Wildfires early alert model

1 Introduction

Fires burn millions of hectares of plant surface in the earth every year. This has a great economic, human and ecological cost. Early detection of wildfires is key to minimizing their effects through early intervention of forest services. Also, could prevent possible loss of human life by alerting people in areas at risk.

Currently, each region depends on its own fire detection system. Despite this, there are areas of the Earth populated with vegetation that do not have any fire warning system or that have inefficient fire warning systems.

A global fire warning solution is suitable both for areas with low or no coverage and for strengthening warning systems in areas with a functional warning system. There are fire detection systems such as the *NASA* which warns of fires within three hours of their occurrence (search.earthdata.nasa.gov). Unfortunately sometimes 3 hours is too long. Fires are hardly controllable once they have begun to spread.

This work proposes a global fire detection system based on combining fire data from textitNASA and other remote sensing systems with real-time analysis of social networks. In some cases this system could reduce the time of the fire detection system from the *NASA*. The system does not require the active collaboration of people although it can benefit from it.

Generally speaking, the early warning model consists of 4 parts:

1. Fire risk model: Based on satellite images, the global fire risk is estimated every 8 days using a model that has been widely validated by the scientific community [1].

2. Selection mask: Excludes those areas that are not of interest to the model.

3. Textual analysis of social networks and APIs: As many text messages as possible are analyzed on social networks and other selected sources in a pseudo-random manner looking for wildfire alarms.

4. Analysis of images: If text analysis is not enough to decide whether to issue an alert, the decision is reinforced by analysing social network images and satellite images.

5. Decision-making based on a linear model: Combining the analysis of social networks and the fire risk model a linear model evaluates whether to issue a fire alert.

2 The model

The following section will develop the model step by step.

2.1 Fire risk model

Startin in the last century fire danger rating systems have been in operation in many countries around the world, especially in Canada, Australia, Russia and the United States [2].

In our case we want to propose a global scale model that is updated every 8 days. We propose to use the Chowdhury et al model[1]. The model requires variables that do not have to be available on a global scale, so if it is not feasible to estimate this model a much simpler model based on satellite data

- Daily surface temperature
- Daily precipitable wter
- Composite of surface reflectance
- Annual land cover map
- Daily aerosol optical depth

obtained form *ladweb.modaps.eosdis.nasa.gov* and the data about burned areas from *search.earthdata.nasa.gov*.

2.2 Selection masks

The early warning fire system proposed in this work operates on a global scale. This implies that it will require a large computing capacity. In order to reduce the load of calculations some areas will not be considered for the model. These areas are:

- Areas with more than 10k inhabitans/km^2 obtained from *landscan.ornl.gov*. We assume that these areas are urban areas. It is not useful to alert of fires in these areas since the goal of the model is to generate wildfire alerts. Furthermore, if a fire were to be observed from a densely populated urban nucleus, the authorities would undoubtedly be alerted in time as a large number of people would be able to see it.
- Any area in which a fire has occurred since 2000 according to the *NASA* fire database *Fire Information for Resource Management System (FIRMS)*.
- Any area in which there is an active fire according *FIRM*.

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2.3 Social network and API text analysis

In this stage as much post geolocalized on social networks and information received from the API SoFiA and related with to is downloaded. Those regions covered by the masks produced in the previous stage of the model will be ignored for the search 2.2. Even ignoring these regions there is too much information on social networks to process it all. A selection criteria is established. It prioritizes the post according to the fire risk fr evaluated in its location. In addition, a minimum threshold of fr from which no post is taken into consideration, t, is established. t will depend on the maximum amount of post that can be processed in each batch, c_{max}.

In each bach c_{max} posts are downloaded and sorted by its fr. We set $n = 10$ percentiles in the range $fr > t$. In each of them as many post as $\int_{fr_i}^{fr_{i+1}} g(fr) \times cmax/(\times \int_t^1 g(fr))$ are processed. They are randomly chosen from among the candidates, being $g(fr) = e^{(x-t)/(1-t)ln(2)} - 1$.

The selected posts are processed to be introduced into a dense neural network with a depth to be determined in an optimization process. The following variables are considered for the dense neuaral network:

- Bag of fire-related keywords contained in each post. The keywords will be determined from among those that can be found in a post that alerts about a fire. For example textfire, textsmoke, textfire, etc.
- Reverse of the population density in the position of the post. It is intended to penalize the areas with more population and therefore with more possibility of fire sighting.
- Fire risk estimated in the first stage of the model.

The network has a single softmax output that indicates if the post is alerting or not about fire. Positive reports are clustered whit the *Mean-Shift Clustering* algorithm. This is simply a proposal, other clustering algorithms might be more convenient for the model.

The possibility of it being a real alert is evaluated in each report as

$$AlertRisk = fracpdimesfr$$

, being p the number of positive reports in the cluster. Thus, in an unpopulated area a single report would be enough to trigger the alert for a high fire risk and on the contrary many reports would be needed in a cluster with low fire risk and densely populated.

2.4 Image analysis

If $AlertRisk$ is too high with respect to an established threshold it is considered necessary to issue an alert automatically. If $AlertRisk$ is too low with respect to an established threshold the cluster is discarded. In any other case, images are requested to reinforce the area enclosed by the complex hue of the posts forming the cluster or the posts enclosed in an area of 5 km around each point if there are less than four points in a cluster. The images will be obtained from the following sources: post from social networks that have been evaluated and contain images, the geostationary satellite network *GOES* and the SoFia API. These images are evaluated by a ResNet[3] object detection neuronal network. It is important to note that although the architecture of the networks that process the satellite images, the images from the social networks, and the API may match their sets of images are different.

Users who volunteer will also be able to catalogue images of possible fires. They will receive as many images as possible. The judgment given by the user will prevail over the model if it is the case that a same image has been classified by a human and the object identification network.

2.5 Decision making based on a linear model

Finally, the results are entered into a linear model with two input variables:

- The percentage of images evaluated as fires.
- The average fire risk at the points where warnings have been issued.

This last regressor will decide whether or not to issue a warning.

3 Training

Different parts of the model are machine learning algorithms that require training. This section indicates where the tagged data is obtained for each of them.

It will be necessary to dedicate staff to tagging for the dense network that is used for the detection of alerts in social networks and API. The help of the community of SoFiA users could also be requested. In any case, active learning techniques will be used to determine which samples are to be tagged.

Image recognition networks will be trained with images of places and dates where *FIRMS* indicates that there has been a fire and have also been catalogued as fires by APP users.

4 Conclusions

A fire early warning model based on the use of social networks is proposed, limiting the study area to the maximum in order to make the analysis viable.

The quality of some parts of the model will depend on the collection of sufficient data to make it viable.

This work is a proposal that leaves many points open due to lack of time either to develop them fully or because they require in-depth analysis. Despite this, the proposal is realistic and the model is viable.

References

[1] Ehsan H Chowdhury and Quazi K Hassan. Development of a new daily-scale forest fire danger forecasting system using remote sensing data. *Remote Sensing*, 7(3):2431–2448, 2015.

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[3] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.