College of Software, Department of SW Engineering

Wep Application Development Project

Developing Fire-detection Algorithm based onDeep Learning

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Abstract

Fire disasters are big danger which cause economical and social damages and create climate crisis. To control damages, early de- tection of fire and an automatic response is really important. By help of recent advancements, the CCTV cameras are capable of performing different processing such as object and motion detection and tracking. Considering these processing capabilities, it is possible to detect fire at its early stage during surveillance, which can be helpful to disaster man- agement systems, avoiding huge ecological, live and economical losses. In addition, it can save a large number of human lives. With this motiva- tion, we proposed transfer learning based an early fire detection method based on fine-tuned CNNs. By help of Deep Neural Networks fire can be detected at early stages with higher accuracy during varying indoor and outdoor environments while minimizing the false fire alarms. In this project we used ResNet50 model based on transferlearning. The model migrates the ResNet network trained on an ImageNet dataset and its ini- tialization parameters into the target dataset of fire identification. Com- bined with the characteristics of the target data set, cross entropy loss function and Adam optimizer are added to optimize the ResNet network, and we modified the last layer of ResNet to extract more effectively deep semantic information from fire images. The experimental results show that the recognition accuracy of the ResNet50 model on our dataset was 91%.

Keywords: Fire Detection, ResNet50, Deep Learning, Computer Vision

1.Introductin

Disaster management is the broad area that touches almost every discipline in- cluding but not limited to Computer Science, Environmental Science, Business and etc. The federal emergency management agency policy states that there are two main category of disaster: Technological disasters such as hazardous materi- als, terrorism, nuclear power and etc. and Natural disasters such as floods, earth quakes, fires on forests and etc.[1]. Among them fire disaster is the one which happens in both natural and man-made causes. Different researchers recommend different solutions to handle the problem of fire.

2.Statement of the Problem

Fire disasters are big dangers which cause economic and social damage and create climate crisis [2]. Specially, secure places such as Data Centers, Gas Stations, Big Hotels, Fabriques, Industries, and etc. are vulnerable for such causes and need special treatment.

Existing fire and smoke detectors utilize photoelectric sensors and a light source to detect if the light source particles are being scattered (implying smoke is present). You could then distribute temperature sensors around the house to monitor the temperature of each room. Cameras could also be placed in areas where fires are likely to start. Each individual sensor could be used to trigger an alarm or you could relay the sensor information to a central hub that aggregates and analyzes the sensor data, computing a probability of a home fire. While there are 100s of computer vision/deep learning practitioners around the world actively working on fire and smoke detection (including PyImageSearch Gurus member, David Bonn), it’s still an open-ended problem. The existing approaches are still not be able to answer the question “can we develop an early fire detection model with lightweight and minimized false positive alert?”. Depending on this we propose to make light weight and high accuracy model by using deep convolutional neural network and transfer learning approach by using ResNet50 pre-trained model. So, our project focuses on images containing fire-colored objects and real fire on indoor and outdoor environments to detect fire at its early stage with good accuracy and minimum false fire alarms to solve this problem.

3.Objective of theProject

3.1General Objective

The main objective of this project is to develop an improved transfer learning based fire detection model based on deep Convolutional Neural Network algo- rithm.

3.2 Specific Objectives

The specific objective of this project is to:

- Review related fire detection methods in different areas.
- Review different Computer vision based fire detection tools and frameworks.
- Assess availability of datasets and select proper dataset.
- Prepare training and test dataset for the classifier model.
- Develop prototype for fire and smoke classifier model.
- Evaluate the performance of the Model using Standard Performance mea-suring scales.

4.Related Works

Numerous studies have been conducted over the years using DL approaches to address fire detection tasks. We have analyzed some of these studies; Muhammad et al. [3] proposed a novel energy-friendly and computationally effective CNN design, motivated by the SqueezeNet [4] structure for the fire detection, local- ization, and semantic perception of the appearance of fires observed via CCTV surveillance networks. Gonzalez et al. [5] employed CNNs to identify fires in im- ages with a high accuracy and performance, allowing the system to operate in real-time. This system was part of a new unmanned autonomous vehicle detec- tion system for wildfire monitoring and the calculation of location and range. Two networks, AlexNet [6] and a pure CNN, were used to identify the fire fea- tures from images. In 2020, novel VFD approaches based on sophisticated CNN models for object identification were proposed by Li et al. [7]. These VFD tech- niques, which used FasterRCNN, SSD, and YOLOv3, were compared in terms of their false alarm rates and accuracy. The experimental results revealed that the YOLOv3 algorithm yielded the most robust result with an accuracy of 83.7%. Avazov [8] worked on this improvement based on improved YOLOv4 algorithm, and they adapted the convolutional network to operate on banana Pi M3 board just by using three layers by using large data to improve the performance spe- cially focusing on fire-like lights. Considering aforementioned fire detection methods, it can be observed that some of the techniques are too na¨ıve, whose execution time is fast however such methods compromise on accuracy, producing a giant number of false alarms. Conversely, some methods have carried out proper fire detection accuracy but their execution time is too much, subsequently they can't be utilized in the real-world environments particularly in critical areas where minor lengthen can lead to large disasters. Therefore, for more accurate and early detection of fire, we need a robust mechanism, which can observe fireplace all through various conditions and can ship the essential alert.

5. Methodology

Under this section we will discuss the methods that we used in developing fire detection method based on Deep Learning and Transfer Learning approach.

The design model will be divided into two parts:

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

5.1 Data Collection

Deep learning algorithms, especially Convolutional Neural Networks, can be data hungry beasts. And to make matters worse, manually annotating an image dataset can be a time consuming, tedious, and even expensive process. Considering this we proposed to use datasets helping our problem. The im- ages that we used for training was sourced from

the dataset scrapped from Google which is curated by PyImageSearch reader, Gautam Kumar. Guatam gathered a total of 1,315 images by searching Google Images for queries related to the term “fire”, “smoke”, etc. due to lack of real images of fire. However, the original dataset has not been cleansed of extraneous, irrelevant
images that are not related to fire and smoke (i.e., examples of famous buildings before a fire occurred). David Bonn took the time to manually go through the fire/smoke images and identify ones that should not be included. The dataset contains images which contain only fire, fire and smoke, only smoke, images which create ambiguity like street light. The dataset for Non-fire examples is called 8-scenes as it contains 2,688 image
examples belonging to eight natural scene categories (all without fire) which are Coast, Forest, Open Country, Street, Inside City, Tall Buildings, and Highways. The dataset originally curated by Oliva and Torralba in their 2001 paper [9]. The 8-scenes dataset is a natural complement to our fire/smoke dataset as it depicts natural scenes as they should look without fire or smoke present. While this dataset has 8 unique classes, we considered the dataset as a single Non-fire class when we combine it with Gautam’s Fire dataset

5.2Pre-processing of dataset

Virtually any type of data analysis or AI model development requires some type of data preprocessing to provide reliable, precise and robust results. In data collection methodology we discussed the way data was gathered. Based on our problem we used three classes which are Fire, Smoke, and Neutral. So we divided the dataset in such that 1000 images for each class and saved it in different folders to help us for simple management. Therefore in total 3000 images were used in our dataset. Then we used 900 images for training set and 100 images for validation purpose from each class.

5.3 CNN Architecture

We aim to develop a classification model using Deep learning and Transfer Learn- [1]ing to recognize fires and smokes in images/video frames, thus ensuring early [1]detection and save manual work. 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. The transfer learning that we used is ResNet-50, trained in ImageNet. Trans- fer learning models greatly reduces the training time required for our model. It requires comparatively smaller data set. Deep CNN approach will be taken to detection and localization of fires. Following the success of VGGNet architectures [10], researchers believe that deeper models outperform shallower models. However, as the number of model layers increases, the complexity and training difficulty of the model also in- creases, and the accuracy decreases. In 2016, Kaiming He and colleagues at Microsoft Research solved the problem of gradient disappearance and gradient explosion by building ResNet, making feasible deeper network training. They in- troduced a new learning framework to simplify the training of deeper networks [11], and called the framework residual learning; accordingly, the model using this framework is called residual network (ResNet). ResNet allows original input information to be directly connected to subsequent neurons, and takes as its goal minimization of the difference (residual) between input and output. Specif- ically, the original input to the network is set to x and the final desired output is set to $H(x)$. When the original input x is passed directly to the tail of the network as the initial result, the objective to be learned in this case becomes

$F(x) = H(x) - x$. 1 illustrates the principle of residual learning in ResNet.

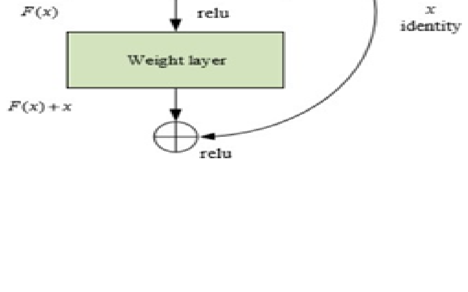

Fig. 1. ***Residual learning module for ResNet***

This project is devoted to extract deeper semantic information from fire images, beyond color and structural features, so the ResNet-50 network was selected as the backbone network of our model. Figure 2 lists the architecture of ResNet-50. ResNet-contains 49 convolution layers, one of which is 3×3, an average pool layer, and a fully connected layer. The classical ResNet-50 model involves 25.56 million parameters, of which the rectification nonlinearity (ReLU) activation function and batch normalization (BN) function are will be applied to the back of all convolution layers in the “Bottle-neck” block, and the softmax function will be applied to the full connection layer.

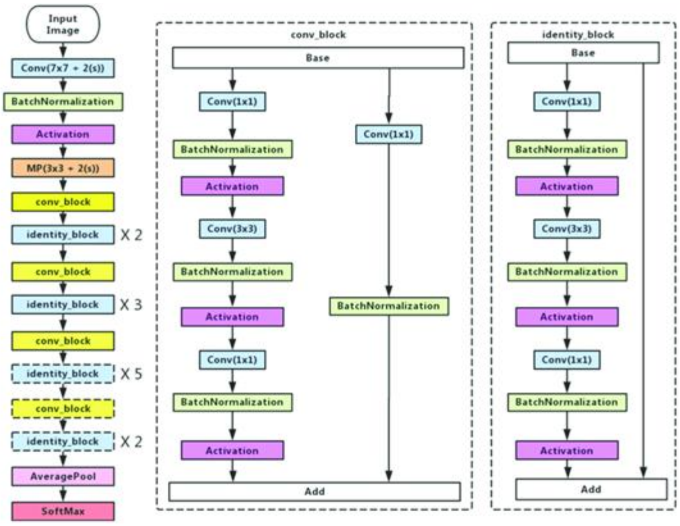

Fig. 2. ResNet50 Architecture Blocks.

This approach is time consuming and training is planned to perform using NVIDIA GPU. Due to lack of NVIDIA Graphics card we used Google Colab as Notebook and Google colab’s GPU running time so that by using CUDA programming we trained our model in minimized period of time than using CPU.

6 .Results

The aim of our work was to develop a model capable of detecting fire in videos and images, which is robust and works in any environment. In this regard, we have experimented we have used ResNet-50 for implementation as it offered the best performance metric values (Accuracy for training and validation of this modal was 93.44% and 92.33% respectively). Table 1 shows the respective recognition accuracy and loss for the proposed method on the training set and validation set. It can be seen that it achieved relatively good results with both the training set and the validation set.

The convergence curves of the loss function and the recognition accuracy with the number of iterations are shown in Figure 3. It can be seen that the per- formance of the proposed network in the validation set also improved, reflecting its relatively reliable generalization performance.

Table 1. Identification accuracy and loss.

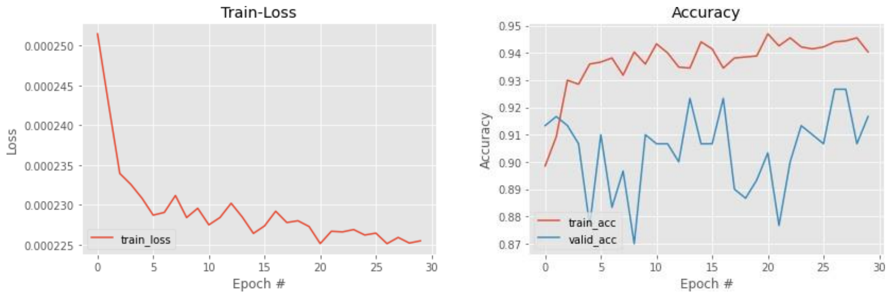

Fig. 3. *Identification loss and accuracy with the number of iterations.*

From our experiment we observed that different depths of the network affect the recognition accuracy and operational performance of the model. With the deepening of network layers, although the accuracy of forest fire identification is improved, the time consumption of operations also increases. So resnet 50 which uses 50 hidden layers can perform well on our dataset.

Fig. 4. Sample Prediction

7. Conclusion

The present decade is marked by huge strides in areas of processing, compu- tation and algorithms. This has enabled great progress in many fields includ- ing 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 and Images using transfer learning for deep learning. Our focus was to minimize false positive alarm and minimized training time. By time complexity ResNet-50 was shown as good architecture for our problem. Comparing with different literature on same problem with our area, our model size was 91MB which is somehow improved than others. We fine tuned the model so that it gave us 92.33% vali- dation accuracy, but we can’t say that this is enough to minimize false positive alarm. So for future we recommend to improve this for someone who want to work on this area.

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