A Framework for Wildfire Inspection Using Deep Convolutional Neural Networks

Novac, Iuliu; Geipel, Kenneth Richard; Gil, Jacobo Eduardo de Domingo; Paula, Lucas Goncalves de; Pedersen, Kristian Hyttel; Chrysostomou, Dimitrios

Published in:
IEEE/SICE International Symposium on System Integration

DOI (link to publication from Publisher):
10.1109/SII46433.2020.9026244

Publication date:
2020

Document Version
Accepted author manuscript, peer reviewed version

A Framework for Wildfire Inspection Using Deep Convolutional Neural Networks

Iuliu Novac*, Kenneth Richard Geipel*, Jacobo Eduardo de Domingo Gil*,
Lucas Goncalves de Paula*, Kristian Hyttel* and Dimitrios Chrysostomou†

* Dept. of Materials and Production, Aalborg University, Fibigerstraede 16, Aalborg East, DK-9220, Denmark
Email: {iuliu, kenneth, lucas, jacobo, kristian}@ student.aau.dk

† Robotics and Automation Group, Dept. of Materials and Production,
Aalborg University, Fibigerstraede 16, Aalborg East, DK-9220, Denmark
Email: dimi@mp.aau.dk

***Abstract*—This paper presents the details of a holistic framework designed for wildfire inspection and estimation of its geolocation. The system is built around a low-cost, commercial quadcopter, and the main areas of interest we address in this paper are the semi-autonomous navigation of the drone, the training and classification of fire using deep convolutional neural networks, the estimation of the size and location of the wildfire and the real-time feedback and communication with the user. The evaluation of the functionality of the system demonstrates that with the combination of the proposed techniques we can successfully detect and classify fire in video streams at 19.2 FPS while we can calculate the size and location of the fire with an accuracy of 60.76%.**

***Index Terms*—wildfire inspection, quadcopter navigation, deep convolutional neural networks**

I. Introduction

As the frequency of extreme weather phenomena increases rapidly [1], and their violent nature escalates due to climate change [2], the initial attack success rate of wildfires eventually raises as well [3], [4]. Emergency response personnel, across the globe, struggle to contain the increase of wildfire size, numbers and severity. In the summer of 2018, California experienced the largest wildfire in the state's history, [5] in Sweden emergency personnel were overwhelmed by the numbers of forest fires, [6], [7] and in Greece, two violent fires left 250 injured and 105 dead. Considering the above, emergency services are investigating how flying robotic technologies can facilitate a faster and more accurate data gathering procedure from wildfires, to increase the efficacy of firefighting operations [8], [9].

The needs of the firefighters and requirements for timely response to a wildfire were determined through a collaboration with the Danish Emergency Management Agency (DEMA) and interviews with Evan Bek Jensen, the second in command of the Herning drone unit. Discussing the potential of a new product versus current available methods, it became evident that accurate information about the location, size, intensity and direction of a wildfire were essential for better allocation of their resources.

The backbone of the proposed framework is based on the integration of a low-cost, commercially available quadcopter with an off-the-shelf RGB-D camera and DCNNs that enable semi-autonomous navigation, inspection of the wildfire and remote control via a handheld device. The contribution of this work lies in the holistic combination of the presented technologies to collect, process and transmit the data acquired from the area of interest to the user providing the emergency services with a quick and accurate overview of a wildfire.

A. Related Works

A number of systems have been developed in order to triangulate the location of a wildfire. Most of these include multiple sensors in order to acquire an accurate location of the fire. Martínez-de Dios et al. recorded the same fire pattern or smoke from different angles and compared the position of the sources recording the fire and key terrain features to each other using four sensors, two UAVs and two ground based cameras [10]. Merino et al. used multiple sensors, mounted on three UAVs, and compared the location according to each of the UAVs while recorded the contour of the fire, in order to predict the direction of the fire spread [11]. In our case, we only utilise a single quadcopter equipped with an off-the-shelf RGB-D camera and on-board altitude and GPS sensors to identify the properties of the fire in the area of interest.

Studies in regards to fire recognition have been presented via a consumer grade monocular camera system. Lum et al. were able to detect wildfire, but also predict its development with regards to vegetation or burned area [12]. Furthermore, Yuan et al. showed that detecting fire can be based not only on the fire palette, but also on the optical flow of the moving flames [13]. In our work, we estimate the size and location by utilising edge and BLOB detection to detect the edges of the fire inside the area of interest provided by the firefighter.

Firefighters have been using quadcopters for gathering data during the last decades, and accommodate a wide range of quadcopter sizes, sensors and classification approaches [14]. In order to distinguish fire from other objects, that is within the same color spectrum, such as fire trucks or firefighter uniforms, DCNNs can be utilized in order to classify the BLOBs within the same color spectrum [15]. In our work, we train the DCNNs with video streams instead of single static

(a) Intel Aero Ready-To-Fly Quadcopter

(b) Intel RealSense R200

(c) Microsoft Surface Go

Fig. 1. Hardware setup used for the proposed framework

images and we achieve a classification accuracy of 60.76% in a relatively high frame rate of 19.2 FPS.

II. Proposed Framework

The hardware used for this work relies on an open-source quadcopter, the Intel Aero Ready-To-Fly quadcopter coupled with the Intel Realsense R-200 RGB-D camera, as depicted in Fig. 1. In order to have the required computational power to process the acquired data, a computer acts as a master, although the system is controlled by an intuitive user interface on the handheld device. Fig. 2 illustrates the framework's main functionalities. Upon arriving at the site of an emergency, the operator of the quadcopter works in collaboration with the incident commander, to assess the situation and identify in which area the quadcopter must be put into action (Fig. 2a). Utilising the GUI on the tablet, the operator is presented with a topological map, to select an area of interest (Fig. 2b). The quadcopter autonomously flies to this area and begins to search the area for signs of a fire (Fig. 2c), flying in a snake pattern (Fig. 4). The quadcopter streams the collected data to the master computer for further processing, and in the event that a wildfire is recognized, calculates its location and size. This information is then overlaid onto the topological map of the GUI, providing data visualization for the firefighters to consider when allocating resources (Fig. 2d).

(a) The firefighter arrives on site and assess the situation

(b) The firefighter selects the area of interest

(c) The quadcopter scans the selected area

(d) The operator receives a visual feedback of the fire's size and location

Fig. 2. Infographic of the stepwise process on the use of the developed framework

III. System Overview

The proposed framework can be separated into three main pillars, which are described in the following subsections. Fig. 3, illustrates an overview of the subsystems. The process starts with the operator interacting with the GUI on the tablet and provide the area of interest. The coordinates are transmitted to the drone which autonomously navigates and inspects the area. Potential features are extracted and DCNNs assist with the their classification to different classes related to wildfire. Based on this data, the size and location of the fire is calculated and the quadcopter later transmits the coordinates and video video stream of the search area to the operator's tablet.

A. Autonomous Area Navigation

In order for the quadcopter to acquire and process the footage of the fire, an area navigation algorithm was developed to autonomously cover the area around the wildfire. To begin with, the quadcopter receives the message from the master computer containing the user's input. This message features a set of two coordinates and two lengths to determine the edges of the rectangle where the area navigation is to be performed. This is then implemented into the autonomous flying algorithm. An area sweep is performed inside the designated rectangle following a snake pattern, as shown in Fig. 4. The pattern is followed alongside the Fire Detection Algorithm, described in subsection III-B. Once a fire is detected an alarm is sent which stops the quadcopter from moving forward. This occurs to stop the quadcopter from flying inside a smoky environment that will potentially damage the on-board sensors.

B. Feature Extraction and Classification

In order for the feature extractor and classifier to be lightweight and provide a close to real-time data processing performance, the initial search of wildfire is contained within the fire color spectrum by masking the input frame. The BLOBs extracted from this color spectrum search, can be seen in Fig. 5a and 5b. A region of interest is created surrounding these BLOBs and they are later passed forward to a deep convolutional neural network where the rest of the image is cropped.

A custom built database was used for the training and validation of the DCNNs using an image scraper that contains the keywords listed in Table I, running through Google, Yandex and Bing search engines. Furthermore, this database is built to

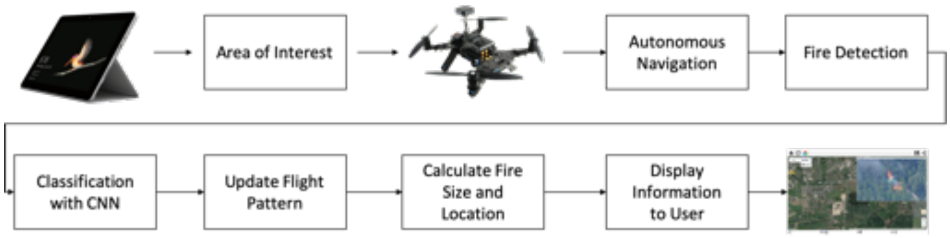


Fig. 3. The overall functionality of the framework

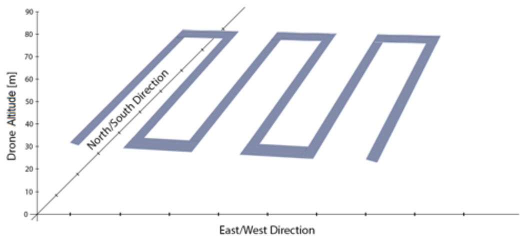
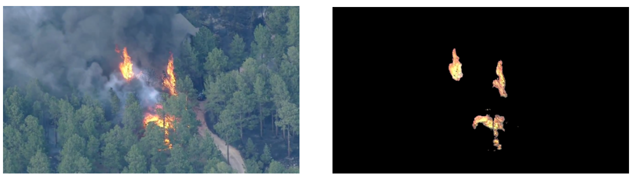


Fig. 4. The quadcopter navigates in a predefined pattern



(a) Original Frame (b) Extracted features of interest

Fig. 5. Results of the feature extraction process in data from the search area

be continuously evolving as every 100^{th} frame of the video input, when the quadcopter is in operation, will be passed onto the database, with a label depending on the classification at that moment. Moreover, as a collaboration with DEMA was established, operational footage was provided which is also integrated into the database. In order to establish which CNN architecture would best suit this system, six different CNN architectures were trained and tested on the data from the built database. These are: VGG16 [16], DenseNet [17], Inception v3 [18], MobileNet v2 [19], ResNet 50 [20] and NASNetMobile [21]. These architectures where primarily chosen as they are lightweight models, while VGG16 will serve as a reference of performance. Their respective performance in our classification task is compared in Table II.

TABLE I
IMAGE SCRAPPER KEYWORDS

Keywords for Fire	Keywords for Firetrucks
Fire	Firetruck
Forest Fire	Firetrucks
Forest Wildfire	Fire Truck
Wildfire	Fire Trucks
Wildfire Drone Footage	
Wildfire from Above	
Wildfire Top View	

C. Wildfire Size and Location

Due to the collaboration with DEMA, video footage of real firefighting operations in Denmark, was obtained as Fig. 6 depicts. This is footage from Dokkedal, Denmark, where a real fire in a field is shown. DEMA operates with thermal imagery, and scans the area within a range of 80-800° Celsius, in order to eliminate any noise.

In order to estimate the location and size of the fire, the algorithm first determines the edges of the scanned area by applying Canny edge detection. The presented image is required to be in grey scale, while the algorithm detects differences in intensity, which can be adjusted by a threshold. Finally it sets the edge pixels to 1 while non-edge to 0.

Once the edges have been identified, the second part of the algorithm calculates the distances to the edges, compared to the quadcopter's GPS position, in order to calculate the size of the fire. Fig. 7 illustrates a general approach of this, visualized viewing from the side to highlight how this is calculated. The height of the quadcopter is represented with H which is provided from the quadcopter's altitude sensor. Knowing two angles, and the altitude of the quadcopter, $L2-L1$ represents the fire size and can be calculated by 1.

$$L2 - L1 = tan(A2 + A1) * H - tan(A1) * H \quad (1)$$

Based on 1, an algorithm was developed to calculate the

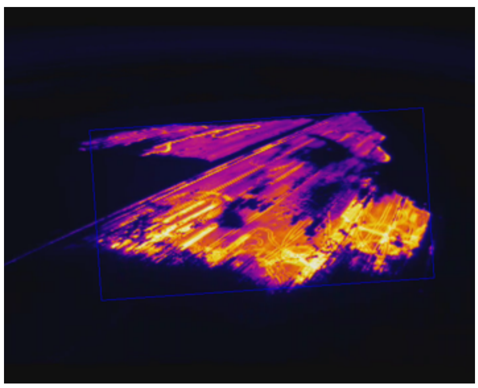


Fig. 6. Snippet of thermal imagery from Dokkedal, captured by DEMA quadcopter unit.

location and the size of the detected wildfire, and determine the optimal way of combating the wildfire. This algorithm is based on the camera's lowest FOV point aimed straight down from the quadcopter's position. Therefore, the entire FOV of the camera can be used rather than only half, from the standard front-facing mount of the camera. This is also done due to the necessity to address the error that arises near the horizon of the input image.

The algorithm uses the angle of the camera and ratios to calculate the size and position of wildfire accurately. In 2 we calculate a ratio of where the wildfire's initial position is, in relation to the height of the image, given as a percentage.

$$FireStart = 100 - \frac{FireEdgeStart}{ImageHeight} * 100 \qquad (2)$$

Where, *FireEdgeStart* is the position of the pixel at which the fire starts and *ImageHeight* is the entire height of the input image. This value is subtracted from 100 to find the ratio from the bottom of the image instead of the top. This is necessary because the origin of pixels in the image is in the top-left corner. Eq. 2 is applied twice to find the initial and final position of the fire. Using these ratios, the angles related to the two points can be calculated with 3.

$$FireStartDeg = FireStart * \frac{FOV}{100} \qquad (3)$$

Where, *FireStart* is the value of 2 and *FOV* is the field of view of the camera. This calculation is also performed twice. The results are angles in degrees from the bottom of the image, which represents the point at which the fire starts and ends. After these two calculations have been completed, the distance to each point can be established applying the trigonometric functions as shown in 4.

$$FireDistStart = \tan(FireStartDeg) * Height \qquad (4)$$

Where, *FireStartDeg* is the result of 3 and *Height* is the altitude of the quadcopter when the input image was taken.

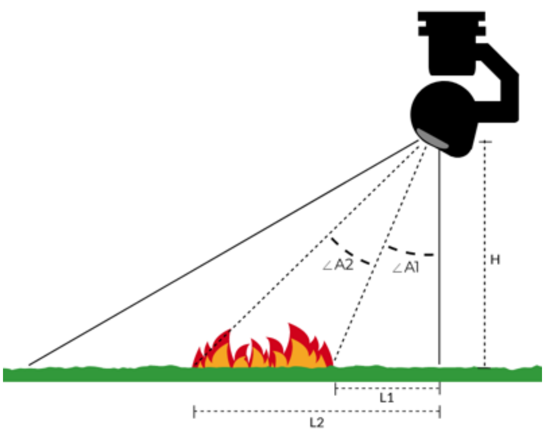


Fig. 7. Side view of the fire size calculation algorithm

D. Graphical User Interface

In order for the operator to interact intuitively with the handheld device, simple GUI was designed. The GUI acts as a command unit for the quadcopter and it acts as the main means of communication and visualization between the operator and the quadcopter. It sends the coordinates for the delimited area of navigation and displays the output feedback sent from the quadcopter. It is a Python-based interface combined with Google Maps API, to display the topological map and overlay the rectangle for the desired area.

Fig. 8 illustrates the main display of the GUI and showcases the functionalities of the GUI. This includes a pop up window featuring the RGB footage streamed from the quadcopter while the acquired footage from the fire is shown with a bounding box set by the fire detection algorithm.

An editable rectangle in the middle of the screen allows the user to delimit the area where they want the navigation to be performed. A new message will be sent to the master computer every time that the rectangle is changed, containing *(i)* the length of the north/south direction, set in meters and *(ii)* the east/west direction in meters are set to establish how much the quadcopter should move to either side, before the quadcopter moves back along the north/south direction.

IV. Communication

Communication between the operator and the quadcopter is essential in emergency cases such as wildfire identification. Therefore, a special subsystem is designed to organize the communication to be established among the different parts of the system. This consists of managing what information and channels are established between the quadcopter, the master computer and the handheld device, as seen in Fig. 9.

The first step requires the establishment of a constant stream between the quadcopter and the master computer to enable stable transmission of the video stream, GPS Location, altitude measurements and orientation data. This is then relayed from the master computer onto the tablet to keep the telemetry readers updated for the user in real-time. After this point, the communication follows the steps of the process as described in the block diagram in Fig. 3. The master

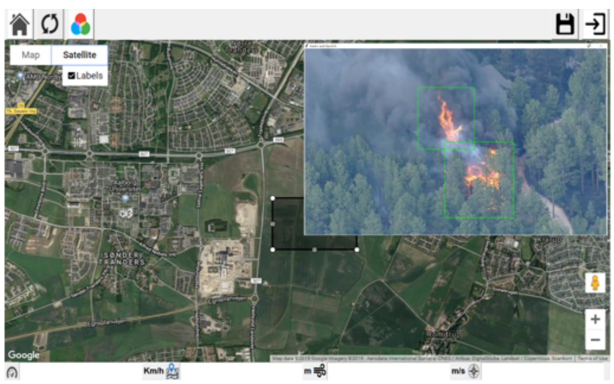


Fig. 8. Illustration of the Graphical User Interface

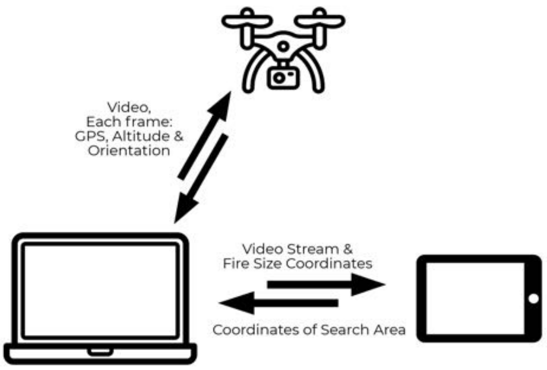


Fig. 9. The main communication channels of the proposed framework

computer acts as an intermediate point during the entirety of the connection. This is done to process the footage and run the feature extraction and classification algorithms.

The handheld device transmits the coordinates based on the square boundaries set by the operator. The quadcopter uses these coordinates as inputs for performing the autonomous navigation of the desired area whilst running the fire detection algorithm. Once the pixels in the video match the RGB threshold, the classification algorithm will determine the nature of the detected objects. This triggers the master computer to send a new flight pattern in order to avoid flying directly on top of the fire, which could potentially damage the on-board sensors. The quadcopter then proceeds with flying around the fire while running the size and location estimation algorithm and relaying this information back to the tablet. Finally, the tablet overlays a graphic of the identified fire on the topological map for the user to see.

V. Evaluation

To evaluate the functionality of the framework, a series of tests were performed following the steps of the block diagram in Fig. 3. Initially, multiple tests performed to evaluate the ability of the system to transmit successfully the coordinates of the area of interest. As every test resulted to a drawn rectangle around a certain area in the map and the coordinates saved into external files of the northeast and southwest corners and transmitted to the drone, this subsystem is considered that performs adequately every time. Regarding the autonomous navigation, the quadcopter was able to fly following the snake pattern inside a rectangle of 60×80 meters at an altitude of 30 meters in every test.

The fire identification algorithm was able to successfully detect the right RGB threshold and draw a bounding box around the fire objects in the video stream. According to the results presented in Table II, MobileNet v2 performed optimally as it was able to differentiate both fire and non-fire objects, having the smallest amount of parameters compared to the validation accuracy and loss and able to run faster than the rest at 19.2 FPS. Lastly, numerous tests for the fire size algorithm were performed showing that it could successfully calculate the location and size of the fire with an average accuracy of 60.76%.

VI. Conclusions

This paper describes a framework for identification of wildfires using an autonomous quadcopter, image processing algorithms and classification based on DCNNs. The main outcome of the performed tests shows that the system can autonomously navigate through an area of interest, successfully detect and accurately classify a suspicious area as wildfire and then calculate its size and location in correlation to the quadcopter's GPS position. The framework's performance provides significant edge during the decision making on allocating resources when combating wildfires by providing a deeper understanding of the current situation.

Further development of this system will integrate a thermal camera, in order to enhance the detection capabilities of the vision system and increase the accuracy of the size and calculation of the fire. Moreover, as this framework is based on the premises that the area of interest is flat, future development of the algorithm will consider 3D areas and inclined areas with multiple heights and occlusions. Lastly, as the frames utilised here should always contain the whole area of the fire, there is a potential interest in adapting the framework to detect the same location of the fire when only fragments of the area of interest are provided.

References

[1] A. Mackay, "Climate change 2007: impacts, adaptation and vulnerability. contribution of working group ii to the fourth assessment report of the intergovernmental panel on climate change," *Journal of Environmental Quality*, vol. 37, no. 6, p. 2407, 2008. [Online]. Available: https://doi.org/10.2134/jeq2008.0015br

[2] I. P. on Climate Change, *Climate Change 2013 The Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, 2014. [Online]. Available: https://doi.org/10.2134/jeq2008.0015br

[3] D. M. Romps, J. T. Seeley, D. Vollaro, and J. Molinari, "Projected increase in lightning strikes in the united states due to global warming," *Science*, vol. 346, no. 6211, pp. 851–854, 2014. [Online]. Available: https://doi.org/10.1126/science.1259100

[4] D. G. Woolford, C. Dean, D. L. Martell, J. Cao, and B. Wotton, "Lightning-caused forest fire risk in northwestern ontario, canada, is increasing and associated with anomalies in fire weather," *Environmetrics*, vol. 25, no. 6, pp. 406–416, 2014. [Online]. Available: https://doi.org/10.1002/env.2278

[5] M. Park, "California fire explodes in size, is now largest in state history," 2018 (accessed 04-02-2019). [Online]. Available: https://tinyurl.com/y5t7uapf

[6] E. Toft, "80 skovbrande i sverige: Nu skal folk forlade et helt omrde," 2018 (accessed 04-02-2019). [Online]. Available: https://tinyurl.com/dr-sverige

[7] S. Coogan, "Rekordstor europisk hjlp mobiliseret til bekmpelse af svenske skovbrande," 2018 (accessed 04-02-2019). [Online]. Available: https://tinyurl.com/dr-sverige2

[8] B. Smith, "Are drones the future of firefighting?" 2014 (accessed 13-02-2019). [Online]. Available: https://tinyurl.com/y5yvqv7k

[9] D. Gates, "Drone tracks fire hot spots in successful olympic forest test," 2015 (accessed 13-02-2019). [Online]. Available: https://tinyurl.com/y4egvn9o

TABLE II
PERFORMANCE COMPARISON OF THE CHOSEN CNN ARCHITECTURES

	Parameters	FPS	Validation Accuracy	Validation Loss
VGG16 [16]	41,458,499	1	0.9974	0.02092
ResNet 50 [20]	23,593,859	16.4	0.9938	0.02339
Inception v3 [18]	21,808,931	13.7	0.9929	0.01811
DenseNet [17]	7,040,579	14	0.9965	0.02442
NASNetMobile [21]	4,272,887	12	0.9894	0.03812
MobileNet v2 [19]	2,261,827	19.2	0.9947	0.01980

[10] J. Martínez-de Dios, L. Merino, F. Caballero, and A. Ollero, "Automatic forest-fire measuring using ground stations and unmanned aerial systems," *Sensors*, vol. 11, no. 6, pp. 6328–6353, 2011. [Online]. Available: https://doi.org/10.3390/s110606328

[11] L. Merino, F. Caballero, J. Martinez-de Dios, and A. Ollero, "Cooperative fire detection using unmanned aerial vehicles," in *Proceedings of the 2005 IEEE international conference on robotics and automation*. IEEE, 2005, pp. 1884–1889. [Online]. Available: https://doi.org/10.1109/ROBOT.2005.1570388

[12] C. W. Lum, A. Summers, B. Carpenter, A. Rodriguez, and M. Dunbabin, "Automatic wildfire detection and simulation using optical information from unmanned aerial systems," SAE Technical Paper, Tech. Rep., 2015.

[13] C. Yuan, Z. Liu, and Y. Zhang, "Vision-based forest fire detection in aerial images for firefighting using uavs," in *2016 International Conference on Unmanned Aircraft Systems (ICUAS)*. IEEE, 2016, pp. 1200–1205. [Online]. Available: https://doi.org/10.1109/10.1109/ICUAS.2016.7502546

[14] C. Yuan, Y. Zhang, and Z. Liu, "A survey on technologies for automatic forest fire monitoring, detection, and fighting using unmanned aerial vehicles and remote sensing techniques," *Canadian journal of forest research*, vol. 45, no. 7, pp. 783–792, 2015. [Online]. Available: https://doi.org/10.1139/cjfr-2014-0347

[15] W. Lee, S. Kim, Y.-T. Lee, H.-W. Lee, and M. Choi, "Deep neural networks for wild fire detection with unmanned aerial vehicle," in *2017 IEEE international conference on consumer electronics (ICCE)*. IEEE, 2017, pp. 252–253. [Online]. Available: https://doi.org/10.1109/ICCE.2017.7889305

[16] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014. [Online]. Available: https://doi.org/10.1109/ACPR.2015.7486599

[17] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 4700–4708. [Online]. Available: https://doi.org/10.1109/CVPR.2017.243

[18] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 2818–2826. [Online]. Available: https://doi.org/10.1109/CVPR.2016.308

[19] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "Mobilenetv2: Inverted residuals and linear bottlenecks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 4510–4520. [Online]. Available: https://doi.org/10.1109/CVPR.2018.00474

[20] K. He, X. Zhang, S. Ren, and J. Sun, "Identity mappings in deep residual networks," in *European conference on computer vision*. Springer, 2016, pp. 630–645. [Online]. Available: https://doi.org/10.1007/978-3-319-46493-0_38

[21] B. Zoph, V. Vasudevan, J. Shlens, and Q. V. Le, "Learning transferable architectures for scalable image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 8697–8710. [Online]. Available: https://doi.org/10.1109/CVPR.2018.00907