



# Smart Forest Fires Detection Information Technology in Disaster Risk Reduction



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Comwork is an IT services company founded in Tunisia by a team of dynamic and passionate people! Today, Comwork brings together professionals in several new branches in Paris and Saudi Arabia.

Our strong sustainable development culture also came from our training from the 2nd most eco-responsible university in the world



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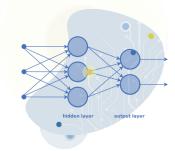
DevOps administration & Infrastructure



Développement web mobile & design UX/UI



IoT & Big Data embedded software and data analysis



Intelligence Artificielle machine learning & OR optimization

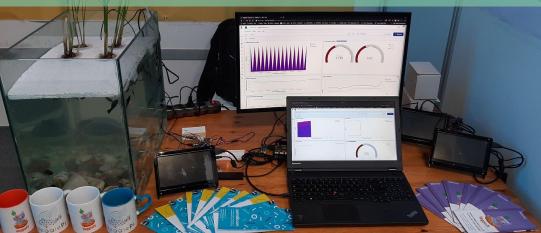




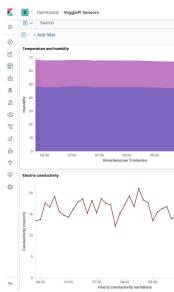


# CONNECTED AQUAPONICS MODULE www.veggiepi.com

VeggiePl



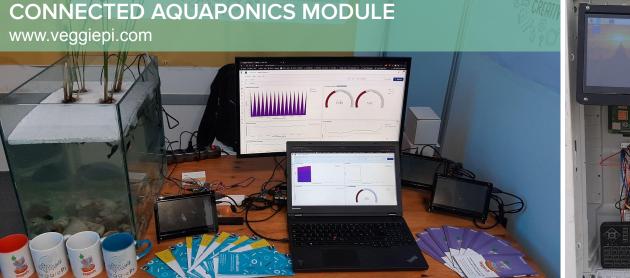






## **TECHNICAL MODEL**

- A RaspberryPi collects sensor logs in a so-called Time-series Database.
- Sensor units communicate with the RaspberryPi by different protocols depending on their distance: directly connected, by WiFi within a range of 800m maximum, LoRaWan, etc.
- The data is then sent to the cloud and analyzed to send alerts if abnormal thresholds are observed.







## **REMINDER OF THE SITUATION**

The objective of this project is to implement a pilot project in GDA Sidi Amor.

The concerned area, surrounded in this map, consists of 5 hectares of forests and olive groves.

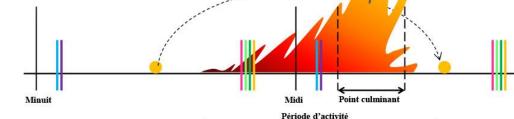
Measure distance Click on the map to add to your path Total area: 50,037.34 m² (538,597.42 ft²) Total distance: 1.22 km (3,992.78 ft)

# STATE OF THE ART



## **Canadian Fire Forest Strategy**

Simulation Software: <u>https://d1ied5g1xfgpx8.cloudfront.net/pdfs/32530.pdf</u> Firesmart: <u>https://www.firesmartcanada.ca/what-is-firesmart/</u> WildFireSat: <u>https://www.asc-csa.gc.ca/fra/satellites/wildfiresat/default.asp</u>





## **Californian Projects**

IA Video Recognition: <u>https://www.azocleantech.com/news.aspx?newsID=29087</u> Swaying of tree: <u>https://www.science.org/content/article/self-powered-wildfire</u> <u>-detector-could-help-prevent-deadly-blazes</u>

AlertWildfire Camera Network: <u>http://www.alertwildfire.org/</u>

https://www.govtech.com/products/artificial-intelligence-is-helping-to-spot-califor

nia-wildfires.html

# A TOPIC ALSO INCREASINGLY STUDIED IN THE LITERATURE

#### Convolutional neural network based early fire detection

Faisal Saeed<sup>1</sup> · Anand Paul<sup>1</sup> · P. Karthigaikumar<sup>2</sup> · A

Received: 5 October 2018 / Revised: 14 March 2019 / Accepted: 15 May 20 Published online: 20 June 2019

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#### Abstract

The detection of manmade disasters particularly fire is damages in terms of human lives. Research on fire detecti and video-based methods is a very hot research topic. Ho model need fire happens and a lot of smoke and fire for models also have some drawbacks because conventional al high rule-based models for detection. In this paper, we prope is based on powerful machine learning and deep learning data as well as images data for fire prevention. Our proposed networks i.e. a hybrid model which consists of Adaboost Adaboost-LBP model and finally convolutional neural n model to predict the fire. After the prediction, we pro

Adaboost-LBP model and convention and images taken from the car generate the ROIs from the ima quite good, and the accuracy is reduced more using further train

Keywords Fire · Machine learning Network

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#### Additive neural network for forest fire detection

Hongyi Pan<sup>1</sup> · Diaa Badawi<sup>1</sup> · Xi Zhang<sup>1</sup> · Ahmet Enis Cetin<sup>1,2</sup>

Received: 27 July 2019 / Revised: 12 September 2019 / Accepted: 8 November 2019 / Published online © Springer-Verlag London Ltd., part of Springer Nature 2019

#### Abstract

In this paper, we introduce a video-based wildfire detection scheme based on a connetwork, which we call AddNet. This AddNet is based on a multiplication-free vec and sign manipulation operations. In this regard, we construct a dot product-like define dense and convolutional feed-forwarding passes in AddNet. We train AddNet cameras. Our experiments show that AddNet can achieve a time-saving by 12.4% convolutional neural network (CNN). Furthermore, the smoke recognition performance and substantially better than binary-weight neural networks.

Keywords Computationally efficient · Neural network · Additive neural network ·

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tect wildfires using regular

[1-18]. Video-based forest

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as the smoke is within the

lhicago, USA

#### 1 Introduction

Despite recent advances in weather forecasting and firefighting technology, devastating forest fires occur throughout the world. For example, in November 2018, the "Camp Fire" in California burned about 153,336 acres and resulted in a death toll of more than 85 people. Early detection of wildfire mental and human losses.

#### Forest Fire Smoke Detection Using Back-Propagation Neural Network Based on MODIS Data

#### Kiaolian Li, Weiguo Song \*, Liping Lian and Xiaoge Wei

State Key Laboratory of Fire Science, University of Science and Technology of China, Jinzhai 96, Hefei 2300027, China; E-Mails: lxl1988@mail.ustc.edu.cn (X.L.); lplian@mail.ustc.edu.cn (L.L.); wxg2010@mail.ustc.edu.cn (X.W.)

Author to whom correspondence should be addressed; E-Mail: wgsong@ustc.edu.cn.

Academic Editors: Joannis Gitas and Prasad S. Thenkabail

Received: 14 December 2014 / Accepted: 15 March 2015 / Published: 15 April 2015

Abstract: Satellite remote sensing provides global observations of the Earth's surface and provides useful information for monitoring smoke plumes emitted from forest fires. The aim of this study is to automatically separate smoke plumes from the background by analyzing the MODIS data. An identification algorithm was improved based on the spectral analysis among the smoke, cloud and underlying surface. In order to get satisfactory results, a multi-threshold method is used for extracting training sample sets to train back-propagation neural network (BPNN) classification for merging the smoke detection algorithm. The MODIS data from three forest fires were used to develop the algorithm and get parameter values. These fires occurred in (i) China on 16 October 2004, (ii) Northeast Asia on 29 April 2009 and (iii) Russia on 29 July 2010 in different seasons. Then, the data from four other fires were used to validate the algorithm. Results indicated that the algorithm captured both thick smoke and thin dispersed smoke over land, as well as the mixed pixels of smoke over the ocean. These results could provide valuable information concerning forest fire location fire spreading and so on

Keywords: smoke plumes; fire detection; MODIS; multi-threshold; neural network

recognition tasks tion capabilities. DNN-based wildf

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way or saturine surveinance, viace-used me carection is much cheaper and can work in real-line. Different with the other fires, forest fire monitoring has in own properties. Its view range is not limited, can be 3-5 km generally or even 8 km. Focal length of the camoras is constant. The cameras are usually installed on the top of mountains, and they are not very stable because of wind ple processor. Su or remote monito as little computat blow. All of them cause a great deal of truthle for fire detection. Therefore it is necessary to specially study the case of forest fire recognition. Until now there have been some reported algorithms for computation redu

Units follo uncer neve nexts some reproves algoritants tor automatics fire recognition, but her accuracy of them is still not satisfactory, especially for distinguishing between fire and its similar objects [4-7]. In our paper, a novel method is proposed for image based forest fire detection using some dynamic charactentistics with the holp of BP neural network, and it has good performance in recognizing forest fire from it librances. its likenesses. The structure of our paper is: fire segmentation by color

The structure of our paper is: the segmentation by coort paper is introduced in section 2, extraction of fine features is described in section 3, dynamic characteristics are defined in section 4, application of BP neural network is provided in section 5, results and conclusion are given in section 6 and 7.

978-0-3695-3615-6/09 \$25.00 C 2009 HEE DOI 10.1109/3CAL2009.79 mulation) and bis activation over the

multiplication operations are the most computationally consuming operation in a typical processor [19]. In this paper, we

**GOOGLE SCHOLAR** State Key Laboratory of Earth Surface Process About 50,000 [2005 - 2021] mainly open-access results for keywords like : fire forest + (detection || avoidance || prevision) + (neural || sensor) + network

[20]. Instead of multiplications, the mf-operato sign multiplications and addition operations in a typical neu-

#### Forest Fire Susceptibility Modeling Using a Convolutional Neural Network for Yunnan Province of China

Guoli Zhang<sup>1</sup> · Ming Wang<sup>1,2</sup> · Kai Liu<sup>1,2</sup>

entember 2019

res have caused considerable losses to

and economies worldwide. To mini-

and reduce forest fires, modeling and

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2009 International Joint Conference on Artificial Intelligence

#### Image Based Forest Fire Detection Using Dynamic Characteristics With Artificial Neural Networks

Dengyi Zhang<sup>1</sup>, Shizhong Han<sup>1</sup>, Jianhui Zhao<sup>1</sup>\*, Zhong Zhang<sup>1</sup>, Chengzhang Qu<sup>1</sup>, Youwang Ke<sup>1</sup>, Xiang Chen<sup>2</sup> Computer School, Wuhan University, Wuhan, Hubei, China, 430079 <sup>3</sup>Computer Science Department, Doughu College, Wuhan University, Wuhan, Hubei, China, 430079 \*Emsil: jianhuizhao@wha.edu.cn (corresponding suther)

Advance - In this paper, we recover a relations bereaf the extension logicities in significant energy in the strength basics of dynamic downers built in the strengthenergy with the high ex-tension. For energies is solviered from integrating with the high ex-tension of the strength o II. SEGMENTATION BASED ON COLOR. Compared with RGB color model, HSV (hue, saturatio Compared with RGB color model, HSV (hue, saturation, value) is very suitable for providing a more people oriented way of describing the color, because the hue, saturation and value components are initimately related to the way in which human beings perceive color. Thus we convert the images from RGB to HSV color space, and define it as

 $V = \{x \mid x(H) \in [0,359], x(S) \in [0,255], x(V) \in [0,255]\}$  (1) where x is a pixel in HSV color space, x(H), x(S), x(F)

Keywords - color segmentation; feature extraction; dynamic characteristics; BP neural network are H, S, and V component value of x respectively. The fire color distribution is obtained from sample images containing fire regions, and the collected sample color values form a 3D I. INTRODUCTION point cloud, as shown in Fig. 1. Then the 3D shape of the INTRODUCTION The mediocring of forest fine has mainly depended on margower and satellite for a long time. In recent years, with the development of video survivalimec, the method of image-based automatic forest fire detection has received more and more automatic forest fire detection has received more and more automatic forest fire detection has received more and may of satelline survivalinare, video-based fire detection is survivalence and the satelline detection is and the satelline survivalinary, video-based fire detection is the satelline sat point cloud, in another the second by Gaussian mixture model, and the pixel whose color lies within the range of the

tion model can be taken as a fire pixel

sample libraries. A Ch he prediction of forest fu н hyperparameters were ion accuracy. Then, the model to construct the fire susceptibility in Yu (2)

ion performance of the several statistical measu eceiver operating char

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Forests are the protectors of earth's ecological balance. Unfor anately, the forest fire is usually only observed when it has already spread over a large area, making its control and stoppage arduous and even impossible at times. The result is devastating loss and irreparable damage to the environment and atmosphere (30% of carbon dicoide  $(CO_2)$ in the atmosphere comes from forest fires) [1], in addition to irreparable damage to the ecology (huge amounts of smoke and carbon dicoide  $(CO_2)$  in the atmosphere). Among other terrible consequences of forest fires are long-term disastrous effects such as impacts on local weather patterns, global

warming, and extinction of rare species of the flora and fauna. The problem with forest fires is that the forests are usually note, abandoned/unmanaged areas filled with trees, dry and parching wood, leaves, and so forth that act as a fuel source. These elements form a highly combustible material and represent the perfect context for initial-fire ignition and

act as forl for later stages of the fire. The fire (minimary be caused through human actions like smoking of barbeque parties of yn attural reasons such as high temperature in a hot summer day or a broken glass working as a collective lens to remedy, by means of detection of a forest fire at the ver

A Review on Forest Fire Detection Techniques Ahmad A. A. Alkhatib The University of South Wales, US forest Correspondence should be addressed to Ahmad A. A. Alkhatib: hamadhcumm@vahoo. Received 36 March 2013: Accented 18 Neuropher 2013: Published 5 March 2014 iously Academic Editor: Shuai Li eived Copyright 0 2014 Ahmad A. A. Alkhatib. This is an open access article distributed under the Creative Con recent ense, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly uman Context. Apart from causing tangic loss of lives and valuable natural and individual properties including thousands of hectares of forent and handneds of houses, forest free are a great menace to ecologically healthy grown forents and protection of the environment. Every year, thousands of struct free across the globec same dansets beyond menare rand doesriptien. This issue fires has been the research interest for many years there are a base amount of yery well studied solutions available out there for testin of the or even ready for use to resolve this problem. Airs. This work will summarise all the technologies that have been used for forest fir concernst wan conserver surveys or their techniquestanderlos used in this application. Methods A for of methods and systems are available in the market and for research. The paper review at the methods and discusses camples of meanch experiment results and an emarking routest methods for before the methods and admontage. A full discussion provided after each type. Conclusion, A full table is provided at the red to summarine a comparison between the four methods. et al. fected mplex focusing the sun light on a small spot for a length of time thu sk to leading to fire-ignition. Once ignition starts, combustible material may easily fuel to feed the fires central spot which

1. Introduction

Review Article

material may easily fuel to reed the fires central spot which then becomes bigger and wider. The initial stage of ignition is normally referred to as "surface fire" stage. This may then lead to feeding on adjoining trees and the fire flame become higher and higher, thus becoming "crown fire." Mostly, at this stage, the fire becomes uncontrollable and damage to the landscape may become excessive and could last for a very long time depending on prevailing weather conditions and the terrain.

Millions of hectares of forest are destroyed by fire every

year. Areas destroyed by these fires are large and produc more carbon monoxide than the overall automobile traffic Monitoring of the potential risk areas and an early detection of fire can significantly shorten the reaction time and also reduce the potential damage as well as the cost of fire fighting. Known rules apply here: 1 minute--1 cup of water, 2 ninutes-100 litres of water, 10 minutes-1.000 litres of water









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higher accuracy of the proposed CNN model (AUC 0.86)

than those of the random forests, support vector machine,

multilaver perceptron neural network, and kernel logistic

regression benchmark classifiers. The CNN has stronger

fitting and classification abilities and can make full use of

neighborhood information, which is a promising alternative

for the spatial prediction of forest fire susceptibility. This

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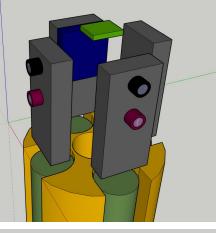
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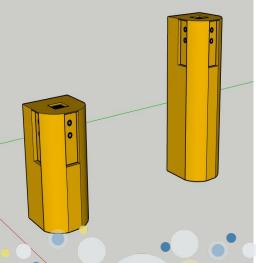


# FIRST APPROACH A network of connected sensors and activators (IoT)

## **TECHNICAL MODEL**

Small-profile, self-contained, fire detection units with:

- 2/3 thermal cameras and 3 traditional cameras and 200° of visibility
- Temperature, Humidity, CO2 combination sensor on top
- 4 to 8, 18650 batteries which will allow them to have between 12000mAh and 24000mAh of battery storage. (given a 3v system, and 3000mAh per battery)



## **TERRAIN COVERAGE**

- Minimum of 56 units covering 900m<sup>2</sup> each (30m of coverage in each direction)
- Minimum of 80 units covering 625m<sup>2</sup> each (25m of coverage in each direction)
- Minimum of 125 units covering 400m<sup>2</sup> each (20m of coverage in each direction)
- Each configuration will require a minimum of 2 Gateway Nodes to ensure redundancy

Article	Quantity	Unit Price	Total Price	
Cost breakdown of components per Gateway				
RaspberryPi 4 8Gb	1	€169.99	€169.99	
LoRa Hat	1	€35.68	€35.68	
GSM Hat	1	€31.99	€31.99	
Gateway Units	2	€237.66	€475.32	
Cost breakdown of components per unit				
18650 3000mAh Batteries	4	€9.25	€37	
100mA 3v Solar Panel	4	€3.5	€14	
Optical Cameras	2	€8.04	€16.08	
Thermal Cameras	2	€62.96	€125.92	
ESP32 LoRa Gateway	1	€36.73	€36.73	
DHT22 Temperature and Humidity sensors	1	€13.29	€13.29	
Co2 concentration sensor	1	€19.59	€19.59	
Plastic Injection Housing	1	€3	€3	

56

€265.61

€14.874.16

Fire Detection Units

## FIRST APPROACH A network of connected sensors

Sensor cost calculator: https://fire-detection.comwork.io

### ISSUES

The prices do not take into account (i) the engineers' allocation time for development and set-up, (ii) the assembly of parts into a finished product (resistance to water and heat, etc.) or (iii) the amount of material needed to test the product, etc.



# second арргоасн Machine Learning - Video Analysis

## Machine learning

Only requires knowledge and engineer development time, little or no material to import

# r

## Require only already finished and industrially objects

Conventional cameras + Computers to train the neural network model and apply detection in the image stream



## THERMAL CAMERA (China)

Performant but expensive: https://shandongsheenrun.en.made-in-china.com/ product/pBKxRJivVaUz/China-Forest-Fire-Detecti on-IP-Thermal-Imaging-PTZ-CCTV-Camera.html





Thank you for your attention !