Wildfires Detection Using UAV Images

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Abstract—This my abstract And this is how it ends

Index Terms—CNN; Deep Learning; Wildfires

1 Introduction

Convolutional neural networks (CNN's) currently are one of the must explored topics due to their high efficiency in several areas of ML, in particular Computer Vision and Image Recognition. This led to the creation of popular datasets such as MNIST and ImageNet, which are used nowadays to introduce the topic or to pre-train the CNN's to be able to perform Transfer Learning for more specific tasks. This had led to the researchers to not only improve the performance of the CNN's but also found a use for them, one of these cases have been for the detection of Wildfires.

Wildfires currently are on of the must dangerous natural disasters that are threating the world. According to an investigation done by the NOAA (National Oceanic and Atmospheric Administration), the emissions produced by the wildfires often lead to harmful pollution not only in the area near the wildfire but also can extent even farther from the area, harming humans and other specials alike [1]. In addition to that, there are ecosystems which fauna and flora are being threatened due to the fires and to human intervention. Being that the case of the Amazon Rainforest, where the mentioned causes alongside droughts, could led to a possible "tipping point" where the Reinforces would be unsustainable in the case that there's no effective intervention of the matter [2].

Due to the formerly mentioned there have been attempts by the scientific community to develop models that can detect based on the image if there is fire or not. Leading to the creation of datasets such as FLAME, a dataset created and provided by the IEEE [3], or less academic but still important FIRE dataset hosted on Kaggle which is also home of several images showing environment with and without fire [4].

Nevertheless, the models are not very accurate, as an example the model trained with the FLAME dataset had only a 76% accuracy [3], showing that there are still are of improvement in the regard. And with the knowledge that the FLAME model was trained only with the FLAME dataset, it's possible that using both the FLAME and Kaggle dataset in addition to some data augmentation and a new model it will be possible to improve the score previously obtained solely by the FLAME dataset.

2 Background / Literature Review

2.1 Convolutional Neural Network

Are a type of Neural Networks commonly used for the areas of Image Recognition and Computer Vision, this type of networks have the main feature of being divided in several deeply connected convolutional and pooling layers, to finally end with a classifier which is a fully connected layer comparable to a layer of traditional Multi-Layer Perceptron (MLP).

2.1.1 CNN Architectures

As CNN's are one of the state of the art topics in research nowadays, there have been many popular architectures that either have very high performance, or have very little parameters with the objective of having a lightweight model with good performance. For developing actual applications for a problem researchers actually use this predefined architectures to solve the problem they're facing as this provides the advantages of being a proven useful architecture.

In addition that due to their popularity people train these models with popular datasets so researchers can use these pre-trained weights enabling to do transfer learning, which is when using an already trained model, retrained the top layer to be able to have a good performance in the new problem.

Actually in the case of the FLAME research done, it's mentioned in the paper that the model that achieved a 76% of accuracy was using an architecture called Xception [5].

Another example of an architecture is EfficientNet published in September 2019, that wanted to tackle the problem of scaling up an architecture by having a smaller amount of parameters, but also by keeping/increasing the accuracy of the model, this was able by the use of compound coefficient [6].

Also it exists the architecture of ReXNet which was proposed in July 2020, aiming to follow the trend of creating accurate and lightweight architectures, distinguishing themselves by the use of representational bottlenecks. The result was quite good improving the accuracy when doing transfer learning from trained models using the COCO dataset, while keeping a small amount of parameters to train [7].

2.2 Data augmentation

Is a method that allows to increase the amount of data that we have in a dataset, allowing to be persistent being that you generate new data based on the previous one and save it on the same dataset. Or add randomness prior to training a batch, making that every epoch and batch should not consist of the same data in the same order [8].

For images datasets, normally the transformation/augmentations done to increase the dataset is by performing modifications in the same image being by simple image transformations such as shearing, rotation and translation. But it also may be the modification of the brightness, flipping the image vertically or horizontally, or by cropping it [9].

TABLE 1: Final ReXNet model metrics

Dataset	(Loss) Accuracy
Training	(0.0293) 99.62
Validation	(0.0153) 99.62
Testing	(-) 71.46

TABLE 2: Final EfficientNet model metrics

Dataset	(Loss) Accuracy
Training	(0.0582) 98.28
Validation	(0.0530) 98.32
Testing	(-) 61.46

3.3.2 Hyperparameters

- Batch-size: 32
- Learning Rate: 5e-5
- Max epochs: 15

3.3.3 Callbacks

- LRScheduler, this callback modifies the current learning rate based on the current epoch, leading to a function that has the following structure

```
if epoch <= num_warmup_steps:
    return log(max_lr / lr) /
           log(num_warmup_steps)
return log(min_lr / max_lr) /
       log(num_training_steps)
```

Using as max_lr: 5e-3, min_lr: 1e-5, num_warmup_steps: 6 and num_training_steps: 9

3.3.4 Transformations

All random transformations have a probability of 50% of happening. And the random transformations are only for the training dataset

- Resize the image to a size of (254, 254)
- A reduction or increase of brightness and contrast within a range of 0.75-1.25. The final number is defined by a uniform probability
- A random rotation of 5º
- A random horizontal flip and a random vertical flip
- Normalization using the mean and std of each channel of the ImageNet dataset

4 Results

4.1 ReXNet results

4.2 EfficientNet results

4.3 Best Model vs FLAME's model

As shown with the tables 1 and 2, it's evident that the best model that was trained is the ReXNet nevertheless the results overall doesn't seem as favorable, the new model shows a current accuracy of 71%, being that a 7% decrease in the accuracy compared to the model done by the FLAME team. Nevertheless this seems to be a case of over-fitting as the current model outperforms FLAME's, with a significantly decrease in both the validation and training loss, showing also an increase in the accuracy.

Some other things it should be consider is that due to hardware constraints and to be 100% to transfer learning, it was only trained the top layer of the CNN. This brought improvements, such that it was necessary to train the model to the nature of the architecture itself, nevertheless it could also be the reason that it's difficult to tune for a better generalization more specific to our current situation. This shows the advantages and disadvantages that can bring transfer learning.

5 Conclusion

This is my conclusion

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