FIRE RECOGNIZING IN IMAGES BY USING CNN CLASSIFICATION & SEGMENTATION OF IMAGES

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ABSTRACT

This document describes an use of an integrated Artificial Intelligence technology for image classification and segmentation to detect coordinates of attributes.

The document describes a jointly use an integrated Artificial Intelligence technology for image classification and segmentation to detect the position of attributes.

Main objective of this project is to develop a prediction model through CNN neural networks able to detect fire at different levels when reading new images. The secondary objective of this, is to explore the use existent methodologies for image processing and segmentation, in order to identify the characteristics provided in Encoded Pixels that are useful for their classification.

INTRODUCTION

The set of images were compiled by NASA Space Apps Challenge in 2018, with the goal of using it to develop a model that can recognize the images with fire.

The images are labeled from their upload with the categories "Fire" and "Non Fire", having a proportion of 50-50%. This classification could be simple, but the use of this set of techniques is proposed to solve similar problems in other fields such in science and engineering that involves a similar needings.

METHODOLOGY

1. Extraction and preparation. The images are loaded in zip format and is built a data frame with the path and label tags. A stratified sampling is carried out to reduce the dimensions of the dataset with the library StratifiedShuffleSplit. Then is executed the cleansing of data.

As a data preparation for classification, the size of the images is normalized, the pixels of the images are extracted, and these are vectorized and saved in variables X (images) and Y (label).

2. Exploratory and descriptive analysis. The dataset is analyzed in its characteristics of size, color, etc. comparing the differences between the two groups, for this are used the libraries seaborn and plotly.

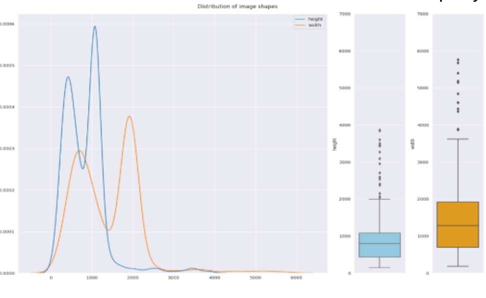

Figure 1 Descriptive Analysis of Images sized distribution

3. Statistics. The existing correlation of image characteristics is analized is using the PCA from sklearn decomposition and for analizing the visualization of results there are used libraries as load_img and image from tensorflow.

4. Clasification Model

It is adopted a residual learning to every few stacked layers. A building block is shown in Fig. 1. Formally, in this paper we consider a building block defined as:

$$y=F(x,\{W_i\})+x.$$

Here x and y are the input and output vectors of the layers considered. The function $F(x,\{W_i\})$ represents the residual mapping to be learned. For the example in Fig. 2 that has two layers, $F=W_2\sigma(W_1x)$ in which σ denotes ReLU (Nair 2010) and the biases are omitted for simplifying notations. The operation F+x is performed by a shortcut connection and element-wise addition.

The binary convolutional neural network works for the classification of both groups. Functions are defined to download an archived dataset and decompress it, in order to normalize the set. The dataset files are then divided into training and validation sets. The training set works for defining a Pytorch class dataset, and albumenations are used to define transformation functions for the training and validation data sets. The training parameters for the neural network are defined, and all the objects and functions necessary for training and validation are created.

Table 1 Input Patameters of CNN model

Aspect	Parameters
Model	CNN Resnet-50
Device	CUDA
Learning rate	0.001
Batch size	64
Num workers	4
Epochs	10

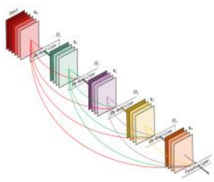

Figure 2 Reference of Resnet-Architecture

5. Segmentation

The dataframe was created with the id, path and label of the images of both groups and it works for extracting a segmentation code in binary values.

This is then used to display the images with masks and generate a dataframe with these results obtained from its transformation. In future work, we seek to perform a segmentation with U-Net that allows us to focus on the exact area of fire in the image. The following libraries were used to create the function that would transform the images and extract the masks.

RESULTS

Performance result of Classification model:
Loss of 0.236 and Accuracy of 0.908

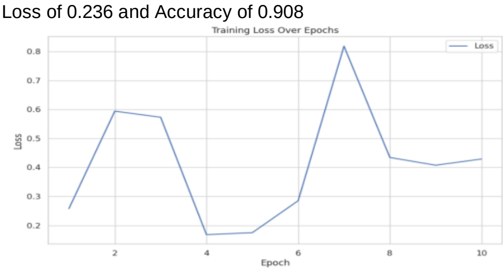

Figure 3 Loss between epochs of the model

The results obtained with the Resnet-20 CNN suggest that the model is learning effectively on the training data, resulting in an improved ability to accurately classify new images. These results suggest good progress on the image classification task.

Future Work suggests that the difference in colors between groups in the images is crucial. In technical terms, it is mentioned that image segmentation will be essential to accurately identify the location of the fire. Image segmentation is a process in which an image is divided into regions or segments with similar visual characteristics. In this context, it is suggested that image segmentation will be used to highlight and precisely delineate specific areas associated with fire in images, taking advantage of color differences between the different groups or elements present in the scenes. This could improve the system's ability to efficiently locate and analyze the presence of fire in images.

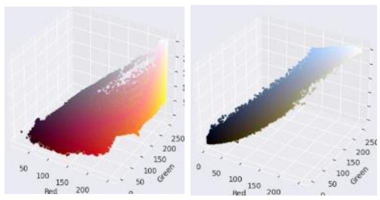

Figure 4 RGBplot of Fire Images vs Non-Fire Images

CONCLUSIONS

The model has been efficient for image classification, the technique could be replicated for other needs, but is important to consider that the results may be different when applying different preprocessing and data cleaning. Consider the required precision for the model develop, the parameters of the neural network can make it more capable of processing images with more details and complexity.

REFERENCES

He, K. (2015, 10 diciembre). Deep residual learning for image recognition. arXiv.org. https://arxiv.org/abs/1512.03385

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