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DC-Fire: a Deep Convolutional Neural Network for Wildland Fire Recognition on Aerial Infrared Images

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Abstract

This paper presents a novel deep learning method, called DC-Fire, for recognizing wildland fires using aerial infrared images. Experimental results show that DC-Fire achieved a high performance with an accuracy of 100% and an F1-score of 100% using a large dataset and data augmentation techniques, better than classical machine learning and baseline CNN methods. In addition, DC-Fire demonstrated its potential in detecting smoke and flames, surpassing challenges including small areas of fire/smoke, background complexity, and the variability of forest fires in terms of size, shape, and intensity.

1. Introduction

Wildland fires cause damage and impact numerous aspects of human life and the environment, including economic losses, air pollution, ecological imbalances, and human safety. For example, in 2023, more than 2000 fires affected 5,291,261 hectares in Canada, causing the evacuation of tens of thousands of people [1]. In addition, firefighting costs in Canada over the past decade ranged between $800 million and $1.5 billion per year [2]. Researchers are therefore developing and implementing early fire detection and recognition systems to improve early detection of wildfires and to reduce their impact [3, 4, 5, 6, 7].

Recently, IR (infrared) sensors were adopted to accurately recognize wildfires and identify their affected areas, thanks to their ability in detecting the heat patterns emitted by fires, even when smoke and/or flames are not visible. Numerous wildland fire systems were developed to prevent the damage caused by wildfires, by using RGB and IR sensors, as well as by applying deep learning (DL) techniques to identify wildfire areas [8, 9, 10]. Among them, Huang et al. [11] presented a Wavelet-ResNet50 method to improve fire detection performance and reduce false alarms. First, the 2D Haar transform was employed to extract spectral characteristics from RGB images. Then, ResNet50 [12] was adopted to identify and recognize fires. Using fire and fire-like images, test results showed that Wavelet-ResNet50 achieved a high F1-score of 94%, better than the state-of-the-art methods. Reis and Turk [13] employed deep learning models, including Inception v3 [14], DenseNet-121 [15], ResNet-50 v2 [16], VGG-19 [17], and NASNetMobile [18] in classifying wildfire using aerial RGB images. The pretrained DenseNet-121 with ImageNet dataset performed well, with an accuracy of 99.32%, compared to other DL models. Ghali et al. [19] also proposed a DL method, which combines the EfficientNet [20] and DenseNet methods to classify forest fires on RGB aerial images. The proposed method obtained an F1-score of 84.77%, outperforming the baseline methods. Bahhar et al. [21] developed DL method, namely MobileNetV2 Baseline, to recognize wildfires using aerial RGB images. MobileNetV2 Baseline is a modified MobileNet v2 method [22], by adding a pooling layer, a dropout layer, and a classification layer. Using FLAME dataset as aerial data, MobileNetV2 Baseline reached a great performance with an accuracy of 99.3%. In [23], a simple CNN (Convolutional Neural Network), namely IRCNN, which comprises nine convolutional layers, was used to extract features from IR images. Then, an SVM (Support Vector Machine) was adopted as a classifier to detect flames. Testing results showed that the hybrid model achieved a high precision of 98.82%. In [24], five deep CNNs (LeNet5 [25], MobileNet v2, Xception [26], ResNet-18, and VGG-16) and logistic regression method as a classical machine learning method were studied in recognizing wildfires from aerial IR images. Using a large dataset FLAME2, VGG-16 achieved the best F1-score of 97.35%. Deng et al. [27] developed a two-layer concatenated CNN model to identify the fire zones and the type of burning substances using infrared images. They used two simple CNNs, namely front-end CNN and Back-end CNN. The front-end CNN was employed to eliminate the background information and improve the detection performance. The back-end CNN extracts the fire characteristics then generates optimal detection results. Experimental results showed a superior performance with a detection rate of 95.3% compared to AlexNet and VGG-16 [27]. Xavier et al. [28] also studied seven deep CNNs such as MobileNet v2, ShuffleNet v2, GoogeLeNet, and VGG-16 in detecting early fires using IR images. Test results showed that ShuffleNet v2 achieved the best validation performance, with an accuracy of 87.8% in comparison with the other models.

DL methods performed well in detecting wildland fires. However, few DL models were developed to recognize wildfires using aerial infrared remote sensing data and to address challenges such as background complexity, and the variability of fires in terms of intensity, size, and shape. For such, in this work, we present a novel ensemble learning method, DC-Fire, to identify and recognize wildfires on aerial infrared images. DC-Fire combines DenseNet-201 [15] and EfficienNet-B5 [20] methods to extract smoke/fire features in the IR spectrum.

Two main contributions were introduced in this work:

- A novel ensemble learning method, called DC-Fire, was presented for classifying forest fires on infrared aerial images, thus improving the performance of DL-based wildfire recognition methods.

- DC-Fire showed a strong ability in recognizing wildland fire areas as regions with high temperatures and smoke areas as zones with distinct thermal properties, and in dealing with challenges, including background complexity, the detection of small fire/smoke areas, and the variability of fires regarding their size, intensity, and shape.

The rest of the paper is organized as follows: Section 2 introduces the proposed DC-Fire method and the dataset used for training and testing. In section 3, the experimental results were discussed. Section 4 summarizes the paper.

2. Materials and Methods

In this section, we first introduce our proposed ensemble learning method, DC-Fire, for forest fire recognition. Then, we present the IR aerial dataset used to train and test DC-Fire.

2.1 Proposed Method

To detect and recognize wildland smoke and fires, we proposed a new deep learning method, namely DC-Fire, which combines the DenseNet-201 [15] and EfficientNet-B5 [20] models, as shown in Figure 1. First, data augmentation techniques such as rotation, zoom, shift, and shear were used to diversify the training data. Next, the infrared input data and generated data were fed simultaneously into the DenseNet-201 and EfficientNet-B5 models to extract rich and relevant features, including important patterns and characteristics related to smoke and fire. After concatenating the two feature maps generated by DenseNet-201 and EfficientNet-B5, an average pooling was applied to reduce the spatial dimensions of this concatenated feature map. Then, a Gaussian dropout with a rate of 0.3 was applied as a regularization method to improve DC-Fire generalization by adding noise to the input infrared images, as well as to prevent overfitting. Finally, a sigmoid function generated a probability value between 0 and 1, indicating the presence of forest fires and smoke in the input images.

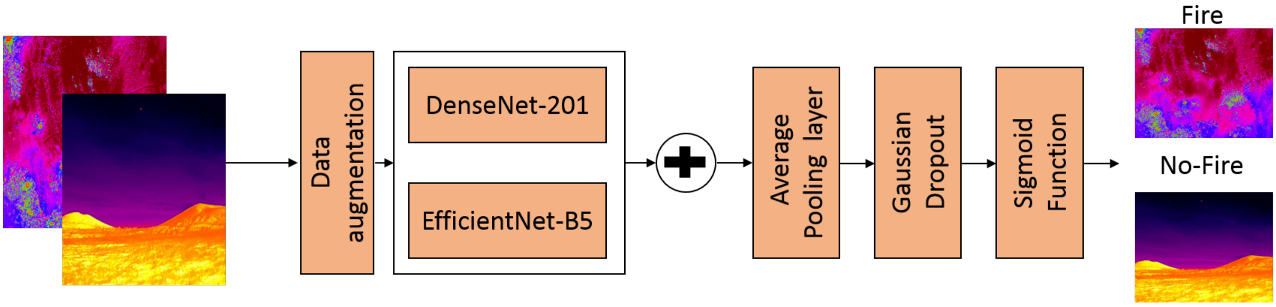

Fig. 1. *The proposed architecture of DC-Fire*

2.2 Dataset

In order to train and evaluate the proposed method, DC-Fire, we used the public dataset FLAME2 [24], collected by DJI Mavic 2 Enterprise Advanced drone in a forest in northern Arizona. Infrared images captured with an uncooled VOx (vanadium oxide) microbolometer sensor, which collects a 640 x 512 pixel array and characterizes temperature from -40 ℃ to 550 ℃ and from -40 ℃ to 150 ℃ for low-gain and high-gain image capture, respectively. FLAME2 consists of 53,451 aerial infrared (wavelength range of 8 to 14 μm) images with a resolution of 254 x 254 pixels, including 14,317 fire/no-smoke images, 25,434 fire/smoke images, and 13,700 no-fire/no-smoke images. Figure 2 depicts FLAME2 dataset examples, including fire/smoke images and no-fire/no-smoke images.

3. Results and Discussion

We developed DC-Fire using TensorFlow on a machine with Intel(R) Xeon(R) CPU (E5-2620 v4), 64 GB of RAM, and an NVIDIA Geforce RTX 2080Ti GPU. We also split the training data into three sets to train and test our proposed model DC-Fire, as shown in Table 1: training (34,208 images), validation (8552 images), and test (10,961 images).

A learning rate of 0.001, a batch size of 8, and 150 epochs were used during the training process. Moreover, we utilized the categorical cross-entropy loss function (see equation (1)) :

$$Cross - entropy = -\sum_{c=1}^{A} z_a \log(p) \tag{1}$$

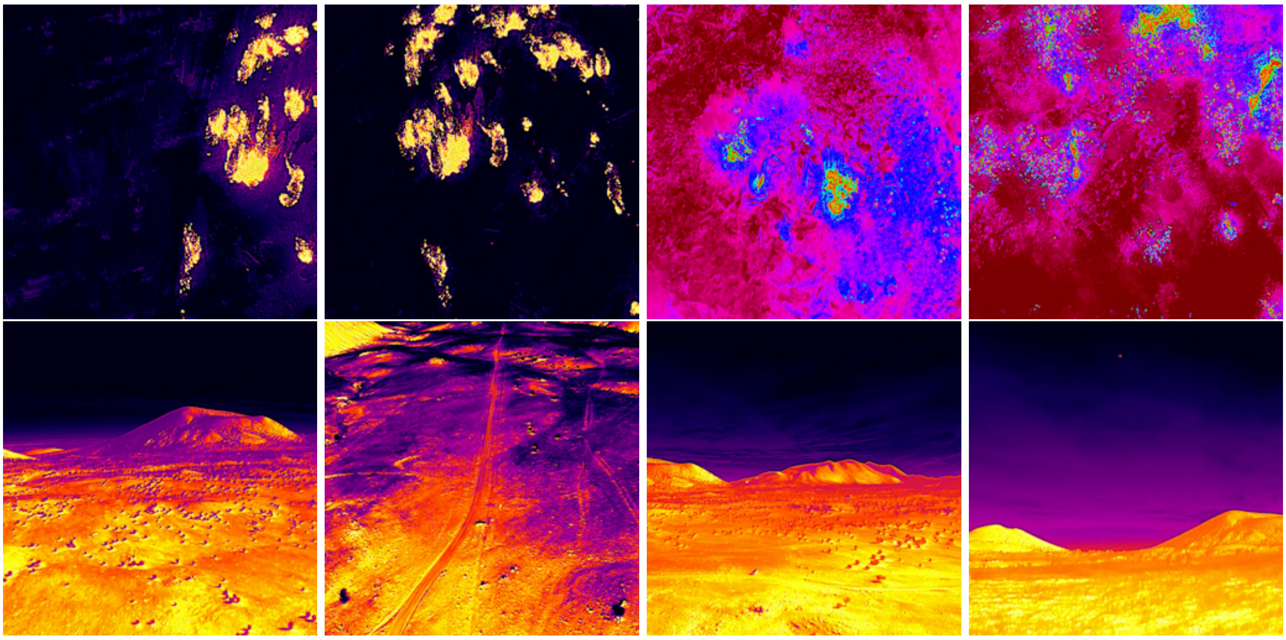

Fig. 2. *FLAME2 dataset example. (**Top**): Fire images; (**Bottom**): no-Fire images.*

Table 1. *Dataset subsets.*

Data	Fire Images	No-Fire Images	Total Images
Training set	25,440	8768	34,208
Validation set	6360	2192	8552
Testing set	7951	2740	10,691

where A is the number of classes (in our case, two classes), z is the binary indicator, and p is the predicted probability.

As shown in Table 2, testing results showed that our proposed method, DC-Fire, achieved excellent performance with an accuracy of 100% and an F1-score of 100%, thanks to the rich and diverse feature maps extracted by the DenseNet-201 and EfficientNet-B5 models. These models select a wide range of characteristics at varying scales, thus enabling DC-Fire to correctly identify and classify forest fire/smoke patterns in aerial infrared images. Based on the F1-score, DC-Fire outperformed the existing DL methods, Xception, LeNet5, ResNet-18, VGG-16, and MobileNet v2 by 13.19%, 7.70%, 3.46%, 2.65%, and 2.49%, respectively, as well as the traditional machine learning method, logistic regression, by 7.39%. It demonstrated its potential in recognizing forest fire/smoke and overcoming challenges, including the detection of small wildland fire areas, background complexity, and varying wildfire intensity (wildfire surfaces with flame lengths ranging from 0.25 to 10 meters).

Figure 3 predicts the confusion matrix of DC-Fire using testing data. We can see that the true positive rate, showing correctly predicted Fire images, and the false positive rate, representing incorrectly predicted Fire images, are equal to 7951 and 0, respectively. Furthermore, the true negative rate, determining correctly predicted no-Fire images, is 2740, and there are no false negative images (representing incorrectly predicted no-Fire images). This demonstrates the strong ability of DC-Fire in distinguishing between fire/smoke and background, and in performing well in recognizing smoke/fire on IR aerial images.

Table 2. *Comparative analysis of DC-Fire.*

Models	F1-score (%)	Accuracy(%)
Logistic regression [24]	92.61	92.43
LeNet5 [24]	92.30	92.15
Xception [24]	86.81	85.79
VGG-16 [24]	97.35	97.29
MobileNet v2 [24]	97.51	97.38
ResNet-18 [24]	96.54	96.29
DC-Fire	**100.00**	**100.00**

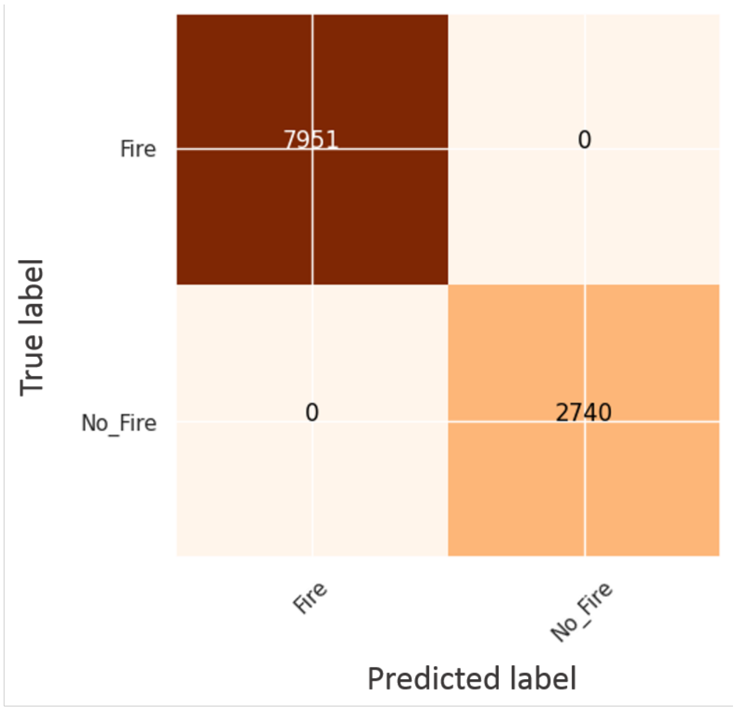

Fig. 3. *Confusion matrix of DC-Fire*

In summary, DC-Fire demonstrated its potential to accurately identify forest smoke and fires on IR aerial images. It performed well in various challenging situations, including background complexity, small forest fire areas, and varying fire characteristics such as shape, intensity, and size.

4. Conclusions

In this work, we introduced a novel deep learning architecture, namely DC-Fire, for recognizing forest smoke and fires using aerial infrared images. DC-Fire achieved an accuracy of 100% and an F1-score of 100%, surpassing existing classical machine learning and CNN methods. It demonstrated its reliability in identifying forest smoke and fires, dealing with numerous limitations, including background complexity, small wildfire areas, and varying wildfire intensity. In future work, we plan to evaluate DC-Fire in detecting smoke/fires using both RGB and infrared images.

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