EARLY FIRE DETECTION SYSTEM USING DEEP LEARNING AND OPENCV

ABSTRACT:

In this work we investigate the automatic detection of fire pixel regions in video (or still) imagery within real-time bounds without reliance on temporal scene information. As an extension to prior work in the field, we consider the performance of experimentally defined, reduced complexity deep convolutional neural network (CNN) architectures for this task. From sprawling urbans to dense jungles, fire accidents pose a major threat to the world. These could be prevented by deploying fire detection systems, but the prohibitive cost, false alarms, need for dedicated infrastructure, and the overall lack of robustness of the present hardware and software-based detection systems have served as roadblocks in this direction. In this work, we endeavor to make a stride towards detection of fire in videos using Deep learning. Deep learning is an emerging concept based on artificial neural networks and has achieved exceptional results in various fields including computer vision. We plan to overcome the shortcomings of the present systems and provide an accurate and precise system to detect fires as early as possible and capable of working in various environments thereby saving innumerable lives and resources

INTRODUCTION:

Fire accidents pose a serious threat to industries, crowded events, social gatherings, and densely populated areas that are observed across India. These kinds of incidents may cause damage to property, environment, and pose a threat to human and animal life. According to the recent National Risk Survey Report [1], Fire stood at the third position overtaking corruption, terrorism, and insurgency thus posing a significant risk to our country's economy and citizens. The recent forest-fires in Australia reminded the world, the destructive capability of fire and the impending ecological disaster, by claiming millions of lives resulting in billions of dollars in damage.

Early detection of fire-accidents can save innumerable lives along with saving properties from permanent infrastructure damage and the consequent financial losses. In order to achieve high accuracy and robustness in dense urban areas, detection through local surveillance is necessary and also effective. Traditional opto-electronic fire detection systems have major disadvantages: Requirement of separate and often redundant systems, fault-prone hardware systems, regular maintenance, false alarms and so on. Usage of sensors in hot, dusty industrial conditions is also not possible. Thus, detecting fires through surveillance video stream is one of the most feasible, cost-effective solution suitable for replacement of existing systems without the need for large infrastructure installation or investment. The existing video-based machine learning models rely heavily on domain knowledge and feature engineering to achieve detection therefore, have to be updated to meet new threats.

We aim to develop a classification model using Deep learning and Transfer Learning to recognise fires in images/video frames, thus ensuring early detection and save manual work. This model can be used to detect fires in surveillance videos. Unlike existing systems, this neither requires special infrastructure for setup like hardware-based solutions, nor does it need domain knowledge and prohibitive computation for development

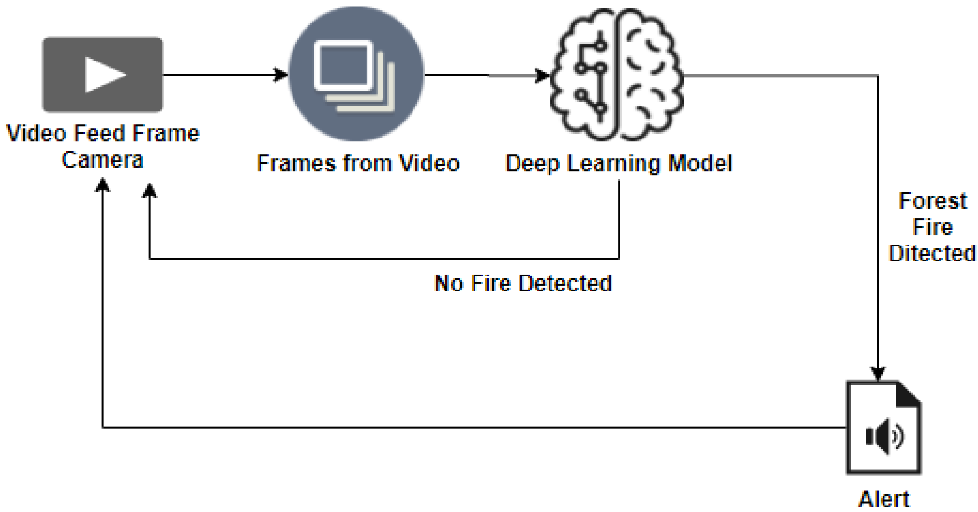
RELATED WORK:

Among the different computer-based approaches to detect fire, the prominent approaches we found were using Artificial Neural network, Deep Learning, Transfer learning and convolutional neural network. Artificial Neural Network based approaches seen in paper [2] uses Levenberg-Maraquardt training algorithm for a fast solution. The accuracy of the algorithm altered between 61% to 92%. False positives ranged from 8% to 51%. This approach yielded high accuracy and low false positive rate, yet it requires immense domain knowledge.

In this paper [3], The author says that the present hardware-based detection systems offer low accuracy along with high occurrence of false alarms consequently making it more likely to misclassify actual fires. It is also not suitable for detecting fires breaking out in large areas such as forests, warehouses, fields, buildings or oil reservoirs. The authors used a simplified YOLO (You Only Look Once) model with 12 layers. Image augmentation techniques such as rotation, adjusting contrast, zooming in/out, saturation and aspect ratio were used to create multiple samples of each image, forming 1720 samples in total. It aims to draw a bounding box around the flame region. It outperformed existing models when the color features of the flames varied from those in training set.

SYSTEM ARCHITECTURE:

The passive components of the system include data preprocessing, feature engineering, model selection scripts which were used to train and develop machine learning model.Source/input data which is in the form of videos is split into frames and preprocessed to convert it into a format that is suitable to be fed as input to pre-built models for feature extraction. The deep learning model returns a feature vector which is also known in transfer learning terminology as bottleneck features.



In the next stage, the bottleneck features are passed through a classification model to obtain the result, which may be either fire of Non-fire. The classification model was built through training using the training data set.

The result of the classification is displayed to the user, and depending on the result, further actions are taken. If the result is a fire then, an email is sent to the concerned stakeholders along with the video frame and date-time stamp to alert them. The email to which the mail is delivered can be changed by the user. An entry will also be made in the cloud database for the purpose of analysis.

METHODOLOGY:

The model is divided into two parts

1. Data Collection and Pre-processing.
2. Building fire detection model by Transfer Learning

The first step is to gather video frames for the problem statement. The dataset has 2 classes - fire and non-fire. Positive samples consist of images with real fire. False Positives consists of images which have objects that look like fire but are not. False positives are easier to collect. Thus, we need to collect diverse video frames which will help better fire detection. The collected dataset is divided into train and test video frames. The dataset currently has 1678 fire images/video frames and 1368 that of non-fire sourced from google since there is no standard data set available.

The second step is to use various available pre trained models in Keras to extract the video frame features. The pre-trained models are trained on very large-scale video frames classification problems. The convolutional layer's act as feature extractor and the fully connected layers' act as Classifiers. Since these models are very large and have seen a huge number of images, they tend to learn very good, discriminative features. In order to do extract, the video frames feature we remove the last layer i.e. fully connected layer. This provides us with a feature vector. The feature vector sizes differ from model to model. The central concept of Transfer Learning is to use a more complex but successful pre-trained DNN model to transfer its learning to our more simplified problem. Instead of creating and training deep neural nets from scratch (which takes significant time and computing resources), we use the pre-trained weights of these deep neural net architectures (trained on ImageNet) and use it for our own dataset. We have used ResNet-50, InceptionV3 and InceptionResNetV2. models to extract the features and various ML algorithms [SVM, Logistic Regression, Naive Bayes and Decision Tree] on the extracted features to detect fire in video frames.

FUTURE SCOPE:

The present decade is marked by huge strides in areas of processing, computation and algorithms. This has enabled great progress in many fields including processing of surveillance video streams for recognizing abnormal or unusual events and actions. Fire accidents have caused death and destruction all over the world, consuming countless lives and causing billions in damages. This implies that developing an accurate, early, affordable fire-detection system is imperative Therefore, we have proposed a fire detection model for videos/video frames using transfer learning for deep learning. The models make use of ResNet-50, InceptionV3 and Inception-ResNet-V2 models to extract the features and various ML algorithms such as SVM, Logistic Regression, Naive Bayes and Decision Tree on the extracted features to detect fire in video frames. Looking at the results, ResNet-50 with SVM works best for our problem statement. Coming to the application on the whole, it works in real-time and has the ability to send alert emails along with offering a user-friendly graphical interface. It's cost-effective, reliable, robust, accurate compared to existing opto-electronic hardware and software-based systems in the market

CONCLUSION:

The present decade is marked by huge strides in areas of processing, computation and algorithms. This has enabled great progress in many fields including processing of surveillance video streams for recognizing abnormal or unusual events and actions. Fire accidents have caused death and destruction all over the world, consuming countless lives and causing billions in damages. This implies that developing an accurate, early, affordable fire-detection system is imperative Therefore, we have proposed a fire detection model for videos/video frames using transfer learning for deep learning. The models make use of ResNet-50, InceptionV3 and Inception-ResNet-V2 models to extract the features

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FUTURE SCOPE:

The application can be enhanced by training the model with a larger dataset consisting of fires at various stages and dimensions. With higher GPU memory, we could use two deep learning models for feature extraction, whose output feature vectors are concatenated and classified to offer more robustness. An R-CNN model can be used to implement fire localization along with classification. We can also expect better deep learning architectures to emerge in the future, offering better feature extraction. The application will also offer a considerably better performance when run on machines having better processing power compared to existing one of which it has been developed.

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