figure. Through the activation of ReLu, we change to dense layer to 256.Again 64 with activation ReLu. Atlast, we get 1 with the activation of sigmoid. Here these layers help the machine in differentiating different environments like dangerous threats, normal environments. This is done by feature extraction and classification using the probability distribution of the softmax layer between fire and non-fire classes.

C. *Dataset Creation*

Dataset used is Fire Detection Dataset

Fire Detection Dataset consists of two classes. They are:

1. Non-Fire Images
2. Fire Images

1. **Non-Fire Images**

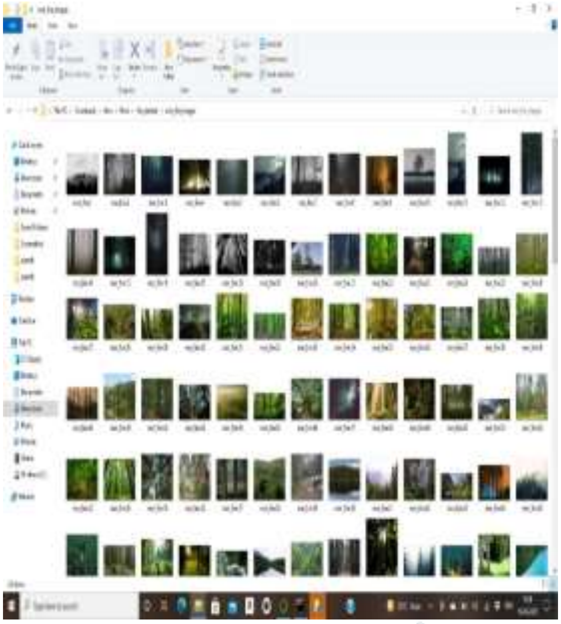

Fig.3: Non-Fire Images

2. **Fire Images**

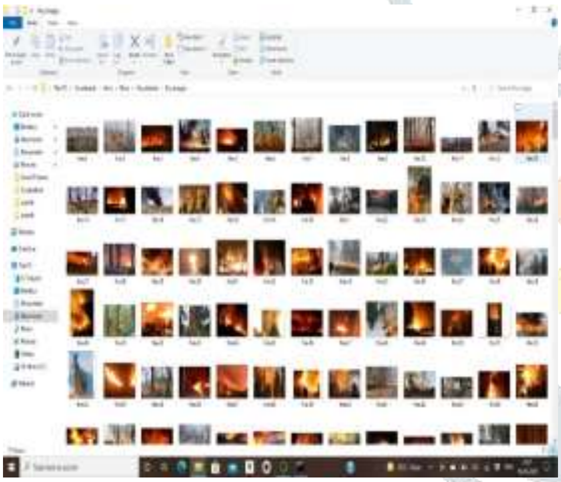

Fig. 4: Fire Images

D. Training and Testing

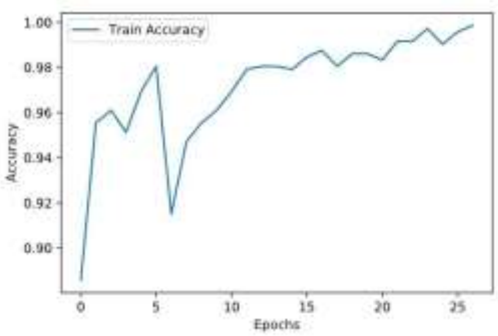

Fig.5: Train Accuracy

The above figure shows the Train accuracy of our proposed model. Here, we can observe the acccuracy to epoch. After every epoch, the accuracy is increasing respectively. Where epoch is a particular period of time. When we use less epoch the accuracy is increasing.

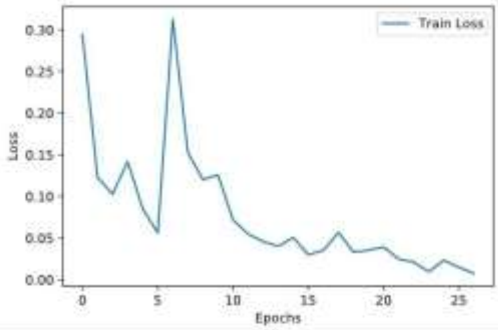

Fig.6: Train loss

The above figure shows the loss to epochs. The above figure depicting that when the number of epochs are increasing the rate of accuracy is decreasing accordingly. Therefore, we can say that number of epochs and the accuracy are vice-versa.

When number of epochs are increasing the accuracy will be decreased, and when then number of epochs are decreasing then the accuracy is increasing.

3.Results and Discussions

Fig.7: Detection of fire image

When it achieve the fire images or fire videos, it gives an alarm continuously to alert the people around.

Fig.8: Detection of Non-Fire image

If it doesn't find or detect any fire it doesn't give any alarm sound but it shows us like No fire with 100% probability.

Fig.9: Detecting in Live with No fire

The above figure depicts that, No fire has been detected. So, it doesn't give any alarm.

Fig.10: Detecting Fire with Fire

The above figure depicts that, the fire has been found or achieved with 100% probability.

4.Conclusion

Using smart cameras you can identify various suspicious incidents such as collisions, medical emergencies, and fires. Failure to control fire at an early stage can lead to huge disasters. Our proposed system shows two custom models for fire detection, which can be of assistance to disastermanagement teams in managing fire disasters on time, thuspreventing huge losses. Using the great potential of CNNs, we candetect fire from images or videos at an early stage. The system achieved a maximal accuracy of 96%. There is a lot of scope scope of this project.

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