FOREST WILDFIRE DETECTION FROM SATELLITE IMAGES USING DEEP LEARNING

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Abstract

This study presents a novel method for automated detection of forest wildfires from satellite images using deep learning techniques. The method uses Convolutional Neural Networks (CNNs) to extract relevant features from high-resolution satellite images, which are preprocessed to remove noise and enhance features like smoke plumes, flames, and hotspots.The CNN model is trained on the preprocessed dataset using transfer learning, taking advantage of pre-trained models like VGG, ResNet, or Inception. Fine-tuning is performed to adapt the model to the specific task of wildfire detection. Performance metrics such as accuracy, precision, recall, and F1-score are used to assess the model's effectiveness. The experimental results demonstrate the potential of deep learning-based wildfire detection from satellite images, achieving high accuracy and rapid identification of wildfire occurrences.Integrating this system into existing satellite image analysis pipelines can provide timely alerts and inform decisions to manage and mitigate wildfire impacts. This research contributes to early wildfire detection capabilities, protecting natural ecosystems and human populations in fire-prone regions.

I. INTRODUCTION

Early forest fire detection is of great importance to avoid the huge damage of forests caused by fires. Early fire detection focuses on smoke detection. The forest area is gradually decreased because of increasing forest fire and human activities. The satellite sensor is used to collect the forest thermal image in different places and analyze the data in these images to detect the fire region if they occur. Image processing technique can effectively predict the fire in the forest. The input image is pre-processed to enhance the image quality, because the input image has the noise, so the pre-processing technique is used to eliminate the noise in this system and enhance the image quality. The pre-processed image is taking to the segmentation process; it processes the image to adjacent the forest sub-area. In this system, the affected area is separately detected, and it gives the accurate forest fire in this system because the output image intensity is better to stabilize the average value of the image. In our proposed system we propose a deep learning method that uses a Convolutional Neural Network (CNN) to predict the forest fire detection. The convolutional layer is the main building block of the convolutional neural network. Usually, the layers of the network are fully connected in which a neuron in the next layer is connected to all the neurons in the previous layer. We are going to detect the fire in the forest result based on the accuracy which we get in train and test of the dataset-based CNN algorithm using that we show the graph result. The objective is to detect the fire as fast as possible and its exact localization and early notification to the fire units is vital. This is the deficiency that the present Invention attempts to remedy, by means of detection of a forest fire at the very early stage, so as to enhance or ensure the chance to put it out before it has grown beyond control or causes any significant damage. There are a number of detection and monitoring systems used by authorities. These include observers in the form of patrols or monitoring towers, aerial and satellite monitoring and increasingly promoted detection and monitoring systems based on optical camera sensors, and different types of detection sensors or their combination

II. EARLIER WORK

Forest fire detection images are based on fire images and non-fire images. It detects the fire accrued area in the forest. Forest fire detection in a particular area is tough to detect. The existing system detects the low level accuracy of performance based on fire occurred in the forest. The existing system doesn’t effectively classify and detect the fire in area of the forest. Given the need for cost-effectiveness, we further evaluated Agni with reduced data. We limited the duration of historical data available to Agni for training and prediction to just 3 months and its performance still remained above 0.81 area under the ROC curve. In summary, our empirical evaluation demonstrates that Agni, a machine-learning based approach using remote sensing data, is effective while being more cost-effective than existing systems that required instruments on the ground. The main

challenges in segmentation of wildfires can be summarized as follows:
1) Wildfires are a complex phenomenon varying in time and space that involve numerous interrelated factors difficult to model by classical, machine learning models.
2) Because of the dynamic nature of wildfires, following acquisitions over the same area observe the wildfire at different states, which makes fusion of multiple acquisitions, labeling and validation of results difficult.
3) Often, thick smoke and clouds obscure the fire signal observed by optical instruments.
4) In most cases, fire segmentation is an imbalanced classification problem where the number of pixels affected by fire is significantly smaller than the number of pixels which are not

Drawbacks:

- High error probability
- Time Consuming
- It is less accurate.

III. PROPOSED METHOD

A system for forest wildfire detection using deep learning involves acquiring satellite imagery data from sources like satellite imagery and public wildfire databases. The raw images are preprocessed to remove noise, enhance contrast, and adjust image size and resolution. The dataset is annotated to label images as containing wildfires or not, and divided into training, validation, and testing sets for training and evaluation. Convolutional Neural Networks (CNNs) are used for feature extraction, and a deep learning architecture is designed for wildfire detection. The model is trained on the training dataset using appropriate loss functions and optimization techniques and tested on the validation dataset to monitor performance. Post-processing techniques are implemented to reduce false positives and enhance the model's robustness. The system is deployed for real-time or near-real-time monitoring of satellite imagery to detect wildfires as they occur. An alerting mechanism is integrated to notify authorities and first responders when a wildfire is detected. GIS tools are used to provide location-based information about detected wildfires. A user-friendly interface is developed for user interaction and historical data access. Regular model retraining and updates are implemented to adapt to changing environmental conditions and improve detection accuracy over time. The system must comply with legal and regulatory requirements for environmental monitoring, data privacy, and emergency response. This scalable and adaptable solution can aid in early wildfire detection, response, and management, ultimately contributing to the protection of natural ecosystems and human safety in fire-prone regions.

Advantages

- Accurate
- Less time consuming

IV. METHODOLOGY

Data Description:
The Web Server Gateway Interface (WSGI, pronounced whiskey or WIZ-ghee) is a simple calling convention for web servers to forward requests to web applications or frameworks written in the Python programming language. The current version of WSGI, version 1.0. 1, is specified in Python Enhancement Proposal (PEP) 3333. A traditional web server does not understand or have any way to run Python applications. In the late 1990s, a developer named Grisha Trubetskoy came up with an Apache module called mod_python to execute arbitrary Python code. For several years in the late 1990s and early 2000s, Apache configured with mod_python ran most Python web applications. However, mod_python wasn't a standard specification. It was just an implementation that allowed Python code to run on a server. As mod_python's development stalled and security vulnerabilities were discovered there was recognition by the community that a consistent way to execute Python code for web applications was needed. Therefore the Python community came up with WSGI as a standard interface that modules and containers could implement. WSGI is now the accepted approach for running Python web applications.

Data Collection:
Convolutional neural networks (CNNs) are a subclass of DNNs that have a known grid-like topology and employ a mathematical operation of cross-correlation between an input signal and a filter (Goodfellow et al., 2016). In ML terminology cross-correlation is often referred to as convolution, which explains the somewhat confusing name. For the purpose of this work, the term convolution will be used to stick with the ML terminology. The convolution operation at the core of all CNNs, is a summation of element-wise dot products between the filter and the input. The filter is convolved with the input by sliding it across the input with a stride parameter determining the number of units by which the filter is moved. In the specific case of processing satellite imagery, both the input and the filter are 3-D cubes of pixels. Convolving an image with a single filter result in a 2-D matrix, a bias b is added to the resulting 2-D matrix and the combined result is passed to an activation function f to produce the output, also called an activation map. The same input can be convolved with more than one filter by stacking activation maps, resulting from convolving with different filters, along the 3rd axis. According to Goodfellow et al. (2016, pp. 330–339), CNNs are particularly well-adapted to process images by implementing three key architectural ideas:

1. Local receptive fields - Unlike in fully connected neural networks, where every neuron interacts with every input, in CNNs each neuron in the hidden layers is connected to a limited number of inputs only. This is accomplished by convolving the input with a filter smaller in size. The region in the input that the neuron interacts with is called the local perceptive field of the neuron. This property allows CNNs to store fewer parameters and require fewer operations, thus increasing their efficiency. Units in the deeper layers have larger receptive fields through indirect interaction with the shallower layers. This allows the network to describe complicated interactions between variables with relatively few parameters. Schematic representation of local receptive field. The outlined red area indicates the indirect receptive field of the neuron in the second hidden layer, and the direct receptive field of the neurons in the first hidden layer.
2. Shared weights and biases - In a CNN, each member of the filter is used at every position of the input. This means all neurons in the hidden layers detect the same feature but in different locations in the input. This property allows CNNs to be well adapted to translation in images, because their output is translated in the same way as the input. Moreover, this property allows to reduce the storage requirements of the network to be determined by the dimensions of the filters, which are significantly smaller that the dimensions of the inputs.
3. Pooling - In addition to convolution layers, CNNs contain also pooling layers. Pooling layers are usually used immediately after convolution layers, and perform a pooling operation. A pooling operation simplifies the output information from a convolutional layer by replacing the output with a summary statistic of nearby outputs. For instance, each neuron of a pooling layer can summarize a region of 3×3 neurons in the previous layer by taking the maximum value of the 9 pixels in the region. This operation is referred to as Max Pooling. The pooling property helps the network to be approximately invariant to small translations and process data of varying dimensions. It is important to note that invariance to small translations can be a disadvantage in segmentation tasks, because it reduces the ability of the net to correctly distinguish borders of semantically similar regions.

Data Analysis:

Flow of the algorithm

At present, most of the applications in forest fire identification are directly applied to CNN on the original image set. Due to the complex background and a number of interference in the original image, the result of the training is not so good. Therefore, in this project, a method is proposed to segment the candidate flame region based on the color feature, and then part of the image is sent to the CNN network for training, which can extract features more specifically and improve the recognition rate of forest fire image effectively

In the training phase, firstly, the binary image of the suspected flame region is segmented, and the result obtained by performing AND operation between the binary image and the original image is used as a training set, and a label is set for each image. A network model is obtained after training the CNN according to the training set. In the testing phase, similarly, the binary image of the suspected flame region is firstly segmented, and the result obtained by performing AND operation with the original image is used as a testing set. The testing set image is sent to the trained network model to obtain the recognition result

Module Description:

1. Active Fire (AF) products - describe geographic locations which are actively burning as a result of a fire. AF products are usually detected by thermal sensors as thermal anomalies, however the detection is only possible if the satellite overpasses over the area that is actively burning.
2. Burned Area (BA) products - describe geographic locations where fire led to the burning of biomass which resulted in deposit of char and ash on the ground. The resulting patterns are sometimes also referred to as "burn scars", and they are typically more persistent in time than the thermal anomalies caused by ongoing fires.

Throughout this work, the term fire affected pixel is used to describe pixels who are either actively burning or are burnt as a result of a fire. Additionally, the terms instrument and sensor are used interchangeably. The following subsections briefly describe the main families of wildfire detection algorithms, followed by a detailed overview of the conducted research in the field, categorized by spectral domain

Thresholding algorithms:

These algorithms are typically used in AF detection. Pixels are considered as potential fires if the brightness temperature in one or more spectral bands exceeds a threshold (Justice, Giglio, et al., 2002). The thresholding can also be applied to a spectral index calculated from two or more spectral bands (García and Caselles, 1991). The main advantage of thresholding algorithms is their simplicity and fast performance, while the main disadvantage of this type of algorithms is their ability to detect smaller or less powerful fires.

Contextual algorithms:

Contextual algorithms are used for active fire and burned area detection and detect pixels as potential AF or BA by comparing the value of the measured radiance or the derived brightness temperature in the pixel to its neighboring pixels (Martín et al., 1999). Often, these methods are combined with thresholding tests to determine whether a pixel is an anomaly or not (Giglio, Descloitres, et al., 2003). Because contextual algorithms compare pixels locally, they allow to detect smaller and less powerful fires. The main weakness of these algorithms however, is the increased false detection rate

Time series algorithms:

These algorithms are used for both BA and AF products. A pixel is considered to be fire affected if a significant change in one or more of the measured properties occurs between two acquisitions taken at different times (Gimeno et al., 2004; Carmona-Moreno et al., 2005). Time series algorithms are especially common when using SAR imagery, due to the fact that even slight changes in the backscattering properties or interferometric coherence, can be detected in SAR images that were taken at different times with similar acquisition geometry. Time series algorithms allow to monitor the area of interest for fires, and to detect fires on a smaller scale. The main disadvantage of time series algorithms is that they require more data per area and specific collection methodology, especially for SAR imagery. Another disadvantage of this type of methods is their strong dependence on the frequency of imaging

Machine Learning:

algorithms Supervised ML algorithms for active fire and burned area detection gained popularity in recent years. These algorithms attempt to predict the probability of a pixel being affected by fire based on learning from examples of input-output pairs (Murphy, 2012, p. 2). One advantage of applying supervised ML algorithms to the problem of fire detection is the lack of need to explicitly determine and model the many complex physical processes and parameters that affect the signal of a fire. ML algorithms develop their own internal logic and "learn" form the data itself, which in the case of complex physical processes like wildfires, can significantly reduce the difficulty of modeling the process. The main disadvantage of ML algorithms is that they usually require high quality reference data which is often scarce and expensive in the field of Earth observation (Jain et al., 2020). Another disadvantage of some ML algorithms is that their results are often difficult to interpret by humans in case they have large number of parameters and functional relationships

V. RESULT AND ANALYSIS

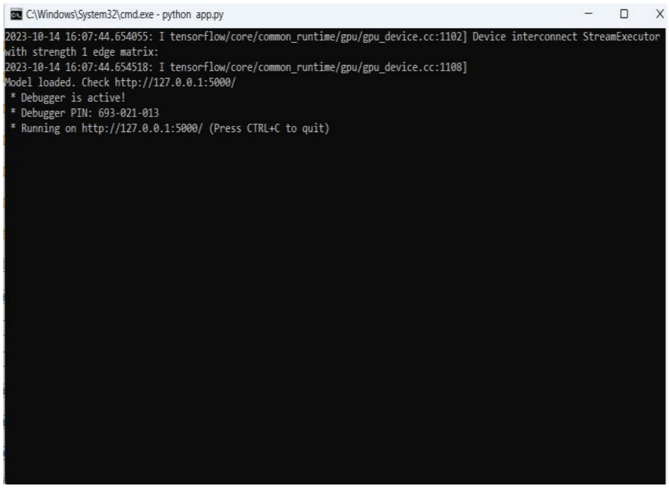

Figure 1: command prompt

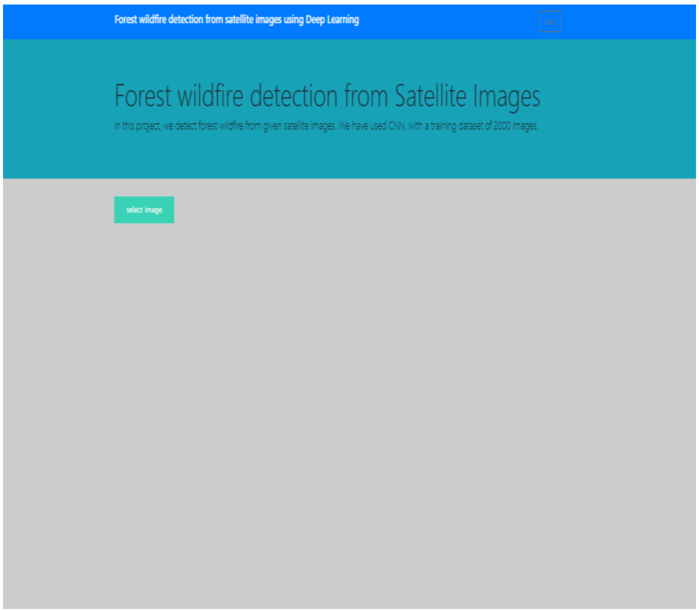

Figure 2: home page

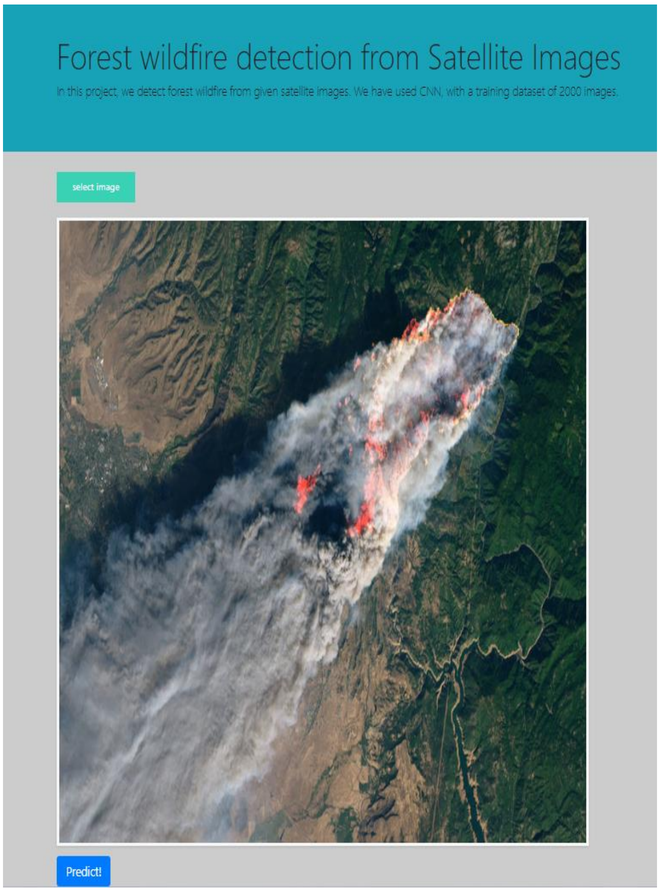

Figure 3: select image page

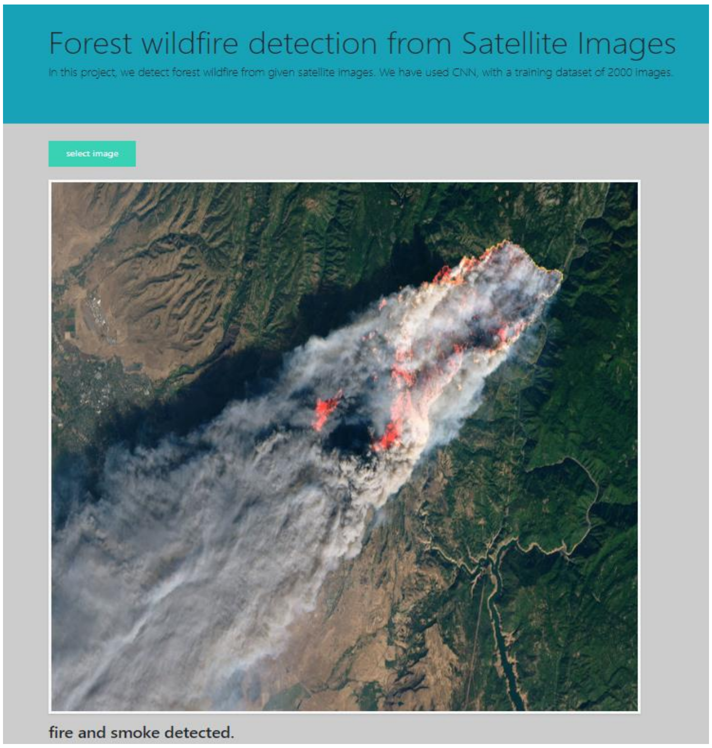

Figure 4: Prediction image

VI. CONCLUSION

In this project, the process of the forest fire image recognition algorithm based on CNN is presented. Its main feature is that the flame image is employed for training and testing. Then, AlexNet model is introduced, and an adaptive pooling method combined with color features is proposed for the problem that the traditional pooling method in CNN may weaken the image features in some cases. The effects of learning rate, batch size, and other parameters on the performance of CNN are analyzed based on experiments, and the optimal parameters are determined. Candidate flame area is extracted based on color feature; thus, the image feature of non-flame area in the hidden layer is reduced, and the feature, such as shape and texture, is enhanced. The information loss of image are avoided as adaptive pooling is adopted, and the rate of flame recognition in which fire area is segmentation than that of original image is adopted without segmentation. It is shown that the proposed algorithm has high recognition rate and is feasible. In this paper, the pooling of CNN is modified and applied on forest image recognition, recognition rate and consuming time will be developed deeply and compared with other algorithms in future.The previous chapter's limitations and conclusions suggest that future work should include expanding the dataset to include more examples from different biomes and regions, using an automatic hyperparameters tuning approach, designing a model that detects patterns in the backscattering coefficient of SAR data, evaluating the Sentinel-3 SLSTR instrument's performance for wildfire detection, improving the results of combining predictions from pairs of instruments, developing a network architecture that can receive both SAR and optical data at the input stage, integrating data from geostationary satellites to compensate for low temporal resolution, and incorporating detection of smoke plumes to improve results in actively burning fires. These suggestions aim to improve the accuracy and efficiency of fire detection systems.

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