Deep Learning Based Forest Fire Classification and Detection in Satellite Images

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Abstract

Forest fires are an important threat to humans and other living creatures, with the development of satellite technology it can be constantly monitored and controlled. Presence of smoke in the atmosphere is the indication of forest wildfires. In fire alarm systems, fire detection plays a crucial part in avoiding damages and other fire disasters that lead to social ramifications. Avoiding large scale fire, effective fire detection from visual scenes is important. To improve fire detection accuracy, an effective approach of a convolutional neural network based Inception-v3 based on transfer learning is designed which train the satellite images and classify the datasets into a fire and non-fire images, confusion matrix is generated to specify efficiency of the framework, then extract the fire occurred region in the satellite image using local binary pattern it reduces false detection rates.

Keywords: Convolutional Neural Network (CNN), deep learning, Inception-v3, fire detection, image classification.

I. INTRODUCTION

Forest fire causes severe hazards in endangering human life, animals and vegetation around the world. In the traditional methods, Fast responsiveness and large detection area is not applicable to detect fire [1]. Generally, the forest is a home for many living things and various resources, it controls the production of CO2 and they have complex eco-system. Wildfires cause disasters and they are an uncontrollable hazard in forests [2, 3]. Because of yearly forest fires, almost 85% of the world's trees are getting destroyed this leads to severe climatic changes and global warming. Forest fires are classified according to its motion, texture, and size. Fire can be natural or man-made they are directly or indirectly depend on the lighting, volcanic eruptions, spontaneous combustion of dry vegetation, smoking near vegetation and farmers setting fire to their fields.

II. RELATED WORKS

Fire detection algorithms in satellite images, researchers have done an enormous role. The papers deal with forest fire detection using CNN is growing exponentially [4]. The classification architecture for Convolutional Neural Network combines convolution (mathematical combination of two functions) and max pooling layers along with fully connected and soft max layers. But to obtain fast classification of image framework choose a small network (one fully connected layer). It has confusion matrix for fire and non fire, which contains false negatives and false positives of fire images. Furthermore, uses a ROC (Receiver Operating Characteristic) curve to the better performance of classification for the fire [5]. Fire control in traditional systems monitoring wide areas and open space cannot do, so AdaBoost and LBP algorithms are combined along with ROI (Region Of Interest) to make the algorithm performance better and reliable. The false positive rate is high, even though combination is fast, but difficult to detect. Therefore, at the final stage, two SVM classifiers are added which gives a conclusion about the presence of fire in the desired image [6]. The issue with the traditional method is their time consuming process and low performance analysis of features in flame detection. Also in the surveillance with shadows, lightings, and fire-colored objects high number of false alarms is generated. To overcome such issue, we use deep learning architectures for early flame detection by using GoogleNet architecture, since they are reasonable in computational complexity and efficiency [7]. The Restricted Boltzman Machine technique is used along with Deep Belief Network used for fire detection which is a stacked layer. This technique classifies and extracts fire and non fire regions simultaneously. Also, they have the highest in the detection rate and the lowest is the time of pre-training and fine-tuning, hence speed is increased for smoke detection [8]. Fire detection using hand-crafted features is a sedate task and time-consuming, so in this paper, deep CNN architecture, by the SqueezeNet architecture for fire detection, localization, and semantic understanding of the scene of the fire is implemented. They reduce fully connected layers by using small convolutional kernels. Also main aim to show a trade-off between fire detection accuracy and efficiency. For testing a given image, it is fed forward to deep CNN, which assign a label of "fire" or "non fire" to the input image. To compute probability scores labels are assigned to the CNN architecture [9]. In fire localization performance are evaluated by true positive and false positive rates and use feature maps to resize ground truth images [10]. Fire detection is done by applying Faster R-CNN to the image and evaluating the color and texture of the pixel to find out the presence of fire [11]. Considered real-time forest fire detection, Faster R-CNN, YOLO (Tiny-Yolo-voc1) and SSD architecture is compared and color, texture, the motion of fire is identified by their pixel values [12].

III. METHODOLOGY

Inception-v3 architecture is used to classify the satellite images. The training data were selected from satellite images containing active forest fires. Training pixels were obtained from representative polygons containing fire and non fire. The network is trained to distinguish fire and non fire with the standard CNN method. Outputs were generated by the CNN, and then confusion matrix is generated to obtain the accuracy of classification by our framework. Datasets which has fire in it is given to the Inception-v3 framework, also LBP is applied to the corresponding image to detect the fire occurred region, from the input image mask the places where fire is present and apply bounding box in fire region. Fig. 1. Architecture diagram of fire classification and detection.

A. Inception-v3

In QuocNet error rate is 15.3%, AlexNet error rate is 6.67%, Inception (GoogleNet) error rate is 4.9%and Inception-v3 error rate is 3.46%, since the error rate is high for other frameworks compared with Inception-v3, the accuracy and performance obtained with our proposed framework will be very high. Inception-v3 is a two-step process feature extraction part and classification part. The input of the model is set with 299×299 pixel.

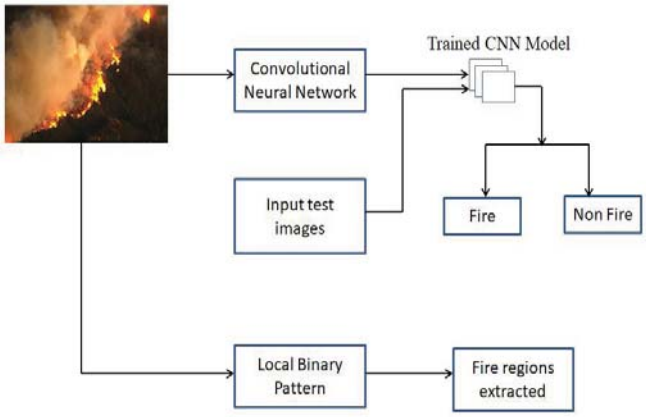

Fig. 1. Architecture of fire classification and detection

B. Feature Extraction

In fire detection, feature extraction for appropriate image feature extraction is the first phase. The storage efficiency, classification speed, and performance of the CNN are directly affected by a large number of datasets and parameters. Using Inception-v3 it selects the image generated on different convolutional layers. To extract features from the CNN model first we need to train the CNN network and label them as fire and non fire. The objective of the training network is to identify the correct fire pixels, by multiple forward and backward iterations, which try to reduce binary cross-entropy. It encodes the labels for extracted features using LabelEncoder in satellite images. The 299×299 pixels with color image dimensions is the input of the model. Here 64 filters of size 3×3 are applied in the first convolutional layer to the input image, generating 64 feature maps. The framework has 64 features maps of maximum activations are selected by the first max pooling layer with a stride of three pixels, it uses a neighbourhood of 3x3 pixels. Then 192 filters of size 3×3 are applied to the input image in the second convolutional layer, generating 192 feature maps. It has one fully connected layer with 448 filters of size 1×1 are applied to the input image.

C. Classification

In general, classification layers contain one or more fully connected layers at the end of deep neural networks. Similarly, our network has one fully-connected layer at the end of the neural network. Learnable parameters in the deep neural networks are often accounted by fully-connected layers. But, fully-connected layers are prone to be over fitting. Each output dimension of the image is dependent on each input dimension image. In fully connected networks nodes are commonly known as neurons. Separating data into training and testing sets is an important part of Inception-v3 models. Generally, separating a dataset into a training set and testing set, max amount of the data is used for training by default, and a min amount of the data is used for testing. When a model has been reclamation by using the training dataset predictions in the training dataset are made by testing the model. Because the data for the attribute value that are already known in the testing set based on our dataset, it is easy to predict whether the model's validations are correct. The training is done on a 299×299-pixel image.

D. Local Binary Pattern

Local Binary Pattern (LBP) is used for detection of the fire in the particular image. It is calculated the neighbourhood pixels and threshold them to find the fire areas. The Gaussian Blur is set with the input of size 21×21, with the lower limit of size 18×50×50 and upper limit of size 35×255×255. After detecting its fire region from the detected input image mask the places where fire is present and apply bounding box in fire region. Finally, multiply the input and mask image to get fire affected region. To evaluate the performance measures and accuracy the precision, recall, and f1-score is calculated of our proposed framework.

E. Performance Measures

To evaluate efficiency and accuracy of our architecture precision, recall and F1- score has been calculated by using our datasets.TP – the number of true positives (classifier detect fire at the image area with flames); FP – the number of false-positive (classifier detect fire at the image area without any flames); FN – the number of false-negative (classifier does not detect fire at the image area with flames). The weighted average for fire detection is 98% accuracy calculated based on our datasets.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (2)$$

$$\text{f1-score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

IV. RESULTS AND DISCUSSION

A. Inception-v3

CNN based Inception -v3 architecture is used for the classification of satellite images, the network is labelled as fire and non fire images, training is processed to distinguish fire and non fire datasets with the standard CNN where the system predicts that in the given satellite image there is an occurrence of fire or not, and confusion matrix is generated to evaluate its performance. Once the classification is processed, detection has to initiated testing is done with the input image which has fire in it, a bounding box is generated in the fire region, mask those fire region, now multiply with the input image and masked image to get the fire affected region alone. In Fig. 3. Results of classification for fire and non fire images are kept which is occurred after training part.

CNN assumes images as pixels and being stored as a binary value, here fire takes the value as 0 and non fire as

1, then labeling starts and features are being saved. In training, it will split the training and testing data with its labels. Then create a model. For confusion matrix, it evaluates the model and saves them this indicates the accuracy of our proposed framework accuracy and efficiency. Fig. 2. Shows the confusion matrix for fire classification, after training part this is obtained.

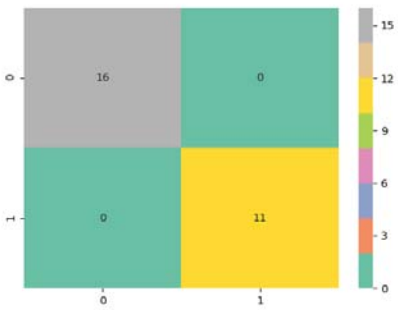

Fig. 2. Confusion Matrix

B. Local Binary Pattern

Satellite image which has fire in it is alone considered and trained. It has one fully connected layer for increasing the speed of processing and soft max for good accuracy. Also it possesses one dimensional data in it, if image is 3d it is being converted into 1d image. Here local binary pattern (LBP) is used for detection of the fire in the particular image. It calculates the neighbourhood pixels and threshold them to find the fire affected regions, from the detected input image, mask the places where fire is present and apply bounding box in fire region.

Dataset was obtained from NASA Worldview, Earth Observing System Data and Information System(EOSDIS), Moderate Resolution Imaging Spectroradiometer (MODIS) instruments on the Terra and Aqua satellites and Google satellite images containing 534 images out of which 239 images belongs to fire class and 295 images belongs to non fire class. 481 images belong to training and 53 images belong to testing. The dataset contains satellite image and other images which have a texture that is similar to fire i.e. sunlight scenarios, lighting in different places. Initially, the dataset has been labeled as fire and non fire images, then it is trained using Inception-v3 CNN framework. Fig. 4. a) & b) testing is done to detect and extract fire region in this images that are not trained given to the network to test. To evaluate the accuracy for fire detection, precision, recall, and f1-score is calculated. TP – the number of true positives (classifier detect fire at the image area with flames); FP – the number of false-positive (classifier detect fire at the image area without any flames); FN – the number of false-negative (classifier does not detect fire at the image area with flames). The weighted average for fire detection is 98% accuracy calculated based on our datasets.

Table I. Evaluation of fire and non fire images to determine the accuracy of the proposed fire detection method. Table II. The comparative study results of different methods are presented. According to the comparison proposed method using Inception-v3 has a better performance and finds the exact fire region.

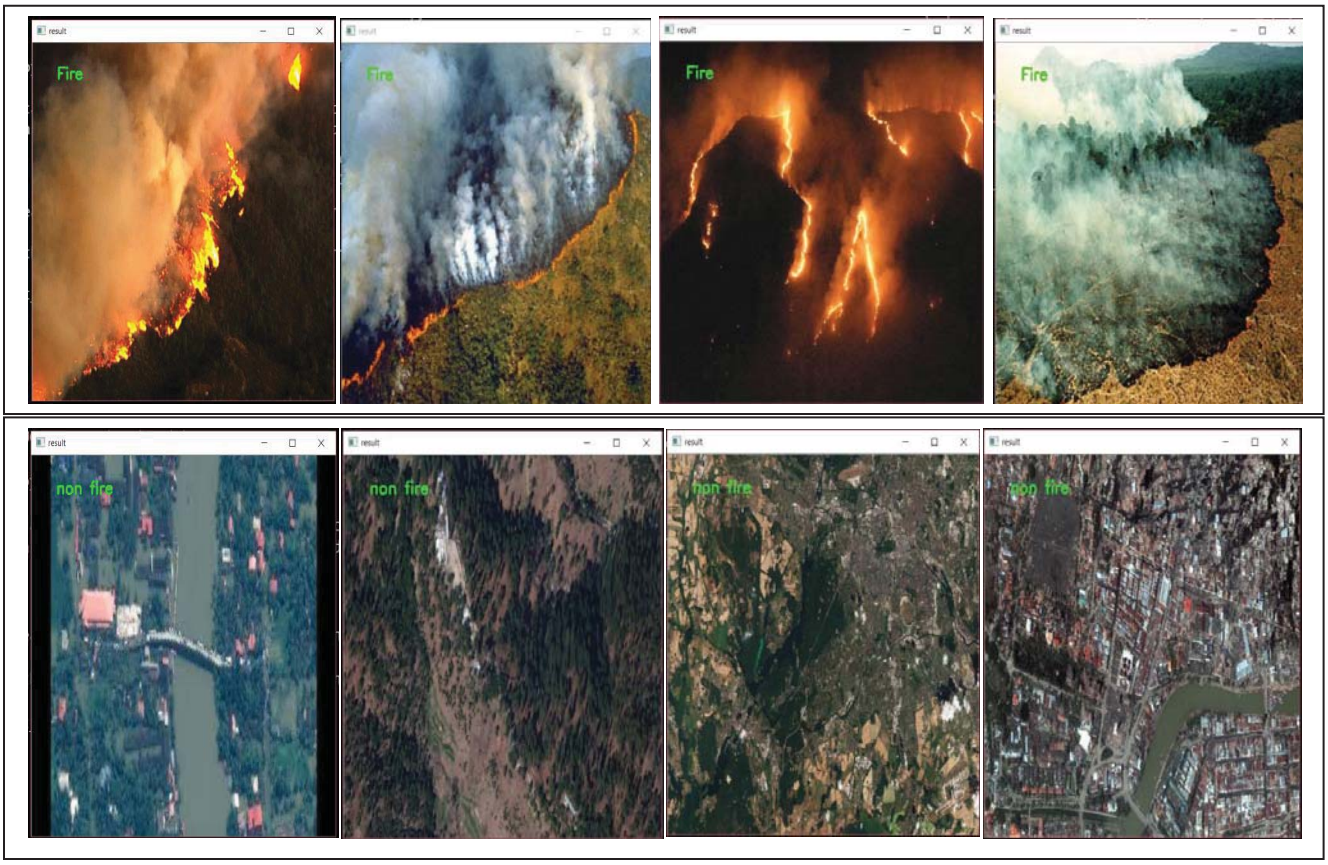

Fig. 3. Classification of Fire and Non fire satellite images

Table I. Accuracy table for fire detection using Inception-v3

Classes	Precision	Recall	f1-score
Fire	0.95%	1.00%	0.97%
Non fire	1.00%	0.97%	0.99%
Weighted Average	97.50%	98.50%	**98.00%**

Table II. Comparison with different fire detection methods and our implemented method

Method	Zhao[3]	Khan[7]	Oleksii[6]	CNN
Detection rate	94%	94.39%	95.2%	98%

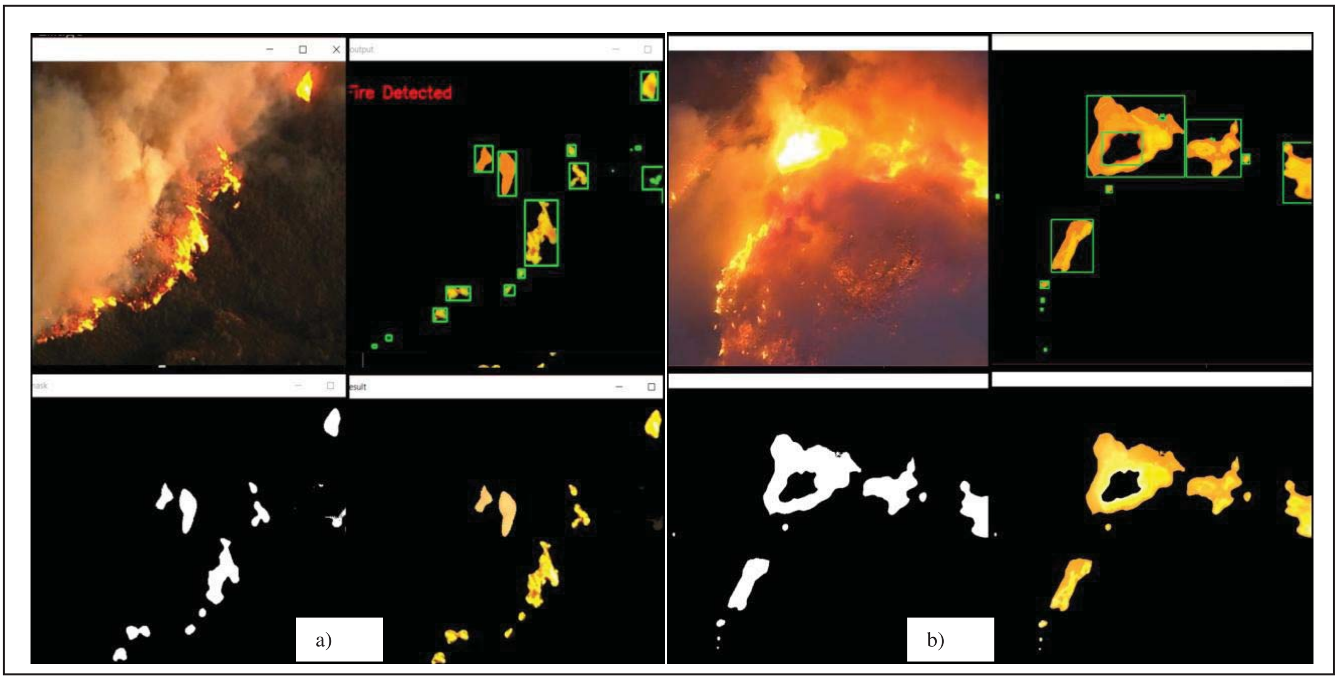

Fig. 4. a) & b) Detection of fire occurred regions

V. CONCLUSION

Features are manually extracted from input images for fire detection and classification methods using the traditional and hand-crafted algorithms and then train a classifier to classify the images, which is complex. Especially in the larger image dataset, the performance of both algorithms declines its speed. To improve the performance, a convolutional neural network (CNN) based Inception-v3 for fire detection is proposed. Inception-v3 can automatically extract features; this architecture achieves high detection rates, proved by experimental results and analysis. In the future, will insert static and dynamic fire features into a deep convolutional neural network and also try to recognize these feature changeable object with various deep learning frameworks. Also, fire detection in video sequences using dynamic textures is inserted into deep learning frameworks which localize each frame of input images using the deep belief network.

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