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An Intelligent Surveillance Model for Wild Forest Fire Detection Using Deep Learning for Drone Application

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ABSTRACT

Wild forest fires are among the most hazardous catastrophes, causing substantial losses in numerous regions; in order to create a well-efficient forest fire detection system, modern methods must be used to create the system, and one of the modern methods at the present time is deep learning. The objective of this study is to develop an intelligent surveillance model for detection and classification of uncontrolled forest fires utilizing a convolutional neural network (CNN) and a forest fire dataset for drone applications. The goal is to develop an intelligent model that can detect wild forest fires and classify their severity. In this proposed system, the CNN consists of 13 layers, starting from the input layer, which is a single layer with dimensions proportional to the size of the image used, and ending with the output layer, which consists of three layers: the FC layer, the SoftMax classifier, and the classification outputs. It determines how many rows this convolutional neural network can use, and there are two categories (fire, no fire). In addition, there are 9 middle layers, where these layers are mainly repeated from the convolutional layer, Max Pooling, and ReLU. Where each layer has its own measurements, number of filters, and method of movement. Extensive simulations were conducted and the findings were recorded from several aspects. Through the results, there is a technical improvement in the proposed system in various measures. On the data set utilized, the proposed system yielded favorable outcomes, with an average prediction accuracy of 98%.

1. INTRODUCTION

Improving forest fire prevention and detection schemes could be considered a primary objective to conserve the environment [1]. At present, fire of forest is frequently causing severe producing natural disasters and threats to the environment and real emergency situations. Emergency response time is very important and greatly impacts the losses and consequences that result from them. The most recent technologies are employed to optimize the detection of forest fires, control and their presence reporting, defensive surveillance systems, and CNNs. Utilizing a variety of techniques to analyze an image in order to identify patterns and significant information [2]. These networks rely on the application of transformational sequences. The advantages of using CNNs and surveillance cameras in systems detection of fire. The network is trained using a vast collection of images depicting fires and other related scenarios. CNNs are then employed to detect fires in the system. that they can accurately identify different patterns so these networks are trained on a large set of pre-classified images. Surveillance cameras are employed by fire detection surveillance systems to acquire real-time images of target areas [3]. These systems are capable of identifying these patterns in new images and determining whether a fire is present. Saeed et al. [4] presented A fire prediction Adaboost MLP model. The model is made up of many MLP models that have been enhanced using Adaboost and was trained using temperature samples for validation and sensor data. Temperature forecasts became more accurate as a result. Additionally, CNN and Adaboost-LBP models are proposed for smoke and fire detection, outperforming conventional CNN models in accuracy. Fire regions of interest are captured by the Adaboost-LBP model, but CNN classifies these regions of interest more accurately. Barmpoutis et al. [5] suggested a unique method for detecting fires that combines spatial texture analysis and deep learning. In order to differentiate between fire-colored objects and genuine fire, it applies a Faster R-CNN and VLAD encoding for the detection of candidate regions. When tested on fire photos and objects, the method shows reduced false positives and high true positive rates. Future research entails growing the dataset and refining the method for identifying fire in video clips. Wang et al. [6] suggested a CNN and a modified Gaussian kernel function are combined to provide a unique segmentation method for apple recognition. With the enhanced Gaussian kernel function, regions from big, complicated areas can be quickly segmented. The suggested method performs better in real-time and accurately identifies small and medium-sized apple photos, according to experimental results, than other methods currently in use. Further research endeavors will concentrate on refining the approach through the integration of deep learning methodologies and using it in real-world engineering scenarios. This work leads to the creation of more reliable and effective segmentation algorithms and opens the door for future developments in Apple recognition. Abdulsalami and Whangbo [7] introduced a novel method for locating and separating shadow pixels from moving objects. The method comprises steps like boosting contrast in the image, taking background information out, applying a geometry-based method to remove shadows, reducing noise and completing the moving object mask's gaps. This method effectively addresses problems such as ghosting artifacts and backdrop resemblance with the current image. In order to tackle difficult shadows in outdoor conditions, the researchers suggest adding a CNN in future upgrades. The ultimate goal is to apply this technique in smart cities so that items in motion may be precisely identified by their forms and efficiently tracked. In the studies [8-10], a novel detection model was proposed to enhance the contrast of images and to detect them, respectively, using histogram techniques and a new CNN architecture. The studies [11-13] have introduced a novel architecture of CNN for the purpose of matching images in an authentication system. In the studies [14, 15], the YOLO algorithm, which is based on deep learning, and the B pi 3 raspberry model have been proposed as a true model for object detection.

The capabilities of these models were then extended using convolutional autoencoder adjustments to better detect forest fires in smoke. It constructed a forest fire and smoke detection model using a CNN and compared it to other algorithms. To make a benchmark that reflects the real impact of such a model in use and the overall performance of a reliable smoke detection algorithm based on a convolutional neural network, he analyzed the direct impact factors. The detection and prediction of smoke and flames are both important and challenging tasks in the process of video-based wildfire search and recognition. The real-time processing of visual information captured by camera devices, network transmission securities, low-bandwidth constraints, embedded system implementations, and other factors make these tasks become more complex [16]. A review of earlier studies confirms that, at the moment, there are few highly efficient fire detection research models. The forest fire detection system is based on embedded algorithms for background subtraction and accelerating fire detection by combining the Gaussian Mixture Model (GMM) and the Support Vector Machine (GMM-SVM), becoming the intelligent video surveillance (IVS) system for fire protection. A survey has shown the basic fire and smoke detection algorithms such as templates, background subtraction, image imaging is not efficient enough for video-based forest fire detection. This research also suggests that conventional data analysis methods do not offer good analysis for image data. Therefore, the development of new methods to analyze image data is essential and interesting for exploratory data analysis in the future. After reviewing UAV-based systems, there are still no systems [17].

In this paper, a new intelligent model has been developed to overcome these limitations, specifically for wild forest fire detection and classification as a high-level surveillance model for drone applications. Analysis is done on the suggested classifier architecture for wild forest fire classification with high accuracy, the least amount of computation time and expense. We recommend the use of deep CNNs that are based on the deep learning model to present an intelligent model and to develop a technological system intended to identify fire incidents.

The paper is structured as: Section 2 presents mathematical model for CNN Layers. The proposed system is introduced in Section 3, which also provides an overview of the CNN and its structure. Section 4 provides findings and a discussion. The conclusion of the research is presented in Section 5.

2. MATHEMATICAL MODEL FOR CNN LAYERS

The study [18] provides a description of the mathematical model for CNN layers. A CNN's convolutional layer uses the input data to extract intricate and abstract features. An activation function using various weights and biases can enhance the abstract properties of the convolutional layer.

Eq. (1) shows how CNN's convolutional process works.

$$x_l^j = f\left(\sum_{i \in Pn} x_i^{j-1} * w_{il}^j + b_l^j\right) \tag{1}$$

where, j = component; w = weight; b = basis; l = number of layers.

The CNN is enhanced with a pooling layer to enhance the quality of features obtained from the convolutional layer. This is because, as Eq. (2) illustrates, discriminant features are critical for precise classification.

$$x_l^j = f\left(w_l^j * \max\left(x_i^{j-1}\right) + b_l^j\right) \tag{2}$$

In which x_1^j is the maximum pooling function. CNN utilizes many convolutional layers and pooling techniques to improve its capacity to extract local information from the input data. The CNN uses the pooling and convolutional layers to extract hidden data, then classifies the input into the relevant categories. CNN does this by using a fully connected layer.

A fully connected layer is represented by Eq. (3), which uses the convolution kernel to classify the latent properties.

$$f x^{j+1} = \left(\sum_{i=1}^{n} w_{il}^j a^{j(i)} + b_l^j\right) \tag{3}$$

3. PROPOSED SYSTEM OR FRAMEWORK

This section introduces the proposed model for wild forest fire surveillance, which involves detecting forest fires and classifying the situation into two categories: forest flames or no fire flames.

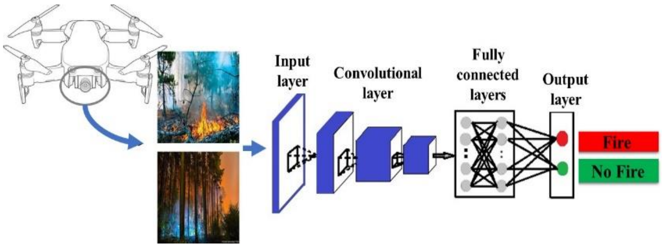


Figure 1. An overview of proposed framework for wildfire detection

This work proposes an intelligent surveillance model for wild forest fire detection and classification using a CNN and dataset for drone application. The proposed surveillance system is based on using CNN and dataset to create a technological system aimed at detecting fire incidents that is applied. The proposed CNN network, which has previously been trained on images of both non-fire and fire environments, receives the processed individual fire detection photographs from the system. Every single fire location is categorized as CNN Net's output.

An overview of the proposed framework for wildfire detection in surveillance network is provided in Figure 1.

3.1 Dataset collection and preparation

One of the system requirements is dataset for fire detection and classification [19, 20]. This database contains many different images of forests depending on time, place, and different environmental conditions. It is of two types, the first type represents forests that contain fires, and the second type represents forests that do not contain fires.

Figure 2. Samples of forest none fire dataset

Figure 3. Samples of forest fire dataset

The images were processed in terms of augmentation and each category contains (1500 for each class) images, size only in order to be compatible with the first layer of the proposed difficult network, which is (512 × 512 × 3), meaning the length is 512, the width is 512, and the depth is 3. The depth here is meant the color image (RGB). No other processing was performed on the images, such as conversion to grayscale or anything else, to preserve the data in the images. Because in any image processing procedure, there is a loss of part of the actual image data. Here we try to keep the information from the real reality and use the most accurate data that represents the real reality. Figure 2 represents examples of images of forests without a fire, while Figure 3 represents examples of images in which there is a fire.

3.2 Test environment

One of the stages of building the proposed model is the training stage. In the training phase, a new neural network is designed and trained on the specified size and type of dataset. In this model, two types of images are trained: there is fire or there is no fire. Figure 4 represents a diagram for the proposed fire detection and classification model. Establishing and training the network requires specific systems, devices, and specifications. The size of the data, the proposed neural network, and the number of categories that must be classified affect the choice of device and system specifications. In this model, the MATLAB programming language was used and a desktop computer with specifications of Intel (R) core (TM) i7- 4790 CPU at 3.60 GHz, fourth generation processors at 3.60 GHz, and a Random-Access Memory (RAM) capacity of 8.00 GB with an operating system. 64 and using Windows 10 pro. GPU type uses NIVIDIA GeForce GTX 1060 RAM 3GB.

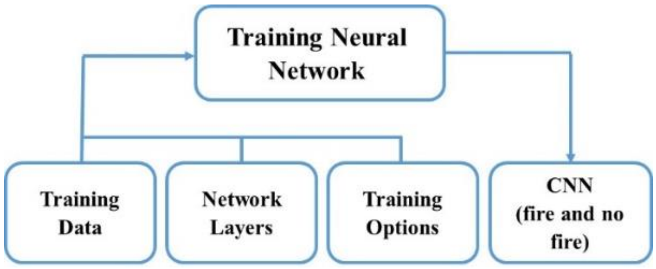


Figure 4. Proposed fire detection and classification model

3.3 CNN

Artificial neural networks, or algorithms modeled the framework and operations of the human brain, are the focus of deep learning, a subfield of machine learning [21]. Deep learning techniques are based on a multi-convolutional layer with a fully connected layer, including CNN, which are based on a reliable technique for classifying and extracting features [22, 23]. A CNN is a transfer learning model, which can be trained with a large amount of data.

Table 1. Detailed description of the proposed CNN layers

No.	Name Layer	Filter Size	Number of Filters	Movement is Horizontal	Movement is Vertical
1	Convolution	33×	7	1	1
2	Max Pooling	33×		3	3
3	ReLU	2		2	2
4	Convolution	33×	10	1	1
5	Max Pooling	2×2		2	2
6	ReLU	2		2	2
7	Convolution	33×	10	1	1
8	Max Pooling	2×2		2	2
9	ReLU	2		2	2

The CNN has been presented since 2012. In this paper, a CNN was proposed for use in the model to detect fire locations and classification fire in forests. This CNN consists of three main parts: the input part, the output part, and there is a middle part. Each part consists of one or several layers, and each layer performs a specific task and depends on a different mathematical process. In this work, the total number of layers in the CNN used is 13 layers. In the input part, there is one layer, which is the input layer, and the dimensions used are length, width, and depth (512, 512, 3), respectively. These dimensions depend on the image used in the training phase as well as the prediction phase. After the input part follows the middle part which consists of 9 layers. The layers of the middle part consist mainly of three types of layers, which are the convolution layer, the max pooling layer, and the ReLU layer. Each layer has a number of filters, which are of specific sizes and movement path. Each filter, its size, method and type of movement are explained in Table 1. The output part consists of three layers: the fully connected layer, SoftMax, and the classification output. Through the output layer's part, the number of classes that the CNN can recognize has been determined, and here two types or classes can be recognized: fire or no fire, after the training process is completed.

4. SIMULATION RESULTS AND DISCUSSION

To create an artificial intelligence system based on deep learning, there is a convolutional neural network. An important aspect of creating this convolutional neural network is teaching it to recognize the things that it will recognize or discover. In this model, a CNN network consisting of 13 layers was used, as shown in Figure 5. To train this network, we rely on a database containing two types of images: with forest fires and without forest fires. Examples of these images are as shown in Figures 2 and 3. To perform the training process, a set of settings was used, as shown in Table 2. The dataset used in this study consisted of 3000 different images. Following that, 80% of the data was used for training, 5% for validation, and 15% for testing. Figure 6 shows the process of training a CNN. A CNN is used after the training process in the proposed model to detect fires in forests. The flow chart in Figure 7 shows the model's operation to detect fires. Likewise, Figure 8(a) and (b) show examples of the model's work, how it detects forests that have fires and forests that do not have fires. It also gives in each model a percentage of whether or not there are fires in the image.

The effectiveness of various techniques and additional variables in classification is evaluated using Eqs. (4)-(8) [24].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{4}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{7}$$

$$\text{F1} - \text{score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

The abbreviations TP, TN, FP, and FN stand for true positive, true negative, false positive, and false negative, respectively. We achieved a 98% training accuracy.

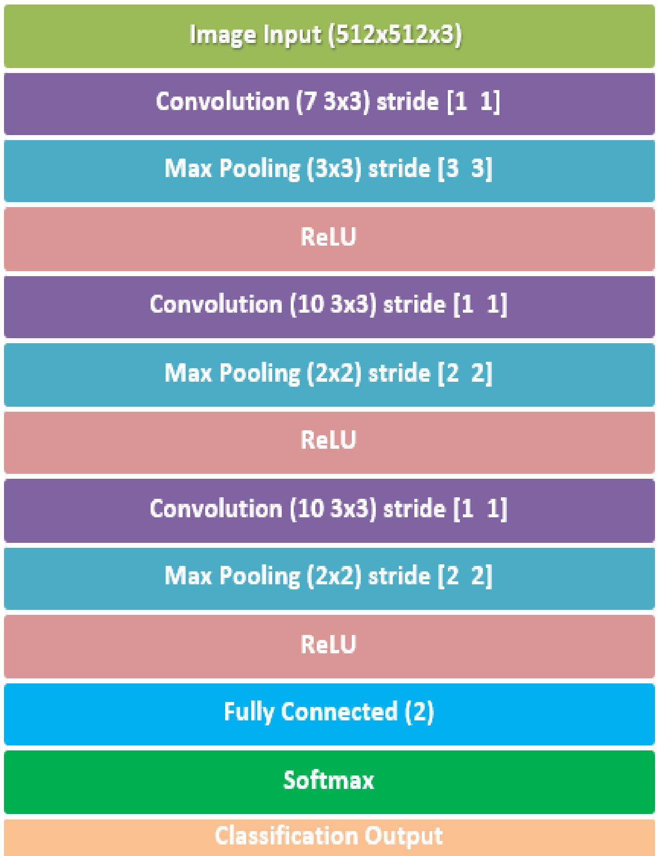


Figure 5. The employed CNN architecture thirteen layers

Table 2. The CNN network's instruction options that were selected

No.	Option	Settings
1	Epoch	700
2	Execution Environment	GPU
3	Validation Frequency	20
4	Verbose Frequency	50
5	Mini Batch Size	128

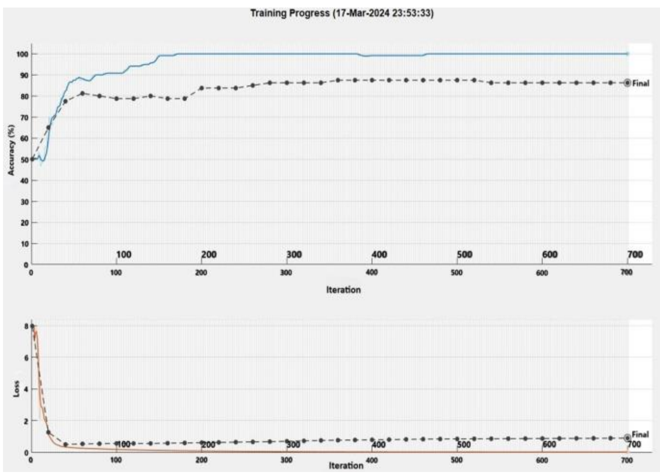


Figure 6. Performance of the proposed system in terms of training progress

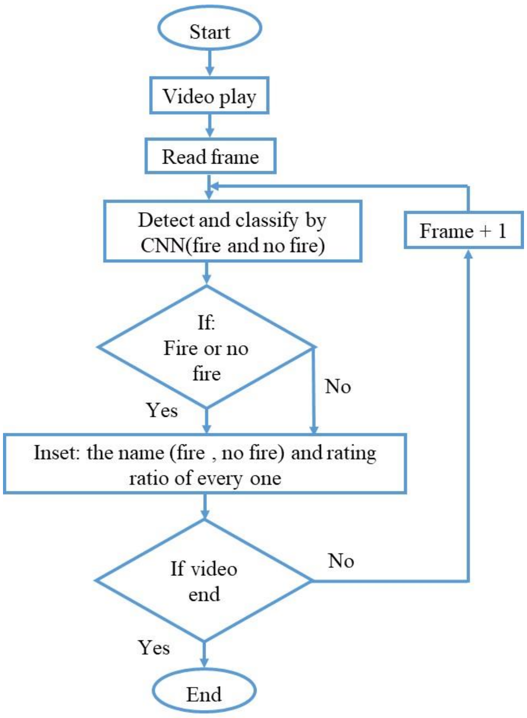
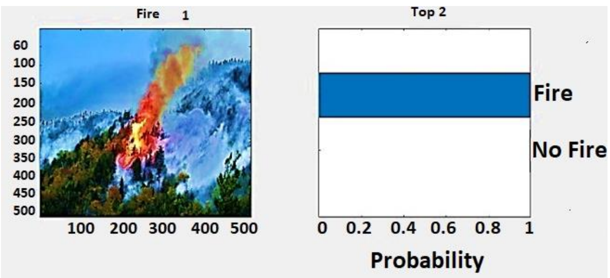
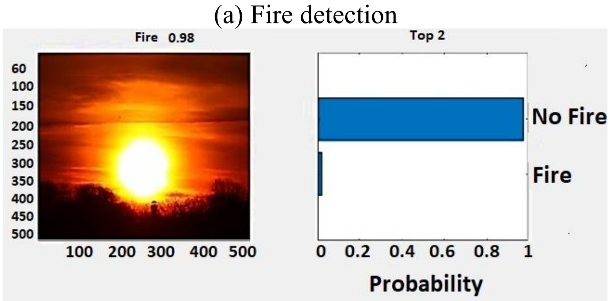


Figure 7. Flowchart of the fire detection system



(a) Fire detection



(b) No fire detection

Figure 8. Examples of the model's work

5. CONCLUSIONS

In this paper, an intelligent model based on deep learning using a CNN for detecting and classification forest fires and issuing an alert in order to avoid the dangers of forest fires and control fires early is proposed. The CNN and dataset are used to build a technological system aimed at detecting fire incidents. The proposed CNN, which has previously been trained on dataset of both classes fire and non-fire environments, receives the processed individual fire detection photographs from the system. Every single fire location is categorized as CNN Net's output. The technology locates fire and no fire areas and creates a map that can be displayed on a screen in a suitable position in order to lead firefighters to the scene of an occurrence. This paper focuses on the development of two sub models for detecting and classifying wild forest fires using pre-determined features from multiple dataset sources, such as in situ and remote sensing from a pair of drone networks. The proposed framework showed great reliability and accuracy, scoring 98% on the forest dataset. The results obtained indicate the proposed model has improved in several measures. The suggested model's overall performance achieved a high training accuracy of 98% using 700 epochs at 19:00 minutes.

On the other hand, the testing accuracy was 100% at a consumption time of 10 seconds. Following training and validation procedures, the overall accuracy was found to be excellent. As part of the future scope, images could be classified as either fire or non-fire using deep learning-based image processing techniques. Taking advantage of the graphics processing unit (GPU): It had an important role in the work of the artificial neural network, especially the CNN, which takes full advantage of the power and utility of graphics processing units (GPUs). Therefore, in future studies, CNN structure optimization will be investigated to increase the learning speed for quick detection and enhance the classification performance of images with noise, multimodal classification will also be applied or delivery system [25, 26], and real-time implementation will be implemented using a Raspberry Pi and a camera sensor.

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