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Conflagration Recognition Using Convolution Neural Networks With Warning System

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Abstract- The main objective of the project is to enhance the existing system for fire prediction and protection systems. Deep Learning approaches have shown the ability to provide better results for the prediction of wildfires. Previous systems are more complicated and sort of complete black box in image analysis. Faster recognition and passing the data to the concerned wildfire authorities in more important. The warning system needs to be automated and should send the information at a set of intervals for proper image analysis. Hence, an automatic warning system to the system is suggested to avoid late actions taken against the wildfire and its damages. Also different types of image analysis for categorizing the fires occurred is proposed. DWT is one of the image analysis methods that has been implemented for better result. This will help any people with less knowledge about the wildfire to understand the fire nature and enables them to take appropriate actions. The neural network model in the Restnet50 was faster in training with large datasets compared to other neural network models.

Keywords: Deep Learning approaches, recognition, wildfire, Convolution Neural Networks, Warning System, Restnet50.

1. INTRODUCTION

Wildfire monitoring has become a very serious issue among the progressive popularity of the installation of visual surveillance systems over the past decades because it is almost related to environmental safety[1]. The most commonly used flame detection techniques in recent times are usually based on temperature sampling and particle sampling. By aiding as the nuclei for the cloud condensation, smoke generated by wildfire changes the cloud's short wave properties [7]. As a result, due to high number of nuclei there occurs the smaller cloud droplets which inturn have high reflectivity than the larger cloud droplets under some inadequate supply of water vapour [2]. Furthermore, they are not always accurate, because the combustion itself is not always identified. Alternatively, they detect the transparency testing, in addition to conventional ultraviolet and infrared flame detectors. However, most of these detection mechanisms suffer from some critical problems. These mechanisms require proximity to the fire regions.

Wildfires often occur in environmentally sensitive regions such as national parks, wilderness areas, or with a growing urban-wildland interface that is environmentally and economically sensitive[3]. Environmental monitoring must be environmentally very easy in such terrains, which requires simple installation, low maintenance, non-toxic and ideally inexpensive instrumentation. And they normally lead to higher fake rates. Much recently many kinds of research have been suggested on visual fire flame identification because images analysed from these methods provide more confidential information. The use of grey-scale images acquired from cameras to detect tunnel fire proves to be reliable from recent researches. Some researches directly examines images that are captured using CCTV cameras, with advancement in Machine Learning Technologies and Computer Vision. Since people doesn't needs costly sensors, they save time and cost much more effectively. Additionally, methods based on video and image are fast and accurate compared to methods based on sensors, regardless of situations [2]. Therefore, the methods can be divided into two groups, that is, those that use flame detection as a fire detection function and those that explore fire texture, color and spatial information in the fire detection video. However, when working well for different situations, the formers may not be robust, while the latter is generally more accurate, and may work well for different situations. Hence, the proposed method falls on to the second category[4]. In this proposed system, we have used Resnet50, a deep neural network is used to learn the fire color features in this project to detect fire and smoke images more accurately, so that fire monitoring systems can be greatly improved [6]. And Discrete Wavelet Transform is a feature extraction method used for extracting fire and smoke images from the image.

2. EXISTING SYSTEM

Automatic fire smoke detection using Artificial Neural Network was applied over the radiometry images, which was developed by Li et.al.[16]. Also forest fire risk prediction was developed using Decision Support systems combining the concepts of Fuzzy logic [5]. Many researches have shown their interest in forest fire prediction using the color images with the concept of Markov process [3]. Spatio-temporal is one of the important interest by most of the research for this fire detection. Cheng et al.[15] described their application to forest fire as follows:

1) Forecasting: It is easier to predict the affected area by fire by the burnt space and it is a bit difficult one to do forecasting the fire prediction.
2) Fire event Detection based on some sequential pattern: It relies upon generating the fire pattern based on spatio-temporal data.
3) Fire area detection and clustering: Based on the pattern generated using spatio-temporal clustering, this may eventually results in identification of area where the fire gets started much frequently.

3. PROPOSED SYSTEM

This proposed system uses following steps where the images are extracted first, then image pre-processing, classification, Fire feature extraction, DWT Feature selection, Warning system and performance comparison with other models is performed [7]. Flowchart of the proposed system is provided below in Fig.1

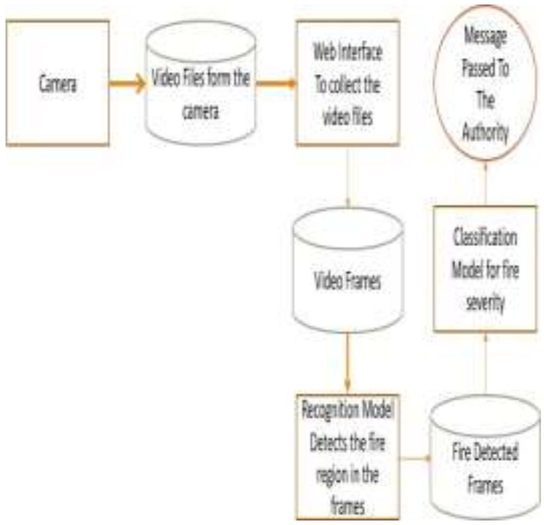

Fig.1. Flow chart for fire monitoring system

a. Video Frame Extraction

The wildfire monitoring system collects the video of the forest either from Unmanned Aerial Vehicles or Stable wireless cameras [8]. The video recorded from these cameras can be stored either in the cloud or physical storage but these things need to be accessed by the monitoring system. Video files are required to be in the mp4 format and this format requires less storage format compared to other video formats. Once the system starts recording the videos and continues storing the files the monitoring systems accessible storage the next step for the model is to extract the frames from the videos for image processing. The frames are then passed to the image pre- processing.

b. Image Pre-processing

This system is designed to help the neural network for increasing its learning system. Once the image frame extracted from the videos, the image processing is done as mentioned below [9]. To increase the processing speed of the classification model, the video frames are extracted in a defined interval time. Then the frame size is set to 240 x 240 pixels for image optimization[12]. The resized image is then converted to HSV format for highlighting the fire and smoke in the image. The converted image is then is converted into a float32 multidimensional matrix for passing this as input to the neural network for classification [13]. This multidimensional matrix is simplified into a 2D matrix for reducing the computational requirements of the monitoring system.

c. Image Classification

Renet50 consists of stages. Its network take the images as input with height and width multiples of 32 and 3 channel each. Here in this system, the chosen dimensions are 244 x 244 x 3 [10]. The max-pooling in Resnet uses 7 x 7 and 3 x 3 Kernal sizes [18]. The above-mentioned details are of the first stage. In the second stage, 3 Residual blocks containing three each are given as input [14]. The kernel size for each layer defaults as 64, 64 and 128. In Resnet due to its deeper network, bottleneck design has been used. Where each residual function has three-layer as stacked one over the other. The convolutions of the three layers are 1 x 1, 3 x 3, and 1 x 1. For reducing and restoring dimensions the 1 x 1 convolution layers are the responsible ones. The last stage of the Resnet is the Average Pooling layer followed by a fully connected layer having 1000 neurons.

d. Fire Feature Extraction

This model extracts the different fire regions from the image that is classified as fire as represented in the Fig.2. The different regions are chosen as dark red region, red region, yellow region, orange region, and smoke region[11]. The RGB values for the respective colours in the HSV format are (0, 120, 20) to (8, 255, 255), (170, 20, 20) to
(180, 255, 255), (20, 100, 100) to (30, 255, 255), (10, 100, 20) to (25, 255, 255) and (0, 5, 100) to (50, 100,
200). Once the regions are extracted successfully, with the help of the OpenCV the different fire images are marked respectively

Fig.2. Fire Region Extraction images

e. DWT Feature Selection

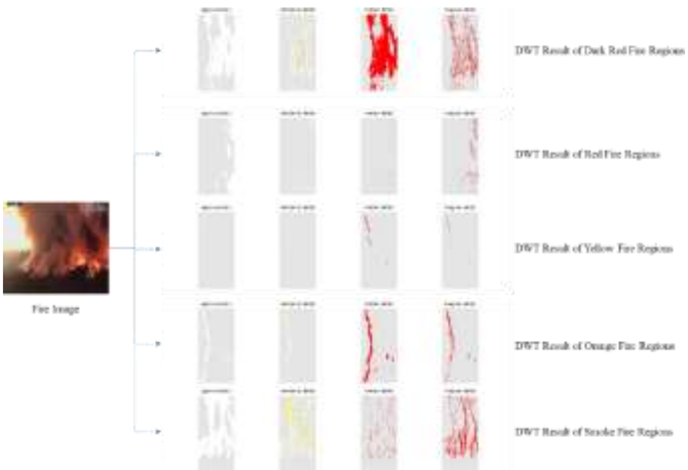

Fig.3. Image Analysis –DWT

This module performs the DWT analysis on the fire regions extracted from the fire region extraction module. It extracts the features in the three spatial features such as horizontal, vertical and diagonal spaces as shown in the Fig.3. Once the analysis results are obtained, it then sends to the report analysis module for the generation bar plot of the results.

f. Warning System

This module helps to send the results to the users for warning the status of the wildfire. Through this module, the user can add messaging details of the firefighters and other concerned authorities. The other functionalities of the module include editing the details, deleting the details, and a search interface for viewing the messaging details. To send warning message this module requires the result from the various modules of the monitoring system. The data are collected from the image classification module, image feature selection module, DWT analysis module, and at last from the report generation module. Once these data are obtained from the respective modules it generates the message with the defined messaging format. At last it sends the warning message including all the details to the persons included in the messaging details table.

g. Performance Comparison with Other Models

Instead of training using fixed values, the cyclical learning rates provides improved accuracy in classification with only lesser iterations. Principle of this learning rate policy comes from the observation that increasing the learning rate might have a short-term negative effect and yet achieve a longer-term beneficial effect. Comparison results of various deep neural network model is shown in the Table 1.1

Comparison			
Network	Year	Salient Feature	top5 accuracy
AlexNet	2012	Deeper	84.70%
VGGNet	2014	Fixed-size kernels	92.30%
Inception	2014	Wider - Parallel kernels	93.30%
ResNet-50	2015	Shortcut connections	95.51%

Table.1. 1 Training results of various deep neural network models

Rather than adopting the decreasing value exponentially, it is observed clearly that the learning rate varies within some bounded values (i.e., minimum and maximum boundary values) [15]. Various other forms like Linear Trainangular window, Parabolic Welch window and a Sinusoidal Hann Window, produced the same result equivalently[16]. Since all the above said forms produced the equivalent results, triangular window is chosen, where the values can be linearly increased and then decreased linearly. Minimum and maximum learning rate chosen for this training are le-4 and le-6. For this training model, the epoch number is chosen is 48 since the same has been used in other reference papers[17]. Batch size for every epoch is 32.

4. CONCLUSION

It is proposed with a different approach for wildfire recognition using one of the best trained deep neural networks and wavelet transform for filtering. The neural network model in the Restnet50 was faster in training with large datasets compared to other neural network models. Frames containing Fire and Smoke are recognized as fire regions using a deep neural network model. The fire and smoke regions from the image are extracted using DWT and it also proves to be more efficient than the existing systems. Analyzed image results are dynamically sent to the concerned authorities at periodic intervals. This removes the requirement of humans in the wildfire watchtowers. The neural network model has trained and validated with more than 1000 images collected from various online sources. The future work would extend the same for implementing an embedding system in a real-life scenario. For better analysis and representation of the analysis results, we plan to store the analysis result in the cloud. The future work would extend the same for implementing an embedding system in a real-life scenario. For better analysis and representation of the analysis results, we plan to store the analysis result in the cloud. Storing the data in the cloud can enable the possibility of performing various other analysis techniques. Moreover, we plan to combine the proposed two models as single full-fledged applications to make the proposed system which can function as a single independent application. The system can also be included with the following feature selection techniques: Gray-Level Co-occurrence Matrix, a statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM). This approach can be best fitted for smoke feature selection from fire regions. Generative Adversarial Networks is an image style transfer technique to create new images so our network can learn more features of fire and smoke as these appear in different seasons, styles, and light conditions.

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