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Fire Detection by Video Surveillance Using MobileNet Architecture

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ABSTRACT- *Fire has been a boon as wells as a disaster for nature and human kind. Since long time world has witnessed many fire disasters, natural or manmade. These fires resulted in huge life loss, environmental loss and financial loss. Various techniques are developed to detect fire, extinguish fire and alerting systems. All these techniques have their pros and cons which make room for new innovations in the fire detection techniques. Recent advancements in deep learning technology have enabled accurate vision based developments. Deep learning techniques are used to recognize patterns in image, object detection and image classification. Convolutional Neural Networks have a huge breakthrough in image recognition and classification. Implementing these advanced techniques in the embedded applications like video surveillance provide an early fire detection technique.*

Keywords*: MobileNet, deep learning, convolutional neural network*

1. Introduction:

Video surveillance has allowed efficacious monitoring of close and open areas. Abnormal events like theft, accidents and disasters can be monitored and controlled. Big disasters like fire, flood can be detected early which can help to reduce the losses. With the development of computer vision, deep learning technology detecting the flame using vision sensors is faster than the traditional fixed smoke sensor or heat sensor.

As of March 2020, in Australia the fires burnt an estimated 18.6 million hectares, destroyed over 5,900 buildings (including 2,779 homes) and killed at least 34 people[10]. The increased rates of fire counts in 2019 led to international concern about the fate of the Amazon rainforest, which is the world's largest terrestrial carbon dioxide sink and plays a significant role in mitigating global warming. Within the Amazon, 6,315 outbreaks of fire were detected between January and August, 2020 burning 1,359 km² of the forest[9]. Incidents like these give a wake-up call to think if fires can't be stopped they should at least reduces at early stages to cause a minimal losses.

In this paper, we propose a deep learning technique for detecting fire by the video surveillance cameras.

The objectives are: (i) Develop an accurate fire and non-fire classification model, (ii) Develop a real time system for detecting fire from a video surveillance camera input, (iii) Develop a method for automated alert messaging to fire station, police station and disaster management authorities, (iv) Increasing the accuracy and reducing false alarm rate and (v) Early fire detection for minimal losses.

2. Proposed System Block Diagram:

Fig. shows the block diagram of the fire detection system. The system architecture comprises of three phase (1) training phase, (2) testing phase and (3) real time implementation. The heart of this project is the deep learning model which will be an integrated model performing feature extraction and image classification.

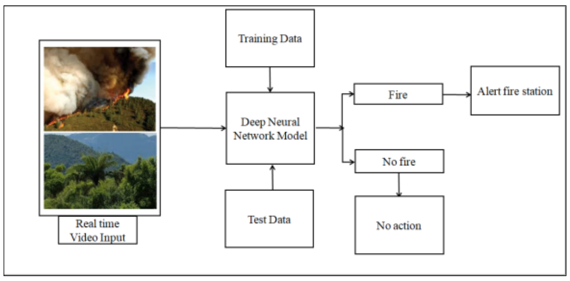


Fig: Proposed Block Diagram

The first phase includes the training phase. In this the training labeled data i.e. image inputs are used train the model. The second phase is the testing phase. The model is tested with new set of images which are classified as fire or no – fire. The accuracy score and confusion matrix are the evaluation metrics of the model. The third and final stage is to use real time video data input and classify it to the fire and non fire classes.

I. Dataset:

The datasets collected from Kaggle sources is as follows: (1) Videos : 11 fire videos and 16 non fire videos (2) Images dataset 1 : 694 fire images and 286 non fire images (3) Images dataset 2 : 901 fire images and 901 non fire images (4) Image dataset 3 : 100 fire images and 100 non fire images.

Below are the sample fire and non-fire images from the datasets.

Fire image

Non fire image

II. MobileNet Architecture:

MobileNet is an efficient and portable CNN architecture that is used in real world applications. It was developed specifically for mobile devices, embedded systems and computers with less or no GPUs.
The table shows the summary of MobileNet architecture.
MobileNets primarily use depthwise separable convolutions in place of the standard convolutions used in earlier architectures to build lighter models. Each depthwise separable convolution layer consists of a depthwise convolution and a pointwise convolution.

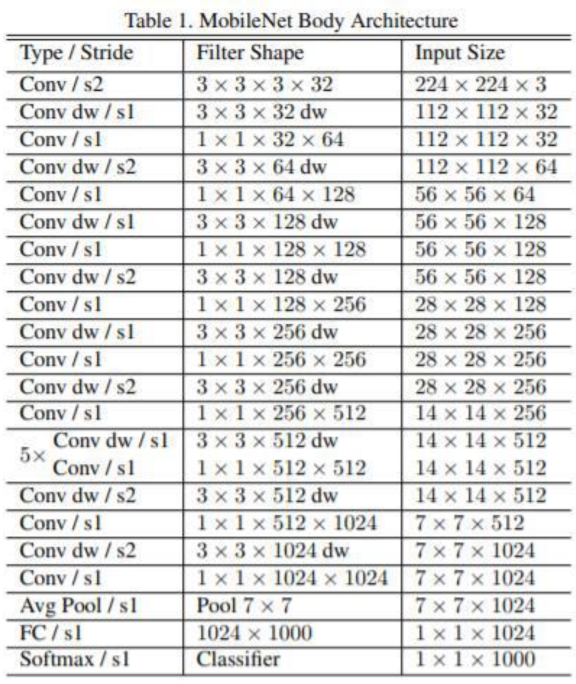


Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	3 × 3 × 3 × 32	224 × 224 × 3
Conv dw / s1	3 × 3 × 32 dw	112 × 112 × 32
Conv / s1	1 × 1 × 32 × 64	112 × 112 × 32
Conv dw / s2	3 × 3 × 64 dw	112 × 112 × 64
Conv / s1	1 × 1 × 64 × 128	56 × 56 × 64
Conv dw / s1	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 128	56 × 56 × 128
Conv dw / s2	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 256	28 × 28 × 128
Conv dw / s1	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 256	28 × 28 × 256
Conv dw / s2	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 512	14 × 14 × 256
5× Conv dw / s1	3 × 3 × 512 dw	14 × 14 × 512
5× Conv / s1	1 × 1 × 512 × 512	14 × 14 × 512
Conv dw / s2	3 × 3 × 512 dw	14 × 14 × 512
Conv / s1	1 × 1 × 512 × 1024	7 × 7 × 512
Conv dw / s2	3 × 3 × 1024 dw	7 × 7 × 1024
Conv / s1	1 × 1 × 1024 × 1024	7 × 7 × 1024
Avg Pool / s1	Pool 7 × 7	7 × 7 × 1024
FC / s1	1024 × 1000	1 × 1 × 1024
Softmax / s1	Classifier	1 × 1 × 1000

Counting depthwise and pointwise convolutions as separate layers, a MobileNet has 28 layers. MobileNets introduce two new global hyper parameters (width multiplier and resolution multiplier) that allow model developers to trade off latency or accuracy for speed and low size depending on their requirements.

A standard MobileNet has 4.2 million parameters which can be further reduced by tuning the width multiplier hyper parameter appropriately. The size of the input image is 224 × 224 × 3.

3. Results:

The model has total 4,253,864 parameters out of which 4,231,976 are trainable and 21,888 are non-trainable parameters. The validation accuracy achieved is 87.24%
Below graph displays the plot of training and validation accuracy of the model over 20 epochs. For initial epochs the validation accuracy fluctuated from 0.85 to 0.3 and eventually it converged at closed to 0.8.

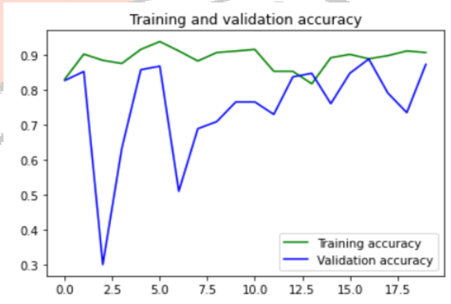


Fig1: Validation accuracy plot

The below figure displays the plot of training and validation loss of the model over 20 epochs. The validation loss though reducing till the final epoch but still fluctuates for consecutive epoch.

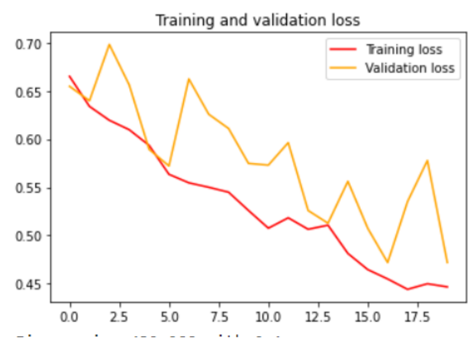
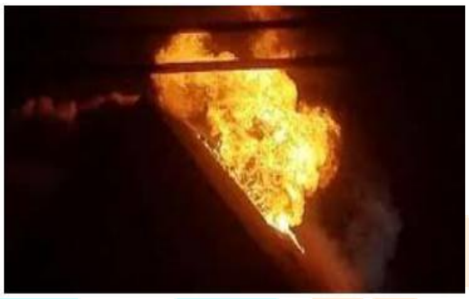


Fig2: Validation loss plot

The model was tested on a sample test data. The results obtained for 3 sample test images are as follows.



Model result: True 73.55%

Model result: False 62.59%

Model result: False 55.58%

The model was tested on 100 fire and 100 non-fire images and generated the following confusion matrix.

	Actual	
Predicted	Fire	Non-fire
Fire	98	67
Non-fire	2	33

Accuracy = 0.655

Percentage accuracy = 65.5%

4. Conclusion:

The model was trained using different optimization techniques and loss functions. The training and validation metrics were plotted to get an insight into the various parameters playing a key role in the optimization of the model.

The training accuracy was 87.24% with a deteriorating test accuracy of 65.5%.

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