Color Detection Technique to Curb Forest Fire

Indentifying Fire, Its Loction and Intimation to Help In Controlling Forest Fire.

Sonal Singh
Data Scientist
Fractal Analytics Bengaluru, India

***Abstract*—Forests are one of the most essential parts of our biodiversity. We tend to underestimate the value that Forests hold. To be precise, Forests are essential for human survival. One of the major threats that forests face today is from Fire. Forest fire destroy hectares of area in turn causing serious problems to biodiversity, climate and human health. One of the methods to mitigate this serious threat is by predicting the fire or at least detecting the forest fires and intimating the officials as soon as possible. In this paper we are going to review the various existent method and technologies which is used for detecting this hazard. We are also going to propose a methodology by leveraging Color Detection techniques using machine learning algorithm to detect Wildfire and sent intimation with location to officials. Besides these we will be understanding about occurrence of Wildfire and risks pertaining to it laconically.**

Keywords—Color Detection, Forest Fires, Machine Learning, Wildfire

I. INTRODUCTION

Forests are in general areas of land where trees are found in abundance along with other flora, fauna and ecological beings. As per United Nations any land greater than 0.5 hectares and having trees making a canopy covering almost 10% of the area with 5metres in height passes the threshold to be called as Forests. They help in survival of human beings by pumping out oxygen. Serving as home to about 80% of world's diversity as well as around 60 million indigenous people who depends on forests for their survival. Notwithstanding the fact that they have serious effects on the climate as help in reducing global warming and improving the quality of air by sinking carbon dioxide. Forests in today's world face risks such as Deforestation, hurricanes, Wildfires, Overgrazing, Jhumming etc. One of the most commonly heard hazards to the forest is Fire i.e., Wildfire. They not only affect the trees but also the flora and fauna thereby disrupting the biodiversity seriously. One cannot ignore the severity of these Wildfires as we have seen multiple forests burning continuously for weeks even after immense efforts taken by firefighters. We cannot completely stop the Wildfire as it is mostly the natural phenomena but we can find some solutions to inhibit and curb it. On such solution could be early detection of fire so that officials can take right actions before its too late.

In this paper, we will be analyzing already existing approaches to solve this issue and alongside we will propose a methodology to detect Wildfire on the onset by Color detection method using Machine learning algorithm. We will also articulate an architecture to create a complete process where we identify Wildfires with its exact location and intimate the respective officials immediately so that they know where the calamity has taken place and can reach the location to take curbing measures. The flow of this paper will be in a manner that anyone can understand the process very easily. Section 2 of this paper deals with the study of already existing solution employed using machine learning and deep learning so as to have a better understanding on how we can improve the process. Section 3 will be about the proposed methodology using advanced techniques, its architecture and its advantages. Section 4 will basically conclude this paper. We will use the term Wildfire and Forest fire interchangeably

II. EXISTING APPROACHES FOR FOREEST FIRE PREDICTION

There is a lot of research already going on in the field of Data Science to help us deal with calamities and is in a very promising direction. Detection of fire occurrences is one of them. We have exploited most of the algorithms for this purpose. The evolution in the development of the UAVs and their technology makes them appropriate for several applications; among them the forest fires monitoring, especially when associated to the machine learning algorithms. The advantage of this approach is the remote sensing that can cover large areas including far away and inaccessible areas. We will be reviewing the most effective and applied algorithms in the paper further.

A. Detecting fires using Neural Network

One of the research projects that was done to identify fires in the forest was by Neural Networks by the technique of classifying images. In this approach, CNN (Convolution Neural Network) is used instead of fully connected layer. CNN is basically neurons arranged in layers and are inter-connected with relative weighted connections. Stochastic gradient descent is used as a training mechanism and regularization technique is used to avoid overfitting. A web digital camera is used to capture the images in 320*420 pixels and some images were downloaded from google. The architecture of this model had 2 base networks and 8 layers for each base network making it 16 layers. Convolution process is performed as same as image processing, followed by normalization and pooling. Choosing activation function attentively is most important and hence ReLu was chosen. The model was developed and the confusion matrix shows that the accuracy is less than 10 % for grey and purple colors and highest 79 %, 72% and 86 % for green, orange and

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yellow color respectively. Further investigation shows that fire color can be detected between forests greenery. The average distance from which it is detected is 2m. The execution time for this model is 30seconds with 1 core CPU. Overall accuracy is around 78%.

B. Detecting fires using Support Vector Machine

A support vector machine-based solution for burned area prediction. The SVM algorithm (Radial Basis Function (RBF) kernel) was used as a classifier of a dataset that includes seven positive and ten negative videos. The SVM model (RBF kernel) allows a maximum true detection rate about 96.6%, and about 90.9% with the linear kernel. According to this study, the proposed temporally extended covariance matrix method can process 20 frames (320 9 240 frames) per second. The SVM model is also adopted by O¨ zbayog˘ lu and Bozer for burned forest area identification. The Mean Absolute Deviation (MAD) and the Root Mean Squared (RMSE) global metrics were used to the overall performance computation, authors reported values about 13.07 and 64.7 for the MAD and the RMSE.

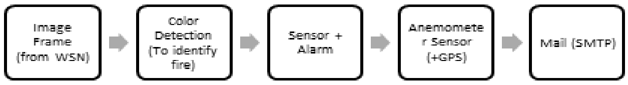
C. Detecting fires Bayesian and Markov Models Based

A Bayesian Belief Network (BBN) model was developed for the selection and ranking of biotic, abiotic and human factors that influence wildfire activity in Switzerland. The satellite-based fire dataset, namely the MODIS active fires in Switzerland from 2001 to 2007 was employed for the BBN evaluation. Authors reported values of about 0.96, 0.72 and 0.96 for the sensitivity, the specificity and the AUC, respectively. The analysis results were used by the Bayes classifier for fire occurrence determination in video frames, the reported false positive and false-negative rates were about 0.68% and 0.028%, respectively. The authors assessed that their model is suitable for real time fire detection and also for automatic newscast videos events retrieval. The proposed color model was based on YCbCr color space and temporal variation to correctly detect fire and avoid other moving object (e.g., trees, animals, bird…) detection after background subtraction. Algorithm was tested on a dataset including 6 video (4 fire videos and 2 fire-like objects videos). The reported performances were about 93.13%, 92.59% and 92.86% for recall, precision and F-score, respectively. A Markov model-based fire detection system was presented in India. The authors discussed a flame flicker process modeling using a hidden Markov model. In fact, the pixels in flame boundaries vary rapidly and randomly, this characteristic makes the Markov model more suitable for modeling this process. Authors proposed a three state Markov model for flames detection in color video. The results of the experiments conducted using 11 videos showed that the Markov model reduces the number of false alarms compared to methods based only on color information and motion detection. The authors reported a processing time about 10 msec. for an image of size 320 9 240.

D. Detecting fires based on Fuzzy logic

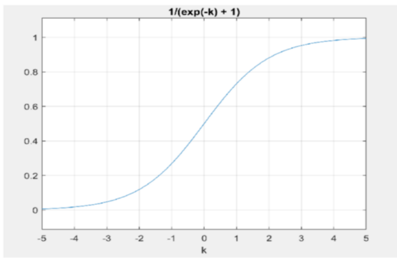
It is an alternative to the classical logic where the variable truth values are only integer '0' or '1', whereas the truth values in the fuzzy logic are real values between '0' and '1'. This approach has been applied in many fields, such as forest fires detection and modeling and residential fire monitoring. The collected data from a unit that combines four sensors, namely temperature, humidity, CO, and smoke was used for fire probability value computation based on the fuzzy rule method. The output value given by the fuzzy rule was used for sleep mode setting to reduce power usage in the sensor node. The reported error ratio was about 6.67% for a test performed for 30 sample data. In the case of fire prediction, a hybrid model that combines a multi-layer neural network (3-layers BP NN) and a fuzzy logic approach was proposed. The model was applied in a multi-sensor data fusion structure that includes three layers, namely the signal layer for multi-sensor data collection (temperature, smoke density and Carbon Monoxide (CO) density), the characteristic layer; this layer includes two units, namely the neural network pickup unit (NNPU) and the expert-database pickup unit (EDPU). The third layer is the decision layer where the data-fitting characteristic (probability) extracted by the NNPU and the experiential characteristic extracted by the EDPU were fused by the fuzzy inference system to predict the fire probability.

III. PROPOSED MODEL FOR WILDFIRES ITS LOCATION DETECTION AND INTIMATION



The method that is proposed in this research paper uses Logistic Regression to identify fires in the forest. Logistic Regression is a discriminative model, i.e., it models the conditional probability distribution P(y|x;w) using the Sigmoid function. Here, 'x' refers to the individual pixel value, while 'y' is a scalar (-1 or 1), it is the label associated with the pixel x, and 'ω' is the weight parameter that needs to be learned during training.

$$\sigma(k) = \frac{1}{1+e^{-k}}$$



The sigmoid function has the property of converting continuous values into a Bernoulli (discrete) distribution which in turn can be used for classification purposes. From the graph above we can see that for large values of k, the function will produce 1, and 0 for smaller values of k. A thing to note is that the sigmoid is used when we are dealing with classification between two classes, i.e., binary classification (which is our case). For more than two/multiclass classification, the SoftMax function is used. the optimum value of 'ω' can be achieved by using gradient descent. Since gradient descent involves minimizing a function; therefore, we will be using the negative of log p(y|x;ω) as the function to minimize.

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$$\omega_{t+1} = \omega_t - \alpha \sum_{i=1}^{n} y_i x_i \left(1 - \sigma\left(y_i x_i^T \omega_t\right)\right)$$

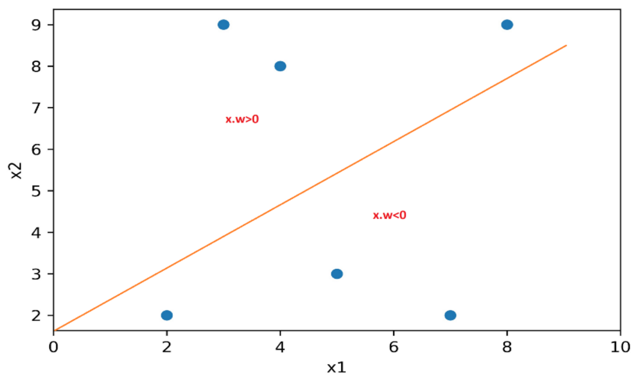
To give a quick primer on gradient descent; it is an optimization technique which can be used for finding the minimum of a function, iteratively. This minimum might/might not be the global minimum. This approach uses a logistic function to model events that can be expressed in binary mode. It can describe the relationship between several variables to dichotomous variables. A mathematical model of a set of explanatory variables is used to predict a logit transformation of the dependent variable with two values (such as '0' and '1' or 'Yes' and 'No'). Suppose two outcomes of a binary variable: an outcome of '1' with proportion of observations (p); and an outcome of '0' with a probability (1 - p). The ratio of the proportions for the two possible outcomes (p/(1 - p)) is called odds. The transformation of the odds using the natural logarithm is called the logit transformation. The logistic regression is widely used in natural events modeling, such as fire modeling by estimating their probability of occurrences. Once we complete color detection which this paper focuses on, the data will pass through sensors that will send the location coordinates and fire alert.

A. *Identifying Forest Fires*

The Dataset used was created based on Remote Sensing data to predict the occurrence of wildfires, it contains Data related to the state of crops (NDVI: Normalized Difference Vegetation Index), meteorological conditions (LST: Land Surface Temperature) as well as the fire indicator "Thermal Anomalies". All three parameters were collected from MODIS (Moderate Resolution Imaging Spectroradiometer), an instrument carried on board the Terra platform. The collected data went through several preprocessing techniques before building the final Dataset. The Data contains parameters with high influence of wildfires occurrence collected using remote sensing. The Dataset is composed of four columns, the first three columns are NDVI, LST, and Thermal Anomalies and the fourth column represents the corresponding class (fire or no fire), the Dataset contains 804 rows: 386 instances of the class "fire" and 418 instances of the class "no fire" with 418 rows. Each row contains the collected data and its class. The data was downloaded from the official website of NASA's Land Processes Distributed Active Archive Center (LP DAAC), and then we preprocessed them using multiple preprocessing techniques to remove noises and correct inconsistencies, and finally extracting useful information.

The study area is composed of multiple zones located in the center of Canada. The surface of this area is approximately 2 million hectares. These zones differ in their size, burn period, date of burn and extent. We have chosen to apply the experiment in a big region of Canada's forests because it is known for its high rate of wildfires and also for the availability of fire information (start and end fire date, cause of fire and the surface of the burned area in hectares), this information was acquired from The Canadian Wild-land Fire Information System (CWFIS) which creates daily fire weather and fire behavior maps year-round and hot spot maps throughout the forest fire season.

We will train the color classifier using gradient descent. The function returns a vector (3x1) of the parameter 'ω'. We will be using this parameter for describing our classification boundary. Logistic regression generates a linear decision boundary which is described by the equation x.ω=0 (the dot product of x and ω). Therefore, for x.ω≥0, i.e., pixel values on or above the linear boundary, will be predicted as a yellow positive pixel, while for x.ω<0, the pixel will be predicted as a yellow negative pixel. This can be best understood by referring to the diagram below for 2 features:



The global accuracy using the logistic regression was about 89.47%. The meteorological conditions including daily minimum temperature, mean wind speed and daily minimum humidity are critical weather conditions of natural\ forest fire occurrences, in addition to the average mean temperature and precipitation. According to this study, the effect of these factors varies from country to country. For example, in Durango State, Mexico the main driving factors of fire occurrence are: the intensity of land use, land use change, vegetation type and precipitation, whereas in the Mediterranean ecosystem central Spain the live fuel moisture content is considered as a main factor of fire occurrence. It is expected to tune the model by including these factors for countries accordingly. We cannot use same set of factors for every country because that will reduce the accuracy of the classification by the model. The performance evaluation results for the 53 models showed that the total percentage of correctly predicted fires was in range of 87.4% to 94.6% (from 0.82 to 0.6 for the Area Under RoC Curve (AUC) value).

B. *Decting location and Intimating about Forest Fires*

Once we have identified the fire occurrence in the forest it becomes far most important to tell about the same to the designated officials so that necessary steps can be taken. One of the ways to do so is to set an alarm on the onset of fire as identified by the model. However even setting an alarm might delay the work of fire fighters as they may not know which area of the forest is affected by the fire. The delay in reaching the accurate location might result in fire becoming wild and hazardous. Sometimes unstoppable for weeks. Hence the need for getting accurate location increases even more. Our goal is to provide this information within minutes, instead of hours, by automating the identification of forest fire hotspots through custom video processing, integrating these results with real time navigation technologies (Wide Area Differential GPS "WADGPS") This information can then be transmitted to the fire control officers for integration into the Fire Control GIS system. The use of LWIR cameras, which sense the heat emitted in the form of infrared radiation, will enable early detection and location of forest fires in reduced visibility due to haze, smoke or darkness. To determine 3-D coordinates of the fire from the images, the position vector (3 parameters per image) and direction/orientation (3 parameters per image) of the camera at exposure times are needed for a pair of images. These parameters will be obtained from the WAGPS. Following the 3D coordinate computation of the hotspots and fires, this information will be sent to the web server using SMTP libraries and a mail with exact co-ordinates will be sent to the officials. This enable faster blowing off the fire and will prevent hazards. We can also use Thermo Anemometer which can sense fire heat from a distance of approximately 500 meters. The precision of Thermal Anemometer depends upon the quality of instrument and the conditions of use. One of the cost-effective measures that can be taken to reduce the expenses by more than 50% by identifying the forest fires by probability mapping where we generally develop a heat map of the area which is most prone to fire. This can be modelled on the previous history of forest fires or by modelling features that incite fire mostly. We can develop a tree-based model along with ANNs to accurately classify the areas which are more prone. Hence, not only detection but locating the exact position and intimation to the concerned authorities can help us fight with Wildfires.

C. Working of the Proposed Approach

The proposed approach uses WSN camera which rotates 360 degrees and is mounted at different places in the forest for real time fire detection Once the fire onsets, it identifies the fires and alerts the sensors which in turn rings the fire alarm alerting the nearby people and communicates with the Anemometer to capture the location for around 500 meters. Once the sensor gets the coordinates it sends the automated mail to the concerned authorities with location and fire alert so that they can take appropriate actions and cam reach the location without wasting time in comprehending the site of fire. To identify the fire, we are using color detection technique where it takes the images from the WSN camera as 50 frames per minute and then runs the classifier – Logistic regression. We have tested the images on several other Machine learning algorithm as well before selecting Logistic Regression. The other algorithm that we used to test images were – Random Forests, K-nearest neighbor, Support Vector Machines and decision Trees. Logistic Regression outstands the performance of other Algorithms in terms of accuracy. Apart from this it takes only 40 seconds to get executed. However, the time can be further reduced by tuning the parameters of the model and reducing the time complexity of the code. The accuracy of the other models in comparison with Logistic regression is given below.

Sl. No	Algorithm	Accuracy
1	Logistic Regression	89.47%
2	Random ForestClassifier	84.21%
3	K-NearestNeighbors	73.68%
4	Support VectorMachine	89.47%
5	Decision TreeClassifier	73.68%

DISCUSSIONS

The main and critical factors in fire ignition and spread are meteorological (temperature, relative humidity, precipitations and wind speed) and climatic conditions. In addition to meteorological elements, the topological and vegetation types are also influencing factors, which are mainly considered in fire risk map development. We reviewed the existing methodology for detecting forest fire and understood that the accuracy for those is not in the acceptability range apart from Convolution neural network which gives good accuracy around 78%. However, the problem in this method is not just the accuracy but also the execution time of the models and numbers of frames they are capturing per minute which is around 20, which in turn increases the time for identification of forest fire. This can sometimes lead to hazardous situations. To overcome these, we have proposed the solution which operates with 50 frames in about 40 seconds. The total reaction time are just few seconds. Hence the proposed method is giving better results than the existing methods. The overall approach to identify, get the location and then intimating the same could be remarkable achievement in

CONCLUSIONS

Forests play a very important role in sustaining the environment. Wildfires or forest fires are not only responsible for the destruction of the natural environment, but also affects the ecological balance. A large number of fires are considered under man made causes and climate change. Although other factors like drought, wind, topography, plants, etc., have an important influence on fire appearance and its spreading. The prediction, detection and intimation of fire onset is important for fire prevention, organization of preventive measures and optimal storage of firefighting resources. We have reviewed the existing approaches for the same and found that they all are effective but the accuracy is quite low. We cannot miss on predicting a fire place as it may lead to very dangerous impacts for everyone on this earth. The proposed method gives the highest accuracy for the data set it has been tested on. And the overall approach not only promises to prevent hazards but can be used by various countries by modifying the features. It is cost effective at the same time. We consider that the present paper is meant to help researchers to have an overview of the state-of-the-art in forest fires prediction and detection systems that still represent an open issue. The development of advanced systems that integrates the artificial intelligence in such systems is a very promising direction that predicts such critical environmental issue and support public policies in the control of forest fires; on the other hand, it facilitates the firefighting task to mitigate the forest fires threat.

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