Chapter 12

Final Base Paper

Fire Detection Using Deep Learning

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Vision: From large cities to dense jungles, fire hazards are a major threat to the world. This can be prevented by uninstalling fire detection systems, but illegal costs, false alarms, the need for dedicated infrastructure, and a complete lack of robustness of current computer hardware and software-based acquisition systems serve as obstacles in this way. In this activity, we try to take the initiative in finding fire in videos using Advanced Reading. In-depth learning is an emerging concept based on sensory networks and you have found amazing results in a variety of fields including computer vision. We plan to overcome the shortcomings of current systems and provide an accurate and precise fire detection system that can operate in a variety of areas thus saving countless lives and resources.

Key Words: - ***Fire accidents, Fire detection, Surveillance video, Machine learning, Deep Learning, Transfer Learning.***

I. Introduction

Fire hazards are a major threat to industry, crowded events, social gatherings, and crowded venues throughout India. These types of events can cause damage to property, the environment, and can be a threat to human and animal health. According to a recent report by the National Risk Survey Report [1], Fire stands third in the wake of corruption, terrorism, and insurgency, thus posing a serious threat to our country's economy and citizens. Australia's recent forest fires are a reminder of the world, the destructive power of fire and the coming natural disaster, with millions of people being killed and causing 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 opt-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.

II. Literature Survey

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 LevenbergMaraquardt 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 colour features of the flames varied from those in training set.

Paper [4] provides two approaches First approach is to perform training on the data set using Transfer Learning and later fine tune it. The next approach was to extract flame features, fuse them and classify it using a machine learning

Classifier. The transfer learning algorithms used were Exception, Inception V3, and ResNet-50, trained in Image Net. In the first approach, accuracy up to 96% was achieved. The second approach, stacking Xgboost and lightbgm achieved an AUC of 0.996. Transfer learning models greatly reduces the training time required for our model. It requires comparatively smaller data set. Both approaches don't require any sort of domain knowledge. In works [7] and [8], Deep CNN approach was taken to locate and make a fire place. The accuracy found was between 90 and 97% in both papers. This method is time consuming and training is done using the Nvidia GTX Titan X with 12 GB of internal memory.

Ordinary machine learning using a feature detector revealed high accuracy and low non-realistic accuracy, yet requires extensive background information, i.e., about colour model, colour space, flame patterns and vectors. When something changes, models require reconstruction of new items. The traditional method of applying engineering [12] is by hand naturally. Includes features that are increasingly manipulated using background information, a tedious, time-consuming, and erratic process. The outcome model depends on the problem and may not work properly on new data. Automated element engineering ([3] [5]) develops into this inefficient workflow by automatically extracting useful and efficient features from data with a framework that can be used for any problem. Not only does it reduce the time spent, but it creates features that can interpret and prevent data leaks. With transfer learning, instead of developing a model from scratch, we can start with a pre-trained model with the necessary adjustments needed. These models can be imported from Keras. The use of pre-trained models saves a lot of integration work, otherwise, you may need high-end GPUs. Implementing V3, Inception-ResNet-V2 has been identified as an appropriate feature algorithms as they show promising results with high accuracy ([3]). With transfer learning, instead of developing a model from scratch, we can start with a pre-trained model with the necessary adjustments needed. These models can be imported from Keras. The use of pre-trained models saves a lot of integration work, otherwise, you may need high-end GPUs. Implementing V3, Inception-ResNet-V2 has been identified as a suitable feature-release algorithms as they display promising results with high accuracy.

III. SYSTEM ARCHITECTURE The passive components of the system include data pre-processing, 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 pre-processed 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.

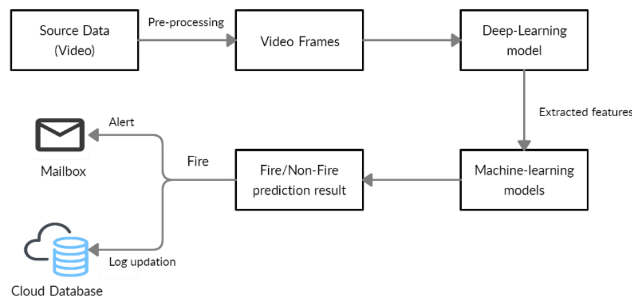

Fig.1: System Architecture

In the next step, the bottle characteristics are transferred to a separation model to obtain the result, which may be a Non-fire flame. The separation model is built on training using a training data set.

The split result is displayed to the user, and depending on the result, additional steps are taken. If the result is a fire, an email is sent to the relevant participants with a video frame and a timestamp to let them know. The email to which the email is sent may be changed by the user. It will also be installed on a cloud website for analysis purposes.

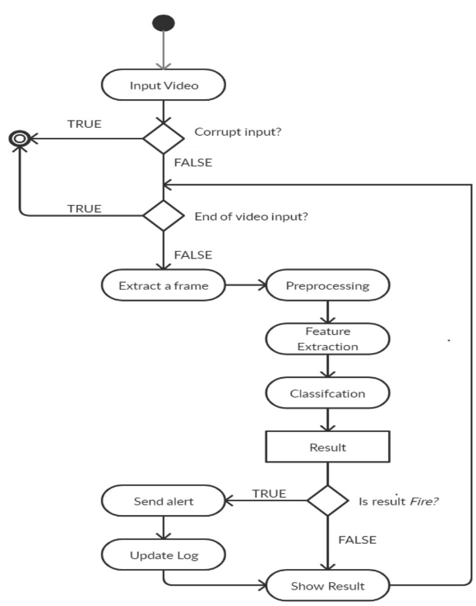

Fig.2: Activity Diagram

IV. METHODOLOGY

The model is divided into two parts

Data Collection and Pre-processing.

2. Build a fire detection model with Transfer Learning. The first step is to compile the video frames for the problem statement. The database has 2 phases - fire and non-fire. Beautiful samples contain images with real fire. False Positives contains images that look like fire but are not. False positives are easy to collect. Therefore, we need to collect various video frames that will help better fire detection. The set of data collected is divided into rail frames and video testing. The database currently has 1678 fire photos / video frames and 1368 that are not available on google as there is no standard data set available.
The second step is to use various pre-trained Keas models to extract the features of the video frame. Pre-trained models are trained in the biggest problems of video frame separation. The convolutional layer acts as an element output and the fully integrated layers act as separators. Since these models are very large and have seen a large number of images, they often learn the best, most distinctive features. To remove it, video frames include that we remove the last layer i.e. the fully connected layer. This provides us with a feature vector. Feature vector sizes vary from model to model. The main idea of Education Transfer is to use a sophisticated but effective pre-trained DNN model to transfer its learning to our simplified problem. Instead of creating and training deep neural nets from scratch (which takes up valuable time and resources), we use pre-trained weights of these deep neural network structures (trained at ImageNet) and use them for our data set. We have used ResNet-50, InceptionV3 and InceptionResNetV2. output output models and various ML algorithms [SVM, Logistic Regression, Naive Bayes and Decision Tree] are extracted features to detect fire in video frames.
All component and element separator combinations were analysed using stratified K collar verification. Table 1 shows the performance metric values obtained for different combinations of in-depth learning networks and division algorithms. The best performance was seen by ResNet50 as an in-depth learning feature output model and Vector Support Machine as an ML filter and the accuracy, accuracy and memory values of this combination were 97.8%, 97.46% and 97.66% respectively. Therefore this will apply to our use.

V. RESULTS AND DISCUSSION

The aim of our work was to develop to an application capable of detecting fire in videos and images, which is robust and works anywhere. In this regard, we tested various in-depth study models and differentiation models and selected the ResNet-50-SVM combination to be used as it provided the best performance metric values (Accuracy, Accuracy and Recognition Values for this combination were 97.8%, 97.46% and 97.66 % respectively). An email alert feature has also been added to our app to provide real-time alerts to affected participants and the logging system, operated using Firebase. The GUI provides easy-to-use information and allows the user with a non-technical background to use the application. The app performed very well during the test. It was able to detect fires in all 12 fire test videos but incorrectly distinguished some non-fire video situations.
Compared to existing hardware solutions, our operating system is affordable, robust, reliable and offers high performance without the need to set up dedicated infrastructure. Due to the use of in-depth learning and transfer techniques, our model is easy to build, modify, improve, requires fewer computer resources and offers better performance than existing software solutions that utilize the most advanced engineering features, background information.

VI. CONCLUSION

The current decade is marked by a major step forward in the fields of analysis, calculation and algorithms. This has enabled a great deal of progress in many areas, including processing video streaming surveillance to detect unusual or unusual events and actions. Fire disasters have resulted in death and destruction worldwide, claiming countless lives and billions of lives. This means that the construction of an accurate, timely, affordable fire detection system is essential Therefore, we have proposed a fire detection model for video / video frames using reading transfer for in-depth reading. Models use the ResNet-50, InceptionV3 and Inception-

ResNet-V2 models to extract various ML features and algorithms such as SVM, Logistic Regression, Naive Bayes and Decision Tree into extruded features to detect fire in video frames. Looking at the results, ResNet-50 with SVM works best in our problem statement. By coming across the app, it works in real time and has the ability to send warning emails and provide a visual interface with an easy-to-use image. More expensive, reliable, robust, accurate compared to opt-electronic hardware and software-based systems in the market.

VII. THE FUTURE PLAN

The application can be developed by training the model with a large database that combines fires in various stages and sizes. With a higher GPU memory, we can use two in-depth reading models to extract features, output that includes vectors which are integrated and separated to provide additional durability. The R-CNN model can be used to facilitate local fire-making and partitioning. We can also expect the best in-depth learning structures from the future, which provide the best features. This app will also provide better performance when used on machines with better processing power compared to existing ones already built.

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