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Forest Fire Detection Using Convolutional Neural Networks

Amogh J Tambad[1], Farooque Azam[2], Anusha Reddy S[3], Apoorva M Y[4], Aditya G T[5]

[1,2,3,4,5]School of Computing and Information Technology, REVA University
Bangalore, Karnataka
[1]amoghtambad@gmail.com, [2]farooque53786@gmail.com, [3]reddyanusha698@gmail.com,
[4]apoorva77810@gmail.com, [5]gtaditya99@gmail.com,

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Abstract

In this paper, we have used a Deep Learning approach called Convolutional Neural Networks to train our model. ResNet-34 is the architecture used to train the model to detect forest fires by taking satellite images as input. The dataset has been obtained online and has been subjected to Batch Normalization and Data Augmentation to achieve better results. The model has been trained using satellite images of forests with and without the occurrence of fires because satellites ensure a continuous supply of images for the model to keep testing. The result obtained has a high accuracy and is therefore able to detect forest fires easily with minimal errors.

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1. Introduction

Forest Fires have become a relevant topic of discussion in the recent times. The Amazon Fires (2019) and the Australian Bushfires (2019-2020) were some of the largest fires the world has ever witnessed with the damage being visible from space.

Forest Fires have become more intense and more frequent in the last few decades all over the world and it is a critical issue in the biosphere-atmosphere interface [1].

Hence, it becomes very important to detect fires at their early stages in order to take quick action to prevent further damage.

Thick forests like the Amazon are massive in size and most of its areas are remotely located and hence, not very accessible to humans in order to get video recordings. Moreover, continuous evaluation is also not possible through video-based detection. Therefore, we used satellite images to train our model as it presents two major advantages. Firstly, satellites are independent of the weather conditions and the extreme changes in temperature on earth. They are robust, built to withstand harsh conditions, and are therefore, a reliable source of continuous supply of images. Secondly, satellite images are available on the internet and hence, we give higher preference to feature extraction and batch normalization in comparison to dataset collection.

For the purpose of image classification, we are using Convolutional Neural Networks (CNNs). CNN is a highly effective Deep Learning technique for image classification and object detection. This is mainly because of the feature extraction process done through Convolution and Pooling.

Convolution is the process of running a kernel or a filter of a preferred size over the image in order to extract the pixel-by-pixel features of the image. This will enhance the important features of the image making it more prominent and hence, will improve the accuracy of prediction. We are using a 3x3 kernel in our convolutional layer. Xie D et al. [2] have proven the importance of a convolution kernel by generating a pencil sketch version of many images by modifying the values on the kernel or filter.

Pooling is the process of reducing the number of parameters in the resultant image obtained after convolution. This makes computation easier, faster and more efficient as the computational time is directly proportional to the number of parameters. We are using a Max Pooling layer with a 2x2-feature map in order to reduce the parameters. Max-pooling

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performs better than the other alternatives because it is the only one which is invariant to the special pad tokens that are appending to the shorter sentences known as padding.[3]

Researchers have used CNNs to detect smoke in fires. Frizzi [4] proposed a CNN with nine layers to detect smoke in videos. Moreover, we are obtaining the dataset from google images, as there is nothing readily available in the form of satellite images for forest fires. Due to this, the dataset is not very big and hence, we are using techniques like batch normalization and data augmentation to process the dataset and present the same images in different forms to the model. The model looks at the same images differently and hence, learns different patterns from each of them.

In this paper, we aim to classify images into two categories – 'Forest Fire 'and 'No Forest Fire' and hence, to detect the occurrence of a forest fire with just the use of satellite images.

Section II of the paper includes a brief description of the related works that we have referred in order to obtain a sufficient understanding of the progress made by people in this particular topic. Section III gives information about the methodology used to solve the problem.

Section V is an analysis of the result obtained after training the model. Section VI concludes the paper and has information about the future scope of the paper.

2. Related Works

Hohberg [5],in the paper 'Wildfire Smoke Detection Using Convolutional Neural Networks' collected video based images from DLR which receives fire alerts from the Fire Watch System that has been deployed across large sections of the world. The dataset obtained was entirely based on fire incidents having taken place in Germany upto the year 2015. Caffe was used as the deep learning framework.

For smoke detection, CNNs with the CaffeNet architecture was used which is closely related to the AlexNet architecture. This paper was one of the first ones to use a deep learning approach to solve this problem and hence, it was also one of the first ones to prove the effectiveness of deep learning in image classification. This is one of the major reasons for adapting CNNs in our paper for the detection of forest fires.

Qi-xi Zhang et al.[6], in the paper "Wildland Forest Fire Smoke Detection Based on Faster R-CNN using Synthetic Smoke Images" have also used smoke detection as their major objective to solve the problem. They have acknowledged the lack of dataset available and hence, have adapted artificial synthesis of images as their method to obtain a larger dataset.

The synthesis of images was done by taking pictures of smoke with forest like backgrounds and then processing it further. Some of the images were even modified with filters to introduce a smoke like effect in them. These techniques became the basis for the data augmentation that was done in our paper to artificially expand the size of the dataset.

K He et al. [7], in the paper " Deep Residual Learning for Image Recognition " have done image recognition based on different neural network architectures like ResNet, VGG, etc. Two particular datasets were used, the first one being ImageNet dataset and the second one being CIFAR-10, having ten different classes. The conclusion reached after obtaining results and analysing it was that ResNet-34 exhibits significantly lower training error and is generalizable to the validation set.

This proved to be the basis for our choice of ResNet-34 as the appropriate architecture for image classification.

Guoli Zhang et al.[8] in the paper "Forest Fire Susceptibility Model Using a Convolutional Neural Network for Yunnan Province of China", have used CNN to predict the susceptibility of forest fires in different regions of the Yunnan province. Since Yunnan province is known to have frequently occurring fires, they have acquired datasets from the same region. Moreover, they have even used other machine learning methods like random forest, support vector machine, multilayer perceptron neural network and kernel logistic regression to do the same and compare the results. They finally concluded that CNNs have a higher accuracy than the other machine learning based methods mentioned above.

Moreover, their project gives information about the regions susceptible to forest fires without taking into consideration the present situation in the region.

Our paper is based on real time forest fire detection and hence, it can predict whether a forest is currently under fire or not.

In this paper, we propose to detect forest fires efficiently and accurately using Convolutional Neural Networks as our method to train the model.

3. Methodology

Dataset Collection

We collect the dataset from google images. Since it is a very tedious and monotonous procedure to download images individually from various sites, we use a web scraping technique to download a large number of images at once. However, google images contain many junk images that are not related to what is being searched. Therefore, we manually clean the dataset by deleting unrelated images.

First, we open a console in our browser where we search for the images and then paste the JavaScript command shown in Fig 1. This downloads the URLs of all images that are on the page. Almost any search will yield an average of 400 images before cleaning.

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```
urls=Array.from(document.querySelectorAll('.rg_i')).map(el=> el.hasAttribute('data-src')?el.getAttr
bute('data-src'):el.getAttribute('data-iurl'));
window.open('data:text/csv;charset=utf-8,' + escape(urls.join('\n')));
```

Figure 1: The JavaScript command used to download URLs of images.

Next, we use a popular wrapper for Deep Learning called fastai, which has the method 'download_images' to download images using the URLs file previously downloaded. This is shown in Fig 2.The fastai library provides most data augmentation in computer vision on the GPU at the batch level [9].
After that, we perform an initial cleaning of the dataset by deleting the images that do not open. We do this with the help of another fastai method 'verify_images' as shown in Fig 2.

```
In [9]:  download_images(path/file, dest)

In [10]: for c in classes:
             print(c)
             verify_images(path/c, delete=True, max_size=500)

ForestFire

NoForestFire
```

Figure 2: fastai methods to download and clean images.

Lastly, we manually clean the dataset to remove irrelevant images. After this step, we finally obtain the dataset required to train the model. The sample images are as shown in Fig 3 and Fig 4.

Figure 3: Sample Images labelled 'Forest Fire'

Figure 4: Sample Images labelled 'No Forest Fire'

Training the model

Batch Normalization

When we feed images to a model, there should be a uniform distribution of images. If that does not happen, then the model will train slowly and might even have a bias factor, as it has not been trained with all kinds of images. This needs to be followed for every layer, otherwise training will not happen as expected. Therefore, we do batch normalization for the dataset being fed to the model as it sets the mean across each channel to zero and standard variation to one. Its tendency to improve accuracy and speed up training have established it as a favourite technique in Deep Learning [10].

Data Augmentation

Augmentations artificially inflate the training dataset size by either data warping or oversampling [11]. In this technique, we apply randomly chosen transformations while loading images from the training dataset. Specifically, we pad each image by four pixels, then take a random crop of size 32 x 32 pixels, and then flip the image horizontally with a 50% probability. Since we apply the transformations randomly and periodically each time a particular image is loaded, the model identifies the image differently every single time thereby picking up on different features of the image and improving the accuracy even further.

ReLU Activation Function

Activation functions activate certain connections of the neural network to nudge the results in favour of the class with the highest probability. There are many activation functions, but we use ReLU or Rectified Linear Unit, which has the following formula:-

$$y = \max(0, x)$$

Where y refers to the output after applying the activation function and x refers to the input fed to the activation function. Simply put, it outputs 0 when$x<0$, andconversely, it outputs a linear function when$x\geq0$[12]
Activation functions like Sigmoid, TanH and Softmax have a common problem called vanishing gradient which halts the optimization of weights and biases. Due to this, the model stops training and the accuracy stagnates. ReLU eliminates this issue.

ResNets

In case of any neural networks, the normal idea is that, we can achieve a greater accuracy with increase in the number of layers. However, this only holds good for a limited number of layers after which the error starts increasing with every single layer.
Therefore, we use a particular variant of CNN called ResNet, which is short for Residual Neural Network. A ResNet has something called 'skip connections' as shown in Fig 5. which prevents saturation and degradation of accuracy.

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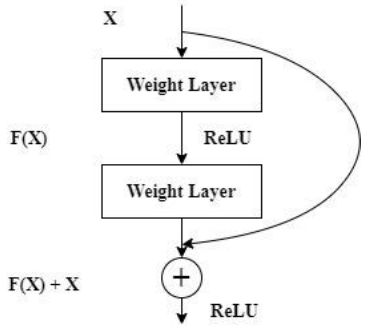

Figure 5: Pictorial representation of skip connection.

There are many variants of ResNets like ResNet-18, ResNet-22, ResNet-34, etc. We have made use of ResNet-34 whose architecture is as shown in Fig 6.

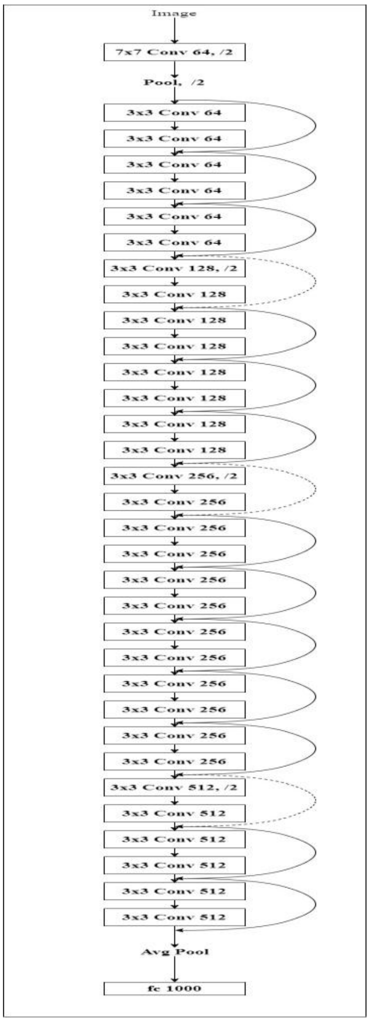

Figure 6: Architecture of ResNet-32

The entire process can be summarized using a flowchart shown in Fig 7.

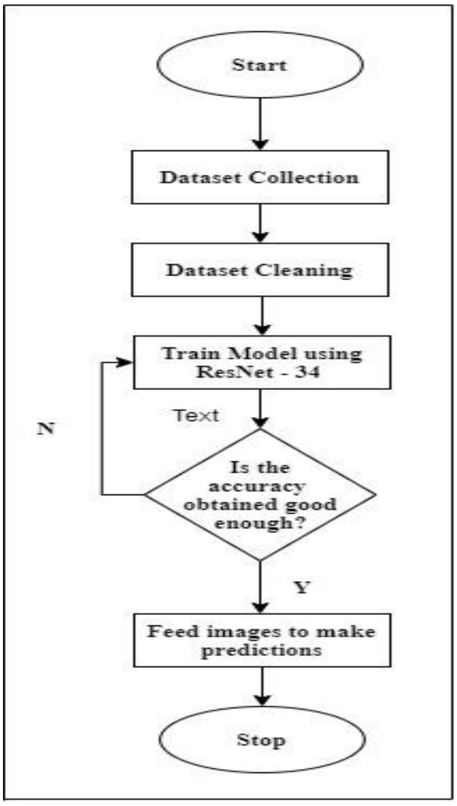

Figure 7: Flowchart depicting implementation procedure

4. System Requirements

Software Requirements	**Hardware Requirements**
Anaconda 3.5.6 Pytorch 1.0.0 fastai v2	Laptop with minimum specifications :- 4GB Ram CPU at 1.60 GHz Intel core i5 64 bit Operating System
IDE - Jupyter Notebook	

5. Experimental Results and Analysis

For this model, we did not divide the dataset into training and validation sets. Instead, we used all of it as training set so as to have a larger dataset to train our model with.
The result of training is shown in Fig 8.

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epoch	train_loss	valid_loss
0	0.059804	#na#
1	0.071775	#na#
2	0.087600	#na#
3	0.087692	#na#
4	0.087956	#na#
5	0.097959	#na#
6	0.091921	#na#
7	0.095144	#na#
8	0.090621	#na#
9	0.094055	#na#

Figure 8: The training loss obtained after each epoch.

We have achieved an average accuracy of around 92% for our model. It is possible to achieve better results with a larger dataset and some changes to the hyperparameters. Hyperparameters are important for machine learning algorithms since they directly control the behaviors of training algorithms and have a significant effect on the performance of machine learning model [13].
The average accuracy was calculated in the following way –

$$Acc = (\Sigma(1-ER_i) / n) * 100$$

Where, Acc, ER,i and n refer to the Accuracy, Error Rate, epoch number and total epochs respectively.

The loss-epochs graph is shown in Fig 8.

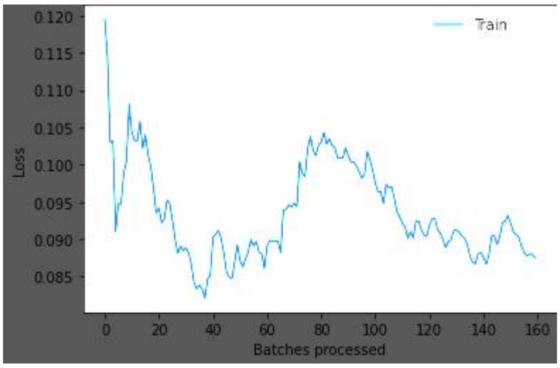

Figure 9: Loss value with increasing number of epochs

We see that the loss value does not vary drastically once it hits the global minima at 0.059. Thus, it goes to show that it is a stable model, which has hit the best accuracy for the particular dataset and hyper-parameters.

6. Conclusion

Džigal, Džemil et al. [14] combined components from three very different color spaces HSV, HSL and HWB and defined a new criterion for the image segmentation. They used the Corsican Fire Dataset (CFDS) to train their model. As a result, they obtained an average accuracy of 91%.

We have trained our model by acquiring our dataset from Google images. We have subjected the dataset to batch normalization and data augmentation before passing it through the CNN with ResNet-34 architecture. In this process, we have obtained an even higher accuracy of 92%.

We propose to use R-CNN in the future so that we can make region-based detection thereby allowing us to know about which region of the forest is burning due to fires.

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