Improving Fire Detection with Efficient Training Techniques

Ricardo Gonzalez, 2003297

Abstract—Pending abstract

Index Terms—CNN; Deep Learning; Image Classification

1 Introduction

Nowadays due to the advancements in AI and the increasing amount of ecological disasters have led that many researchers focused their attention in not only make new advancements in the theory of the field, but also propose ways to solve, prevent or detect those disasters to mitigate the impact that they have [1].

A natural disaster is researched this way are Wildfires. According to [2] wildfires produce emissions which are highly contaminant, leading to an increase in air pollution not only in the area affected by the wildfires, but also close areas near to it. Furthermore, the natural fauna and flora are also threatened, by consequence that the fire was caused due to human intervention. This is explained by [3], who uses as an example the Amazon Rainforest where the human caused wildfires alongside droughts have threatened the Rainforest to reach a possible tipping point, where it would become unsustainable unless there is some kind of intervention.

To be able to tackle this problem, researchers have decided to attempt the detection of wildfires in their early stages having the examples of [4] and [5], whose work have been either proposing CNN models using their own datasets or creating a new dataset containing images to create models that can be used to solve the problem.

Nevertheless, the models normally are not very accurate, an example of this is the one proposed by [4] whose proposed model achieved 76%, which shows that is still possible and worth to achieve a higher score, specially considering that the architecture used is considered an old model, and new and better ones have been published since then. In addition to the prior the training process was a very simple training process that was primarily based on training through a lot of epochs. Thus, new techniques can be used to not only increase the accuracy but also reduce the amount of epochs needed to train it.

That is why the objective of this research is to propose using new architectures, models that can achieve higher accuracy over the same test dataset as the one used at [4], while needing less amount of epochs to be trained.

2 Background / Literature Review

2.1 Data Augmentation

Data Augmentation is a technique that improves the generalization of the network, this is done by performing manipulation of the data, being in the case of images techniques such as: shearing, rotating, saturate and others [6]. This technique is effective because it generates new data each time a new epoch is ran. Thus, resulting quite effective when learning from an overall small dataset. In addition to the prior, it also has been proven effective as it adds randomness to the training as it reduces the changes that the same batch have the same data each epoch [7].

2.1.1 AutoAugment

Nevertheless, one limitation this technique has its effectiveness depends on the augmentations done over the data and which will be its correct parameters, mainly its magnitude and probability. A solution of this limitation is proposed by [8] who created a procedure called AutoAugment that created a search space consisting of policy which consisted of subpolicies that decide which augmentation to do and which are its parameters. This resulted in an improvement of the previous state-of-the-art models.

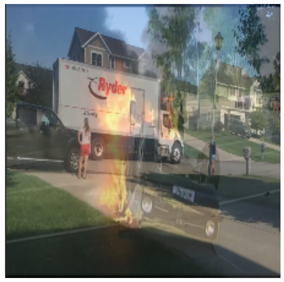
2.1.2 Test Time Augmentation

Even though, data augmentation is commonly used only for the training phase it also has a purpose during the testing phase. This technique is called Test Time Augmentation (TTA), in which the input is augmented and passed as an input for the model n times to result in a total of n outputs. With these outputs, then is performed a merge operation which normally is to perform a mean between all the outputs obtained. This merge result is then used to obtain the desired test metrics [9].

2.2 Mixed-precision training

One of the current problems that people are facing nowadays with DL is the amount of resources that it takes to train a model. Either because the architecture has a lot of parameters and takes a lot of memory of the GPU, or because it takes a lot of time to be trained due to the computational power it needs. To solve this problem [10] proposed what is known as mixed-precision training, where instead of use the full-precision number of 8 bytes, it would use the 4 byte format. This led to a reduction of the amount of memory it took to train the model, in addition to a speedup in the time that the model took to be trained.

(a) Before Mixup



(b) After Mixup

Fig. 1: Example of transformation of an image when using mixup

2.3 Mixup

Is a technique that was proposed by [11] that was aimed to help in the stabilization of adversarial networks in generative model, nevertheless it has found success also in classification tasks. The technique consists of mixing both the data and labels of elements in the batch, resulting in an overall generalization of how it would look the distribution of the data of two different elements of the same or different class. An example of the result of mixup can be seen in figure 1.

3 Methods

4 Results

5 Conclusion

References

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