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Towards an efficient solution to mitigate the forest fire problem based on unmanned aerial vehicles and wireless sensors

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Abstract One of the leading global challenges that the society faces worldwide is related to the forest fire problem, which generates financial losses, threatens ecological systems, and affects public security, putting human and animal life at risk. Despite recent efforts to mitigate the forest fire problem, providing a higher accuracy rate for detecting fire, with a quick response time, without impacting the alert process is still a challenging R&D question that must be investigated. To advance this research front, we propose a solution to detect and monitor forest fires, called DF-Fire, using a UAV (Unmanned Aerial Vehicle) and WSN (Wireless Sensor Network). For this, a deep learning architecture is modeled to carry out the fire detection process. In addition, to cover the area of interest, DF-Fire has a flight plan based on the information that the WSN disseminates. DF-Fire has been evaluated on real devices to prove its efficiency and, when compared to other benchmarking solutions, our solution has advanced in state of the art by: (i) increasing the hit rate to detect the fire; (ii) reduce the response time; and (iii) reduce overhead in processing time without impacting the alert process. Also, DF-Fire takes advantage of the sensors' information to provide efficiency in the flight plan and correlate them to monitor how the fire spreads.

Keywords: WSN, UAV, Forest Fires, Fire

1 Introduction

Every year, forest fires consume millions of hectares of land worldwide. In Brazil, the Mato Grosso Pantanal recorded the worst forest fires in history in 2020, reaching about 3 million hectares, equivalent to 19% of Brazil's biome SOS Pantantal [2020], in addition to registering 15.4 thousand fire spots INPE [2020]. In California, forest fires burned more than 3.2 million acres of land, one of the most massive fires in the state's history CAL FIRE [2020]. In some cases, the fire spreads from rural to urban areas. Frequently, such forest fires cause substantial financial losses and threaten ecological systems and infrastructure. Also, they affect public security, putting human and animal life at risk Skala and Dubravic [2008]; Yuan *et al.* [2015].

Several forest fires cases are unavoidable and occur naturally due to the high temperature of the place, the low relative humidity of the air, or the accumulation of decomposing organic mass. However, some cases are caused by criminal acts to expand the agricultural frontier. Regardless of the causes, minimizing damage by detecting, monitoring progress, and suppressing forest fires early on, is crucial in preventing them from becoming uncontrollable Premal and Vinsley [2014].

It is worth highlight that there are many national and international public policies to stimulate forest fire prevention, such as Prevfogo project of Ibama (Brazilian Institute of Environment and Renewable Natural Resources, Brazil), Queimadas Program of INPE (National Institute for Space Research, Brazil), and CalFire (California Department of Forestry and Fire Protection, EUA). Such initiatives are responsible for monitoring fire occurrences by satellite images, conducting training and planning the positioning of fire brigades, supporting local communities in fire-free farming practices, and promoting environmental education for society in general [Fonseca-Morello *et al.*, 2017]. However, some barriers and challenges limit public policies on forest fire prevention, such as higher budget allocations for fire fighting and not for prevention [Fonseca-Morello *et al.*, 2017], agricultural expansion [Resende *et al.*, 2017], and education inefficient environmental impact on communities. Besides, communities are disorganized and unknowledge about property rights over the land to avoid burning local vegetation [Fonseca-Morello *et al.*, 2017]. Such limitations, combined with the observation towers' precarious infrastructure, make it difficult to see the fire early and delay starting firefighting activities.

Given these limitations and considering the potential that Unmanned Aerial Vehicles (UAV) can offer to carry out missions, its use has shown significant progress in detecting and combatting forest fires [Kalatzis *et al.*, 2018]. However, UAV can fall into the problem of scalability to complete missions when the area to be managed is wide or when the time to provide the service is high [Alzahrani *et al.*, 2020; Faiçal *et al.*, 2016; Neto *et al.*, 2017; Ueyama *et al.*, 2014; Monteiro *et al.*, 2023]. In this scenario, the integration of wireless sensors with UAV could become the new technological revolution in providing services in the next years. That integration provides new application opportunities, offering greater communication power and extensive coverage for the monitored area, as well as to have high mobility to provide their services [Shakhatreh *et al.*, 2019; Alzahrani *et al.*, 2020]. Therefore, this combination offers a promising approach to perform fire detection tasks and monitor the desired area, improving the tasks' performance to be completed. The approach also avoids some risk situations, such as the need for firefighters to risk their lives by staying too close to fires for a long time.

Different works have been proposed to deal with the forest fire problem. Most works are limited to detecting the fire through images, monitoring the desired area, identifying areas with a high frequency of fire, or assessing risks after fires, solving just a specific part of the problem [Dubey *et al.*, 2019; Sharma *et al.*, 2020; Neto *et al.*, 2017; Zharikova and Sherstjuk, 2019]. Other works focus only on the use of UAV [Yuan *et al.*, 2015; Kyrkou and Theocharides, 2020; Zhao *et al.*, 2018] to detect fires by images or wireless sensors to sense the environment [Ueyama *et al.*, 2014; Zharikova and Sherstjuk, 2019; Grover *et al.*, 2020]. However, such works do not investigate the integration with UAV and wireless sensors to detect and monitor fires. In this way, they do not take advantage of the data from terrestrial sensors to assist in the fire detection process, as investigated in this research.

To advance in state of the art, this work aims to answer the following question: How to provide opportunistically high precision in detecting forest fires, maintaining the coverage to complete the mission, and quick response time in fire detection, without affecting the devices' limited computing resources?

With that in mind, this article presents DF-Fire, a solution to **D**etect and monitor **F**orest **Fire**s based on UAV and WSN. DF-Fire has a deep learning architecture deployed within a UAV to increase the fire detection process's reliability with a quick response. Also, DF-Fire has a flight plan based on the information that the WSN disseminates. According to this information, it is possible to restrict the flight plan, maximizing the coverage area and the UAV's autonomy to fly over the area of interest with less time. By the integration with UAV and wireless sensors, the results have shown that DF-Fire is a viable and promising solution to deal with the forest fire problem.

The rest of this article is organized as follows. Section 2 reviews the related works that deal with the forest fire problem to highlight the challenge and the research gap that this article explores. Section 3 shows how our solution was modeled to deal with the forest fire problem. Section 4 reports the experiments anc validation of the application of DF-Fire and, finally, Section 5 presents the conclusions of this research with future work.

2 Related Works

Several studies have been proposed to address the problem of detecting forest fires from remote sensing and aerial images. In addition to preventing hundreds of thousands of forest areas from being devastated, such work aims to preserve the ecosystem and public safety to mitigate its effects on the monitored region. However, it should be noted that modeling a solution to detect and track forest fires in an assertive manner and in an adequate time within the network's infrastructure to alert responsible agencies is not a trivial task.

In Kumar *et al.* [2019], a survey is presented that reinforces the use of WSNs combined with machine learning techniques for some real-time applications, for instance, detecting and monitoring forest fires. In Abid [2021], applications of machine learning techniques for the problem of forest fires prediction and detection are investigated. The works presented in Yuan *et al.* [2015]; Kyrkou and Theocharides [2020]; Zhao *et al.* [2018] use UAV area images to detect forest fires. Particularly in Yuan *et al.* [2015], an approach to detect and track forest fires based on a UAV is proposed. For this, a preliminary analysis of a set of image processing algorithms, such as median filtering, color space conversion, Otsu threshold segmentation, morphological operations, and blob counter, were used. The approach was validated in the laboratory environment in two scenarios, real forest fire images, and real-time fire images. Although the results present a good performance with the images collected by a UAV in a laboratory environment, the approach does not correlate with external data from terrestrial sensors that can assist in identifying and tracking the fire. Still, there is no optimization to perform the real-time fire detection process for devices with scarce resources.

Focused on real-time emergency monitoring, the work Kyrkou and Theocharides [2020] explores aerial images from a UAV for emergency response applications, called EmergencyNet. EmergencyNet is a lightweight Convolutional Neural Networks (CNN) to run on devices with scarce resources that require low power consumption. The goal is to enhance real-time perception capabilities in an emergency scenario with a fast and accurate response on devices with scarce resources. In Zhao *et al.* [2018], a solution for locating and identifying fire based on aerial images is proposed. To discover the central area of the fire was used a protrusion detection method. To determine if the fire occurs, CNN was used in the UAV imagery, called Fire_Net. However, due to not using the data from the WSN, the mentioned works are unable to direct the UAV to track the fire automatically, unlike this research. Also, if the monitored area is large, a battery-powered UAV would not complete the mission successfully. As a result, such work may fall into the scalability problem, making it necessary to add another solution to monitor the area.

Another research front uses UAV with wireless sensors to assist in the monitored environment Ueyama *et al.* [2014]; Neto *et al.* [2017]. In Neto *et al.* [2017], an automated reading architecture based on UAV and wireless sensors is proposed, regardless of the application. For this purpose, the UAV flies over predefined locations to collect data from the region of interest, periodically sending a read request message without the need to pass each sensor. When receiving the information, the UAV can store or notify the base station using, for example, a 3/4G cellular network. The authors at Ueyama *et al*. [2014], explore the use of UAVs to provide resilience in a network of sensors deployed to monitor natural disasters. For this purpose, the UAV can be directed to the disaster site to remedy the failures that may arise in such networks, serving as a router or data mule. Both works are different from this research in that they do not perform the fire detection process in the UAV itself, which can assist in a shorter response time to act. Another difference is related to the merging of information that would be useful to monitor the fire's progress. In addition, the work Ueyama *et al.* [2014] does not explore route planning, which influences the performance of the UAV to complete a given task.

The research Sharma *et al*. [2020] proposed a platform to detect forest fires at an early stage in the context of smart cities. The platform is based on sensors to monitor environmental parameters in real-time. The data collected from the sensors is stored on a cloud server. To better identify the fire event and the use of image processing techniques, a set of rules was defined to carry out the fire detection process. Although the platform is efficient in the fire detection process, such a platform does not investigate the UAV's integration and the WSN to carry out the sensor node's decision-making process. In addition, it does not consider a UAV route planning mechanism with the WSN to monitor how the fire spreads, being aware of the situation for further damage assessment. Therefore, unlike the solutions presented, this research advances in state of the art by proposing a solution that, in addition to detecting forest fires with high precision without compromising the response time, takes advantage of the information provided by the sensors to monitor the progress of the fire, as shown below.

3 A solution to Detect and monitor Forest Fires

This section describes DF-Fire, a solution to detect and monitor forest fires based on UAV and wireless sensors. In DF-Fire, the fire detection process started through notifications from wireless sensors implanted in the monitored environment. A deep learning architecture was modeled to detect fire signals in a device with scarce computational resources (i.e., data processing in UAV). Also, a flight plan module to fly over the area of interest was implemented in DF-Fire. The information obtained from the sensors allows the UAV to restrict the flight plan, maximize the coverage area and its autonomy, and complete the mission with less time. Therefore, the main goal of the DF-Fire is to provide higher accuracy in fire detection without compromising the alert time and maintaining extensive coverage with a shorter response time.

3.1 Problem Formulation

Consider a UAV scenario and n nodes scattered across a region to monitor an event of interest. Thus, such a scenario can be modeled based on an Eulerian graph $G = (V, E)$, where $V(G)$ and $E(G)$ are the vertices and edges of G, respectively. With that in mind, the following definitions have been formulated:

Definition I: *Let be a weighted and oriented graph $G = (W, P)$, where $W = \{w_1, w_2, ..., w_i\}$ represents the set of waypoints in the scenario and $P = \{p_1, p_2, ..., p_i\}$ represents the set of interconnected paths for each waypoint. That is, each p_{ij} of $P(G)$ is the association between two w_i and $w_j \in W \mid w_i \neq w_j$. Considering that each p_{ij} between the vertices w_i and w_j has a unique weight, generating a matrix $M_{i,j} = m_{ij}$ that represents the distances between the waypoints w_i and w_j, $w :\rightarrow \mathbb{R}^*_+$. The scenario is assumed to have static obstacles. Thus, if there is an obstacle between two waypoints $\{(w_1, w_2)\} \in W$, an infinite distance to $m_{1,2}$ is considered. Otherwise, the Euclidean distance is calculated: $d(u, v) = \sqrt{(u_1 - v_1)^2 + (u_2 - v_2)^2}$.*

Definition II: *We assume that the terrestrial region to be monitored is composed of a cooperative network of n sensor nodes and a sink node to form a WSN, being represented by a graph $G = (V, E)$ with the following properties: (i) $V = \{v_1, v_2, ..., v_i\}$ represents the set of sensor nodes, v_1 being the sink node; and (ii) $E = \{e_1, e_2, ..., e_i\}$ represents the communication link between v_i and $v_{i+1} \in V \mid v_i \neq v_{i+1}$.*

The sensor network comprises multi-parameter environmental sensors capable of measuring temperature, humidity, and CO_2 levels. These sensors are distributed across the monitored area to detect anomalies that might indicate the presence of a fire. Upon detecting such anomalies, the sensors initiate the process by sending notifications to the UAV, enabling it to prioritize and navigate efficiently to the identified region of interest. In DF-Fire, we adopted a rotary-wing aircraft[1] to carry out Dull-type missions[2], as shown in Figure 1. To ensure efficient communication and integration between the UAV and the WSN, we assume a communication protocol based on 5G for real-time data exchange. UAV is equipped with a 5G module that facilitates bidirectional communication with the ground sensor base while carrying out its mission from the initial waypoint w_1 to the final waypoint w_n. To synchronize the data between the UAV and the ground sensors, we use a synchronization scheme based on timestamps. Each sensor and the UAV are synchronized with an NTP (Network Time Protocol) server, ensuring that all data has precise timestamps. This is crucial for the accurate correlation of events detected by the sensors with the location and time of data collection by the UAV. In addition, the UAV flies over the fixed height h with constant speed to exchange information with the WSN. Also, we assume that all n nodes know their Cartesian coordinates (i.e., ith node (n_i) has position (x_i,y_i)) via a GPS and that $v_1 \in V$ has two-way communication with the UAV. Thus, it is possible to guarantee interoperability between the different existing systems and more reliable communication. Figure 2 presents an overview of the functioning of DF-Fire, which flies over a forest area with fire signs that a WSN notified. After, the UAV can cor-

[1]Also known as a multirotor, it is a helicopter with high controllability, making it ideal for missions that require precision movement.

[2]Dull-type missions are associated with surveillance that can be long-lasting.

relate the external data from the ground sensors to detect and monitor how the fire spreads to assist the Civil Defense with relevant information, such as the fire area's size, wind direction, and region with possible risks of death. With such infrastructure implanted, it is possible to effectively manage the environment, collaborating with the Civil Defense (i.e., firefighters) and with the population, alerting them through social media.

Figure 1. Characteristics of the UAV used to capture aerial images.

It should be noted that the base station (Figure 2) can process the data locally or send it to a cloud server. Thus, it will be possible to monitor the environment in real-time through devices with access to the Internet. Therefore, both the population and the responsible agencies can view information and receive fire alerts.

3.2 Intelligent fire detection mechanism

In DF-Fire, it is necessary to capture area images using a camera embedded in the UAV to carry out the fire detection process and then process such images and categorize them as fire or not fire. This process is not a trivial task since it is necessary to treat qualitative data from the image to detect the fire. This approach is most challenging when incorporating intelligence into a device with scarce resources, a characteristic present in a UAV. One of the most modern, simple, and effective CNN architectures applied to solve this challenge is AlexNet Krizhevsky *et al*. [2012].

The choice of AlexNet for the fire detection process was motivated by its simple and computationally efficient architecture, which is essential for devices with limited resources, such as the UAVs used in DF-Fire. Additionally, AlexNet has demonstrated solid performance in visual recognition tasks Krizhevsky *et al*. [2012]. Its convolutional layers, combined with the ReLU activation function, provide rapid convergence during training. The simplicity of AlexNet's architecture allows for execution on devices with limited processing and memory capabilities. Moreover, the use of techniques such as dropout helps prevent overfitting, improving the model's generalization. Although more recent CNNs, such as ResNet, DenseNet, and EfficientNet, exhibit superior performance in some metrics, the choice of AlexNet was based on the need to balance performance and computational efficiency, crucial aspects for application in UAVs for forest fire monitoring.

As shown in Figure 3, the AlexNet was modeled based on six convolutional layers, two fully connected layers, and an output layer called softmax. Figure 2 illustrates the architecture's functionality in fire detection, highlighting that the base station can process the data locally. The training of the modeled architecture, specifically AlexNet, was conducted offline at the base station to detect fire. To reduce computational costs, the first two convolutional layers were modified not to perform Local Response Normalization. The Rectified Linear Units (ReLU) activation function, defined as $f(x) = \max(0, x)$ where $x \to \mathbb{R}^+$ is the input for each neuron, was adopted in the remaining convolutional layers. This choice facilitates rapid convergence in the learning process, requiring fewer computational resources and being relatively simple to run on devices with limited capabilities Nair and Hinton [2010]; Krizhevsky *et al*. [2012]. To mitigate overfitting, a dropout technique was applied to the fully connected layers, and the output layer was modified to generate a two-class probability for the fire detection process.

The input layer processes an image of size 227x227x3 (RGB image). The first convolutional layer employs 96 kernels of size 11x11 with a stride of 4, resulting in an output size of 55x55x96, followed by a max-pooling layer with a kernel size of 3x3 and a stride of 2, producing an output size of 27x27x96. The second convolutional layer consists of 256 kernels of size 5x5, yielding an output size of 27x27x256, followed by a max-pooling layer with a kernel size of 3x3 and a stride of 2, resulting in an output size of 13x13x256. The third convolutional layer includes 384 kernels of size 3x3, generating an output size of 13x13x384. The fourth convolutional layer has 384 kernels of size 3x3, producing an output size of 13x13x384. The fifth convolutional layer comprises 256 kernels of size 3x3, yielding an output size of 13x13x256, followed by a max-pooling layer with a kernel size of 3x3 and a stride of 2, resulting in an output size of 6x6x256. Two fully connected layers follow, each containing 4096 neurons, and the final output layer is a fully connected layer with 2 neurons for binary classification (fire or no fire), using the softmax activation function.

3.3 Optimized path planning mechanism

To carry out route planning efficiently in a UAV and understand the objective of the mission, it is necessary to identify the best intermediate points between the start and endpoints to verify the viability of the route. The Traveling Salesperson Problem (TSP) is a classical combinatorial optimization problem that consists of finding a tour with minimal length visiting each waypoint exactly once, including the way back to the initial waypoint. An instance $I = (n, d)$ of TSP with n waypoints $1, ..., n$ consists of the distances between each pair of waypoints, given by $n \times n$-integer matrix *d* (distances). A tour is given as a permutation π of the waypoints $1, .., n$, where $\pi(i)$ denotes the ith visited waypoint. In DF-Fire, the set of optional solutions of an instance $I = (n, d)$ is presented by Equation 1:

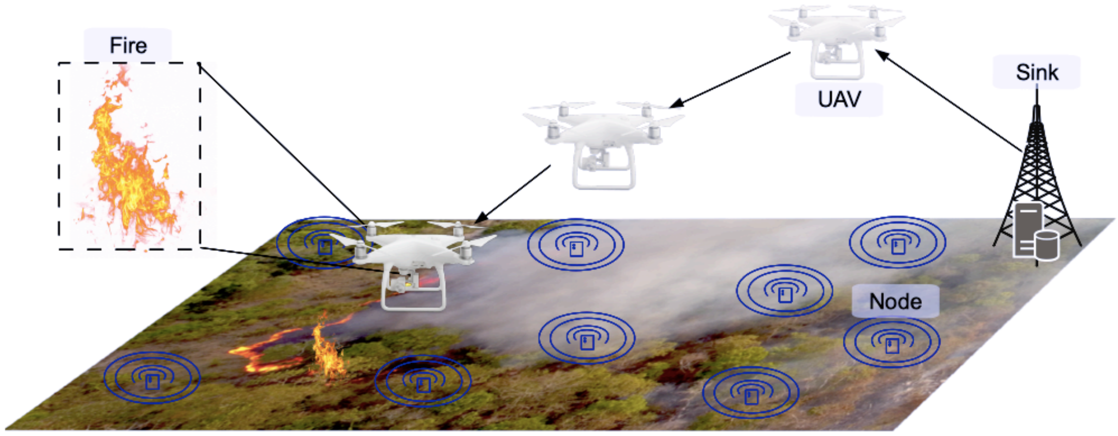


Figure 2. Operation of DF-Fire in a forest area with fire.

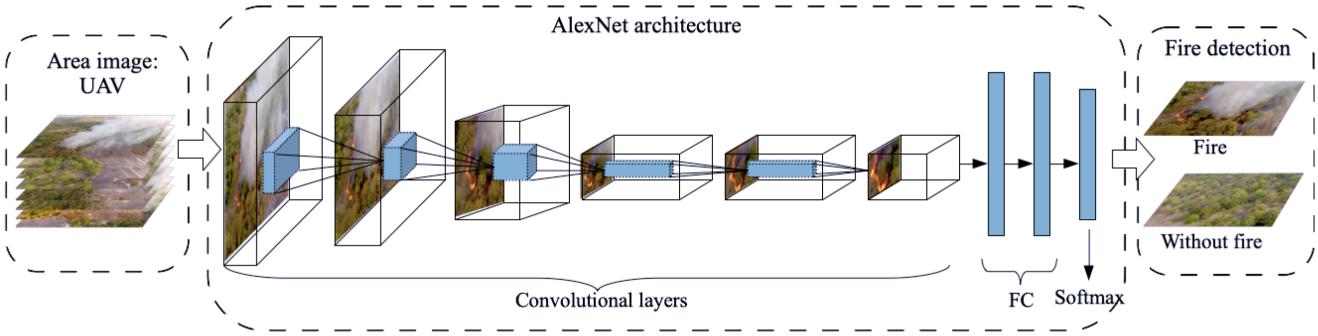


Figure 3. Modeled architecture for the fire detection process.

$$\underset{\pi \in S_n}{\arg\min} \left(d_{\pi(n),\pi(1)} + \sum_{1 \le i < n} d_{\pi(i),\pi(i+1)} \right) \tag{1}$$

where S_n is the symmetric group on $1, ..., n$. However, it is emphasized that the process of choosing points for route planning is not a trivial task, given that there is a lack of knowledge of the monitored location to efficiently direct the UAV in its mission Ueyama *et al*. [2014]; Neto *et al*. [2017]. In this context, that task becomes more challenging, as local knowledge changes as the fire spread.

By obtaining the WSN data, it is possible to understand the dynamics of the monitored environment and the location's knowledge to direct the UAV more efficiently in its mission. For example, it is more important to walk around a location where sensors have reported a high rate of CO_2 in the environment rather than walking through locations of sensors that have reported a low rate of CO_2. With that in mind, we model Lin-Kernighan-Helsgaun (LKH) Helsgaun [2000] in DF-Fire, a variation of Lin–Kernighan (LK) Lin and Kernighan [1973], based on the points provided by the sensors to carry out the planning of the UAV route.

LKH is a local search algorithm, which chooses a region in the search space and moves to a neighboring region to find a better solution. Each movement can convert one candidate solution into another. Given a viable TSP route, the algorithm makes repeated changes to shorten the current route, which only ends when there is no further reduction. The process can be performed several times from randomly generated initial routes.

To do this process, the LKH performs in the DF-Fire k-opt movements on the routes, which changes a route replacing k edges with other k edges, generating a shorter path. For this, we use the proximity metric (proximity - α) that best reflects the possibility of obtaining an edge that is part of the optimal path. Figure 4 shows an example of a 3-opt movement, with the substitution of the edges x_1, x_2 and x_3 with the edges y_1, y_2 and y_3. We used the points provided by WSN as inputs to the LKH. The library elkai[3], written in Python, was used in this study.

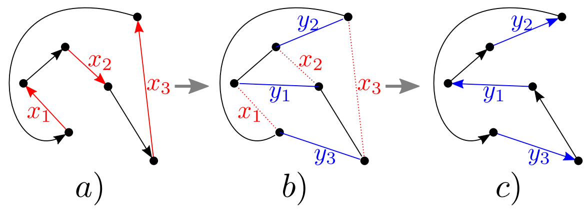


Figure 4. Operation of k-opt movement: a) randomly generated path; b) exchange of edges from x_1, x_2 and x_3 to y_1, y_2 and y_3; c) shortest path that generated from a).

In a previous study conducted by the authors [Freitas *et al*., 2020], an exploratory analysis of algorithms belonging to the TSP class, including LKH, ACO, and GLS, was carried out to comprehend the dynamics of the monitored environment and to effectively guide the UAV in its mission. Based on the empirical findings of this investigation, LKH was selected as the preferred path planning algorithm for DF-Fire, owing to its alignment with the environmental conditions. Both referenced studies present methodologies for data acquisition,

[3] `https://pypi.org/project/elkai`

with a particular emphasis on mitigating issues associated with hotspot detection, and strive to identify suboptimal solutions for TSP instances. However, it is crucial to acknowledge that the selection of an algorithm is contingent upon the specific requirements of the problem and the application. In the context of our research problem, the efficacy of LKH was corroborated by its adeptness in swiftly resolving TSP instances, even when executed on a Raspberry Pi 2 platform. Furthermore, considering the minimal displacement capability of the UAV, the chosen algorithm was deemed well-suited for our solution.

4 Performance Evaluation and Methodology

This section presents the methodology adopted to generate the results through a performance evaluation. For this, DF-Fire was evaluated in two stages. In the first stage, in Subsection 4.1, the capacity of DF-Fire in the fire detection process on a device with scarce resources was evaluated. In the second stage, in Subsection 4.2, DF-Fire's resource management in route planning was assessed. In both stages, the DF-Fire methodology was compared with other traditional methods in the literature. Thus, it was possible to understand the behavior of DF-Fire in the modeled scenarios. Below, we present the modeled scenarios, the metrics used, and the results achieved.

4.1 Performance evaluation to detect fires

To validate the proposed model, we built a dataset of aerial images captured from a UAV. The UAV used to construct the dataset was the DJI Phantom 4 Pro, which has an embedded RGB camera with a resolution of 4000x2250 pixels (See Figure 1). The images were captured in the Guará region of the Federal District of Brazil, as shown in Figure 5, through the Institute of the Criminalistics of Civil Police of the Federal District. The dataset built consists of images of the Brazilian *cerrado*[4] during and after the fire. Each captured image was resized to a fixed size of 300x300 pixels and rotated at a 45-degree angle on its axis until it reached 360 degrees. With that, it was possible to increase the set of images to build the dataset to seven times its original size. To label images and categorize them as fire and not fire, LabelMe Russell *et al*. [2008] was used. Table 1 presents the description of the dataset modeled to validate our solution.

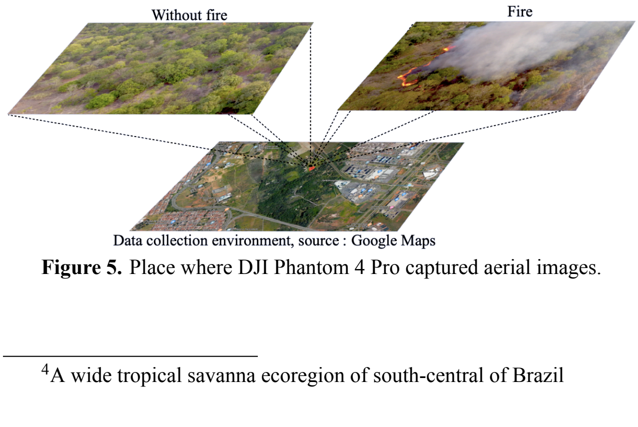


Figure 5. Place where DJI Phantom 4 Pro captured aerial images.

[4]A wide tropical savanna ecoregion of south-central of Brazil

Table 1. Dataset built based on aerial images captured from a DJI Phantom 4 Pro.

Description of the dataset	
Camera model	DJI FC330
Color space	RGB
Dimensions	300x300 pixels
Format	JPG
Label "fire"	107 images
Label "without fire"	180 images

To validate AlexNet's generalizability in DF-Fire, the following image classification algorithms were used in the comparative analysis, namely: (i) DenseNet; (ii) GoogLeNet; (iii) ResNet; (iv) ResNeXt50; (v) Shufflenet; (vi) Squeezenet; and (vii) Vgg11. These algorithms were chosen based on their popularity and established performance in the domain of image classification tasks. Each algorithm represents a different approach to solving image classification problems, which helps provide a diverse set of benchmarks for evaluating AlexNet's efficiency. The k-fold cross-validation with $k = 10$ was used to train and evaluate such algorithms. For this, the dataset was separated into k - 1 training subset and the rest of the test subset. The algorithms of performance was analyzed using two response variables: (i) accuracy represents the percentage of correct answers in the fire detection, and (ii) detection time represents the time that the algorithms take to process a response. To achieve this article's goal, which is to measure the algorithms of viability in environments with scarce computational resources (i.e., UAV), a Raspberry Pi 2 was used to carry out the experiments. To make the training configurations clearer, Table 4 provides a detailed overview of the parameters used. The results of such experiments are presented below.

4.1.1 Impact of the results obtained

Tables 2 and 3 show the results of the metrics about the evaluated algorithms. Note that AlexNet obtained the best results among the comparative algorithms, regardless of the metrics used. It is observed that AlexNet obtained the best performance in 6 experiments out of 10 performed regarding accuracy. In this case, the second-best algorithm, Squeezenet, obtained the best performance in 4 out of 10 experiments. Therefore, in the worst case, AlexNet was 60% more accurate in the experiments carried out to carry out the fire detection process. That happens because the first convolution layers can extract more refined local information, i.e., obtain more treated resources to carry out the fire detection process. Another critical aspect, noted in Figure 6a, is related to the generalization in the results with a slight increase in hits to detect an image with fire. This is identified by the interquartile range of the boxplot and its median, respectively.

When considering the metric of detection time, AlexNet performs the fire detection process with a shorter time in all experiments regardless of the algorithms used (Tables 2 and 3, and Figure 6b). In the best and worst case, AlexNet was at least 2.57 times and 1.1 times faster than DenseNet and Squeezenet to perform the fire detection process, respectively. That is due to LRN's withdrawal in the first two convolutional layers, which reduces AlexNet's computational

Table 2. Impact of the results of accuracy for the evaluated algorithms.

Experiment	Accuracy							
	AlexNet	**DenseNet**	**Googlenet**	**ResNet**	**ResNext**	**Shufflenet**	**Squeezenet**	**Vgg11**
E01	1.0	0.38	0.42	0.50	0.25	0.46	0.92	0.71
E02	1.0	0.54	0.50	0.54	0.42	0.38	0.80	0.92
E03	1.0	0.38	0.58	0.63	0.58	0.38	0.92	0.83
E04	0.96	0.38	0.58	0.50	0.63	0.75	1.0	1.0
E05	1.0	0.42	0.63	0.54	0.67	0.54	0.96	1.0
E06	1.0	0.42	0.54	0.54	0.50	0.58	1.0	0.83
E07	0.96	0.42	0.50	0.83	0.50	0.42	1.0	0.88
E08	1.0	0.30	0.67	0.50	0.54	0.54	0.96	0.75
E09	0.92	0.13	0.38	0.67	0.80	0.54	1.0	0.88
E10	0.89	0.33	0.67	0.63	0.67	0.63	1.0	1.0
Average	0.97	0.37	0.55	0.59	0.56	0.52	0.96	0.88

Table 3. Impact of the results of detection time for the evaluated algorithms.

Experiment	Detection Time							
	AlexNet	**DenseNet**	**Googlenet**	**ResNet**	**ResNext**	**Shufflenet**	**Squeezenet**	**Vgg11**
E01	0.032	0.077	0.051	0.036	0.059	0.051	0.035	0.044
E02	0.030	0.069	0.047	0.033	0.053	0.045	0.033	0.051
E03	0.030	0.070	0.058	0.035	0.060	0.046	0.032	0.041
E04	0.031	0.070	0.050	0.033	0.052	0.048	0.032	0.046
E05	0.030	0.070	0.045	0.033	0.052	0.049	0.031	0.040
E06	0.030	0.087	0.046	0.036	0.057	0.051	0.041	0.047
E07	0.030	0.083	0.046	0.040	0.056	0.057	0.032	0.040
E08	0.030	0.087	0.051	0.039	0.051	0.047	0.032	0.040
E09	0.031	0.080	0.051	0.043	0.051	0.046	0.032	0.040
E10	0.029	0.079	0.047	0.040	0.051	0.045	0.032	0.041
Average	0.030	0.077	0.049	0.037	0.054	0.049	0.033	0.043

Table 4. AlexNet Training Configurations

Training Parameters	
Parameter	**Value**
Initial Learning Rate	0.01
Momentum	0.9
Weight Decay	0.0005
Batch Size	256
Number of Epochs	90
Loss Function	Cross-entropy
Optimizer	Stochastic Gradient Descent

complexity Krizhevsky *et al*. [2012]; Zahangir Alom *et al*. [2018]. Another important factor is related to the low degree of dispersion of AlexNet, indicating stability in the results to detect fire in a shorter time than the other algorithms in the literature, as shown in Figure 6b. That makes sense, as ReLU helps achieve faster convergence in the decision-making process [Nair and Hinton, 2010].

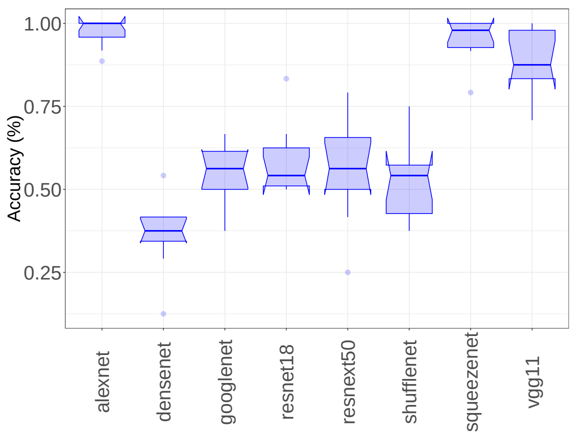
A statistical evaluation with the results obtained was carried out to validate the efficiency of AlexNet with the other algorithms. For that, the results of Tables 2 and 3 were submitted to the post-hoc test. The post-hoc test explores the similarity between the data to ensure whether the results obtained are statistically different or not and provides a performance ranking of each implemented algorithm. For this, the Critical Difference (CD) [Demšar, 2006], which is located at the top of the diagram of Figure 7, informs that two or more algorithms are statistically different if the values of their averages differ by at least the value of the CD. It should be noted that the algorithms closest to the value 1 (Figure 7) are the algorithms that have the best performances.

With this in mind, noted that AlexNet is the algorithm with the best ranking for the accuracy metric (Figure 7a) and detection time (Figure 7b). In other words, AlexNet has a better overall performance ranking regardless of the metrics selected. Still following the algorithms of ranking, squeezenet and vgg11 stand out for the accuracy metric and squeezenet for the detection time metric, which obtained a close ranking with AlexNet. Although AlexNet has no statistically significant difference with Squeezenet, AlexNet has a higher efficiency than the other algorithms with stability in the results. Therefore, AlexNet has a high hit rate, maintaining a fast response time to carry out the fire detection process, making it promising for devices with scarce resources present in a UAV.

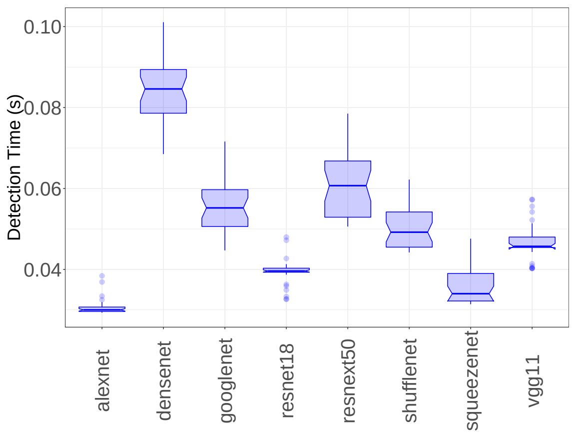
4.2 Performance evaluation in path planning

To validate the route planning in DF-Fire, LKH was compared with the Guided Local Search (GLS[5]) Voudouris and Tsang [1999]. During the evaluation of the LKH scalability in DF-Fire, the experiments were carried out considering the following scenarios: (i) 4x4 km, (ii) 8x8 km, and (iii) 16x16 km. In the three respective scenarios, 15, 62, and 278 sen-

[5]GLS is a global optimization meta-heuristic that uses a local algorithm to find a local search.

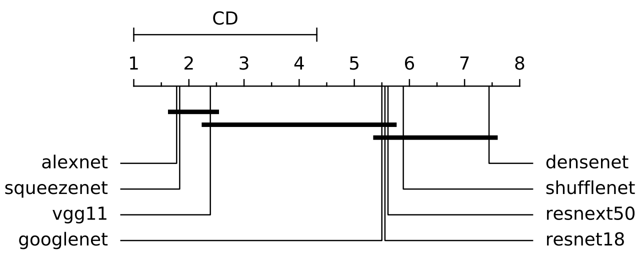


(a) Accuracy

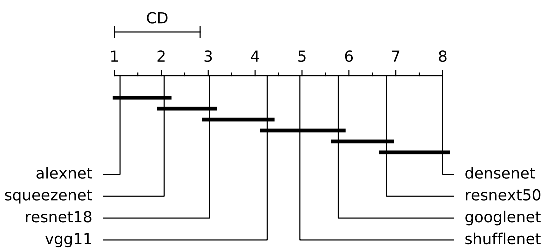


(b) Detection Time

Figure 6. Impact of the performance of accuracy and detection time for the evaluated algorithms



(a) Accuracy



(b) Detection Time

Figure 7. Overall performance ranking of the evaluated algorithms.

sors were randomly distributed. The communication radius used for the sensors was 1km. UAV speed and height were set at 5m/s and 30m, respectively. Figure 8 shows the route plan that DF-Fire made for the three monitored areas. Table 5 presents the parameters used to perform the experiments.

Table 5. Set of parameters used in the experiment.

Description of parameters	
Wireless interface	802.15.4, 2.4 GHz
Monitored area	4x4 km, 8x8 km, and 16x16 km.
Number of Nodes	15, 62 and 278
Communication rage	1km
UAV speed	5m/s
UAV height	30m
Number of replications	33
Confidence Interval	95%

The evaluation aims to determine the efficiency of the route planning in a device with scarce resources. It was used as metric the memory consumption, processing time, and the distance covered by the UAV. The experiments were performed 33 times, with 95% confidence based on the t-student distribution [Student, 1908]. The results obtained are presented below.

4.2.1 Impact of the results obtained:

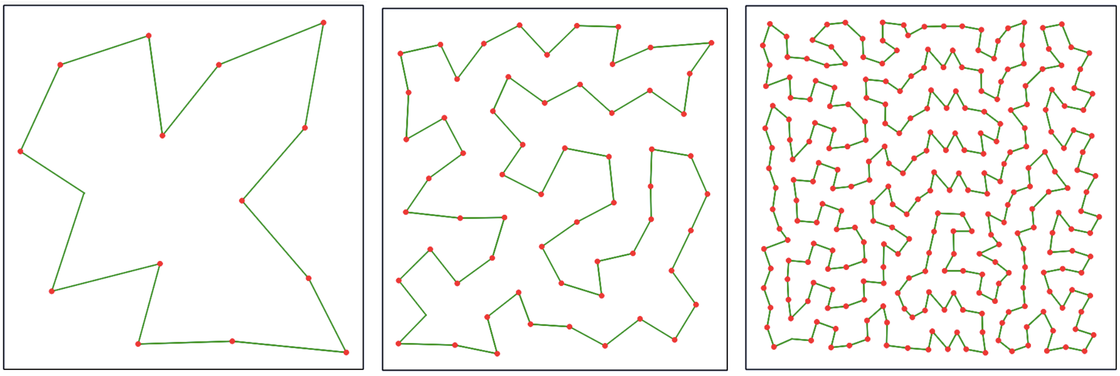
Figure 9 shows the resources management of DF-Fire's route planning through a comparative analysis between LKH and GLS. Figure 9a shows the results of the time metric to solve TSP regarding the monitored area. Regardless of the monitored area, LKH has a shorter time when compared to GLS. In the worst case, LKH is 3.5 times faster to perform TSP compared to GLS. That is related to the k-opt mechanism that converges faster in its sub-searches to reach a consensus on the best route. That can be confirmed by the variation of the time metric that tends to regular growth in the LKH as the monitored area increases, differently from the GLS that there is an abrupt growth in time.

After evaluating the time to solve TSP, we analyzed memory usage during route planning, as shown in Figure 9b. Through these results, it was observed that the LKH memory usage is 1.54 times less in the best case (monitored area 4x4km, Figure 9b) and 1.36 times less in the worst case (monitored area 16x16km, Figure 9b) when compared to GLS. That makes sense because, in GLS, the cost of finding the optimal location in the local search can be penalized and reassessed. As a result, GLS can consume more memory compared to LKH.

Figure 9c shows the distance covered by the UAV, varying the monitored area and the number of sensors visited. The results show that the LKH and GLS are statistically equivalent in the distance covered, regardless of the monitored area and the number of sensors visited. This is consistent since both belong to the same class of TSP. This similarity confirms the efficiency of LKH in our solution, which has characteristics present in an embedded real-time system with little computational resources. Therefore, in addition to consuming less memory with less time, our solution does not compromise the area's monitoring about the distance covered.

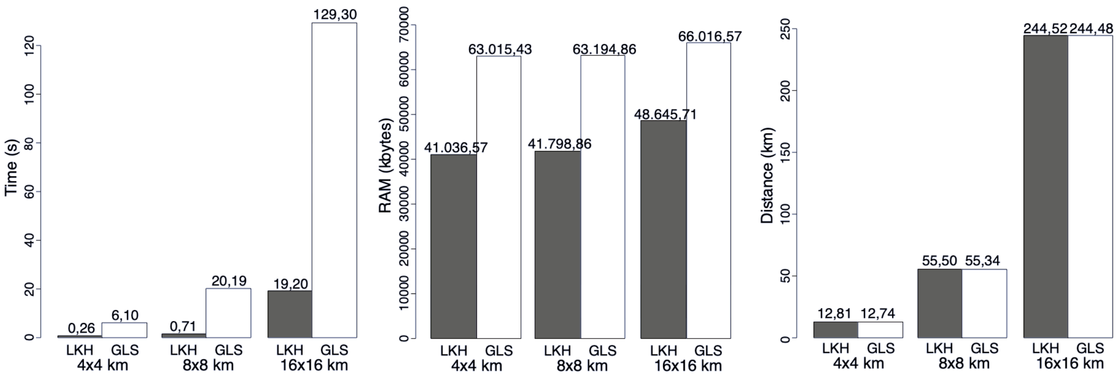
4.3 Discussion of the results

In this study, we conducted a performance evaluation of DF-Fire, focusing on two primary aspects: fire detection capability and route planning efficiency. Our findings offer insights



(a) Monitored area 4x4km **(b)** Monitored area 8x8km **(c)** Monitored area 16x16km

Figure 8. Path planning for three squares.



(a) Time **(b)** RAM **(c)** Distance

Figure 9. Performance impact of time to solve TSP, used memory and travelling distance

into the determinants of accuracy and underscore the potential for model refinement to bolster overall performance in fire detection applications.

The focus on the Brazilian Cerrado in this study was motivated by its critical ecological importance and high fire incidence, making it a priority for fire detection solutions. However, we acknowledge that this focus limits the generalization of the DF-Fire model to other biomes or urban interfaces where forest fires often spread. Variations in environmental conditions, vegetation types, and fire behavior across different biomes require a more diverse dataset to ensure robust model performance in varied scenarios.

The analysis also revealed that factors such as image quality—encompassing resolution, clarity, and atmospheric interference—significantly affect the model's performance. Additionally, the diversity and representativeness of the dataset are crucial in shaping the model's capacity for effective generalization across various fire scenarios. The sensitivity of the selected algorithms to parameters like learning rate and batch size further emphasizes the importance of algorithmic fine-tuning to optimize detection accuracy.

While successful instances demonstrated the model's resilience and efficacy in accurately detecting fires amidst challenging conditions, certain scenarios highlighted the model's limitations. These limitations, attributed to occlusions, misclassifications, and constraints inherent to the dataset, underscore the imperative for ongoing model refinement and adaptation. Such efforts are crucial for addressing emergent challenges and ensuring dependable performance across diverse environmental contexts.

In addition to comparisons with deep learning algorithms, DF-Fire's unique integration of UAVs and WSNs offers advantages over existing fire detection technologies, such as satellite-based systems and alternative AI-powered UAV solutions. Satellite systems are effective for large-scale monitoring and early detection but are often limited by spatial resolution and response time due to data transmission delays. On the other hand, AI-powered UAV systems typically focus on localized detection but may lack the integration with ground-based sensor networks to optimize flight paths or monitor fire spread effectively. DF-Fire bridges this gap by combining real-time UAV responsiveness with the environmental data provided by WSNs, enabling efficient fire detection, optimized flight planning, and continuous monitoring of fire dynamics.

5 Conclusion and future research

In carrying out this research, it was evident that one of the leading global challenges faced by society worldwide is related to the forest fire problem. Such a problem generates tremendous financial losses, threatens ecological systems, and affects public security, putting human life at risk. Despite recent efforts to mitigate the forest fire problem, providing a higher hit rate to detect the fire, with a quick response time, without impacting the alert process is still a challenging research question that this article has investigated.

Given the above, this research proposed DF-Fire, a solution to mitigate the forest fire problem that, in addition to increasing the fire detection process's accuracy, aims to improve efficiency in response time and reduce overhead processing time. Through the real results, DF-Fire showed its feasibility in dealing with the forest fire problem, surpassing the benchmarking solution. The main contributions of our article include the following:

- increasing the hit rate to detect fires with 60% accuracy, in the worst case;
- efficiency in response time with 10% improvement, in the worst case; and
- low overhead in processing time without impacting the alert process.

Also, DF-Fire takes advantage of the sensors' information to provide efficiency in the flight plan and correlate them to monitor how fires spread.

Although it advances the state of the art, DF-Fire has limitations that need to be considered. One of the main limitations is the range, as the communication between the UAV and the WSN can be affected by physical obstacles and electromagnetic interference, which was not taken into account in this research. This can limit DF-Fire's coverage area and the accuracy of collected data. In addition, the UAV can be affected by weather conditions, for instance, winds, which can reduce the accuracy of the fire detection process. Another important limitation is that UAV operation may be subject to regulatory restrictions, limiting the use of these systems in some areas and environments.

As future work, we plan to enhance the robustness of DF-Fire by addressing potential limitations identified in this study, such as occlusions, misclassifications, and dataset constraints. Additionally, we aim to investigate the scalability of DF-Fire to larger and more complex environments, which may involve optimizing computational resources and exploring distributed computing approaches. Finally, we intend to extend our experimental setup to include an analysis of the computational complexity of the algorithms using Big-O notation.

Declarations

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Authors' Contributions

All authors contributed equally to the preparation of this article.

Competing interests

The authors declare no conflict of interest.

Availability of data and materials

The datasets analyzed during the current study are available from the corresponding author on reasonable request.

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