Drone based Fire Detection using Classification

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***Abstract*—The majority of the spaces are covered with jungle and urban. Cataclysmic events are forever unpredictable. Backwoods fire puts numerous lives of people and creatures in harm's way. Many nations are scared. So finding techniques using which minimize the impact and spreading rate of fire. Various algorithms are available for fire and smoke locations. Aerial pictures help in examines rapidly spreading fire. The drone strategy is valuable to gather data in regards to the fire and help firemen group with fire control and plan for future events and furthermore it diminishes the life damage for the firemen. This paper presents methods to discover pile burn utilizing drones with picture characterization and attempt to discover the best classification solution. I'm attempting to discover answers applying various techniques for classification like Convolutional Neural Network, Artificial Neural Network, Deep Learning, Transfer Learning.**

***Index Terms*—Transfer Learning, Deep Learning, Drones, Artificial Intelligence, Unmanned Aerial Vehicles, Convolutional Neural Network**

I. Introduction

Woods contribute to the country's financial riches. Backwoods helps to clean air and water, moderate the environment, settle the dirt. Timberland increment oxygen noticeable all around. The space of timberland region reduce because of wildfire. Timberland performs a major role by giving food, shelter, and medication for the survival of every single living creatures on this planet. Wildfire always harm many lives recent example of Australian wildfires, which cumulatively burned for months, also have been extremely harmful, burning more than 1500 homes and causing the death of more than 23 humans [1]. In Quebec, Canada almost 502 woods fires have happened by June 2020 which burn 63, 400 ha of land, it is more than double the mean burnt land and the number of forest fires across the last 10 years [2]. From these reports saw on-increment fires and increase their seriousness. Early days wood fire recognizes and observes by human patrol and sees from watchtowers, these are boring tasks linked with mistakes and weariness. As New Innovation occurs, heat and smoke finder were put in different places of the timberland. Yet, they can't find the location and the quantity of fire, so need further speculation. At more extensive scales, satellite picture is generally utilized for evaluating fires around the globe [3] [4], however typically at a relatively coarse resolution and with the availability of rehash same pictures compelled by satellite orbital examples.

There are different approaches to recognize the rapidly spreading fire source: fire towers, manned aerial vehicles, and satellite monitoring. These strategies have critical constraints that lessen the observing productivity. Fire towers have a restricted view range, and the precision of perception depends on climate conditions and season of day. Guided vehicles (helicopters and planes) are required in the extraordinary costly framework. Additionally, these two techniques have a human factor and a hazard to human existence. To identify woodland fires, there are two general methodologies using satellite pictures, and sensor networks [5]. However, the satellites can't give constant video or pictures since the nature of their pictures is exceptionally affected by climate conditions [5]. Fire discovery utilizing remote sensor networks is expensive and high-support to cover wide woodland regions [6]. Satellite perception permits you to computerize information assortment, yet the space of the rapidly spreading fire for location is excessively high. At this point, huge powers will be expected to wipe out the fire. Satellite perception gives the most extreme benefit in essential preventive activities [7].

Unmanned Aerial Vehicles (UAVs) are alleviating all inconveniences of past techniques. UAVs are utilized for various areas and reasons like military, individual, cataclysmic events. Utilizing UAVs offer new features and service including quick deployment, high adaptability, more extensive and flexible perspectives, and less human intercession [8] [9] [10] [11] [12]. Timberland executives utilized pile burns for tidying up branches and foliage from forest thinning and reconstruction projects. The UAV have been as of late used in out of control fire discovery and the board as a minimal effort and lithe answer for gather information/symbolism considering their one of a kind highlights like 3-dimensional developments, simple to fly, mobility and adaptability [13] [14] [15] [8] [16]. The UAV organizations can offer a few features in such tasks including following the fire forefront, quick mapping of wide areas and loss assessment, real-time video streaming, and search-and-rescue [11] [17] [18] [19].

The drone was substantially more adaptable for area checking with an alternate climate condition [20]. Appropriation of drone around the area can be made in the optimal way of cost or time [21]. The drone fleet equipped with thermal cameras and air quality sensors makes it conceivable to perceive a smoke or rapidly spreading fire source at the beginning phase [20]. The principal benefit of UAVs is autonomy and minimal

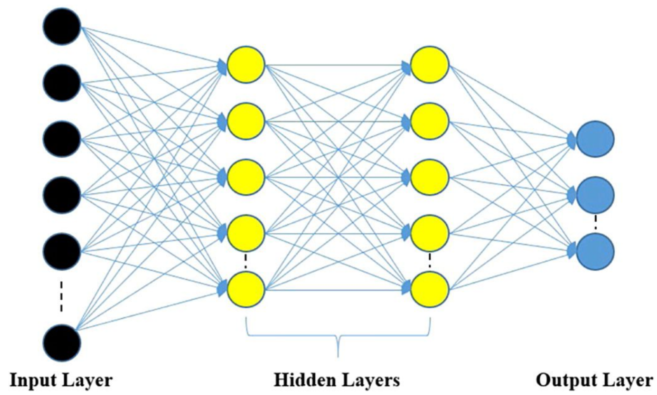

Fig. 1. Artificial Neural Network [2]

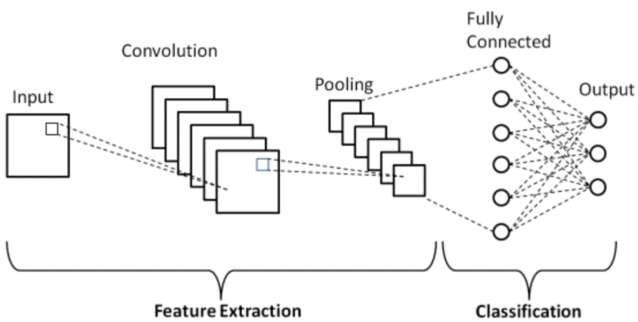

Fig. 2. Convolutional Neural Network [23]

cost against existing forest fire identification techniques [22].

II. Literature Review

There are various sorts of learning classifications: Supervised Learning, Unsupervised Learning, Semisupervised Learning, and Reinforcement Learning. There are diverse Machine Learning methods like Artificial Neural Network, Convolutional Neural Network, K closest neighbor, Decision tree, Support Vector Machines utilizing which we can perform fire identification. Fig. 1 and Fig. 2 show the essential technique comprehension of Artificial Neural Network and Convolutional Neural Network.

In the past, there are different methods used for fire identification like color-based object discovery, smoke detector sensors, image processing-based approach.

Color-based object discovery, which is one of the most initial identification procedures utilized in vision-based forest fire location applications, is very commonly used [24]. By and large, fire blazes show reddish tones, which range from red to yellow during the fire [25]. Accordingly, the scope of fire tone can be treated as a time frame esteems among red and yellow. In light of this marvel, most of the current shading-based fire identification techniques make use of the RGB shading model, here and there in blend with the HSI model too. Notwithstanding this, an elective technique for utilizing the shading-based fire discovery rules, in this work, is planned in the Lab color model to decide the areas of fire applicants. The essential thought of the proposed technique is to embrace the channel ”a” in Lab tone model to separate fire-pixels by utilizing chromatic highlights of fire. Various test approvals are completed, and the test results show that the proposed technique can successfully separate the fire pixels and track the fire zone [26].

A smoke bell is a device that recognizes smoke, consistently as an indication of fire. But there is a limitation detect fire using a smoke sensor like if smoke generated quite later after burning the surroundings, smoke sensors take a long time to detect smoke, false alarm generate [27]. Huge quantities of procedures have been created for fire identification from pictures of recordings because of the quantity of vision-based calculations proposed in different writing reviews [27]. Ordinary strategies for fire discovery have been essentially supplanted with Video-based smoke location techniques because of different benefits over regular strategies like early fire recognition, fast reaction, non-presence of spatial cutoff points, likewise data of the fire progress can be accomplished because of living video and in fire, examination vision-based is competent to give scientific proof [27].

The picture classification issue is one of the difficult tasks in the picture processing field. In Early days, traditional picture processing methods used RGB channel measurement to identify various items like fire in frames or videos [28] [29] [30]. These traditional techniques are not liberated from mistakes and are not completely dependable [31]. For example, RGB value measurement strategies that generally consider a threshold value to identify fire may recognize nightfall and dawn as a false positive result. In any case, training a DNN to make this picture categorization task assists in learning components not apropos to the fire. Additionally, a few examinations, for example, perform pixel-based categorization and segmentation with respect to the HSV (Hue, Saturation, Value) design [32] [33]. The binary categorization model which was utilized in this examination is the Xception network [34] proposed by Google-Keras1 [35]. The model Xception is an example of a Deep Convolutional Neural Network (DCNN) [35]. The Xception model has three main blocks: 1) the input layer, 2) the hidden layers, and 3) the output layer [35].

III. Methodology

Pictures gathered by drones during a prescribed burning piled waste in an Arizona pine backwoods [36]. The FLAME dataset is freely available on IEEE dataport. There is a total of 47,992 images for fire and no fire. We use 31,500 images for the training set and 7,875 images for the validation set. Train images are composed of 25,018 fire images, 14,357 no fire images. We have 8,617 images for the test set. The test set is composed of 5,137 fire images, 3,480 no fire images. Images frames that resized to 254 x 254 and JPEG format for the problem. Images are labeled as fire and no fire. All train image frames are collected using the Matrice 200 drone using Zenmuse X4S camera [36]. All test image frames are collected using the Phantom drone and its default mounted

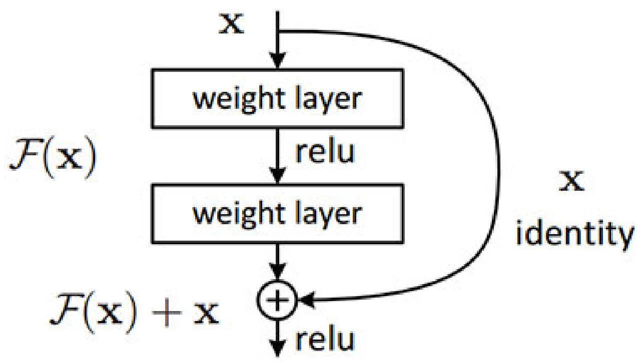

Fig. 3. Block Diagram of residual learning: a building block [37]

camera [36]. Train and test image samples are different from each other. There is a huge covariate shift in data.

The image classification task is divided into Image Preprocessing, Detection of an object, Feature extraction, and Training, Classification of the object. Using an appropriate classification technique that contrasts the image patterns with the target patterns, object classification categorizes observed objects into predefined groups. We will attempt a distinctive strategy and think about the outcome.

ResNets which is known as Residual neural networks are the type of neural network that applies identity mapping [38]. From the above Fig. 3, we can see that the most important concept involved here is the skip connection or the shortcut. Skip connection is the identity mapping where the input from the previous layer is appended directly to the output of the other layer [38]. In ResNet18 and ResNet34 has 2 layers deep ResNet block [39]. In ResNet50, ResNet101, and ResNet152 has 3 layers deep ResNet block [39]. There are two kinds of residual connections: input and output dimensions are the same and not the same. The identity shortcuts (x) can be directly used when the input and output are of the same dimensions [37].

$$Y = F(x, Wi) + x, \tag{1}$$

When the dimensions change, 1) The shortcut still performs identity mapping, with extra zero entries padded with the increased dimension [37]. 2) The projection shortcut is used to match the dimension (done by 1*1 Conv) using the following formula [37],

$$Y = F(x, Wi) + Ws * x, \tag{2}$$

Here, Wi is the parameter given to the CNN layer, and the Ws term can be implemented with certain convolution configurations to make dimensions of input and output identical.

Fig. 4 shows the basic architecture of ResNet152. Here, I have used the ResNet152 model which is a pre-trained model with different convolution layers, activation and batch normalization, global average pooling layers. This is binary classification so I have used dense value "1" and activation "sigmoid" for output. I am compiling the model using Adam's optimization algorithm, binary cross-entropy loss, and accuracy metrics. Fit model using the training dataset and evaluate the model on the testing dataset.

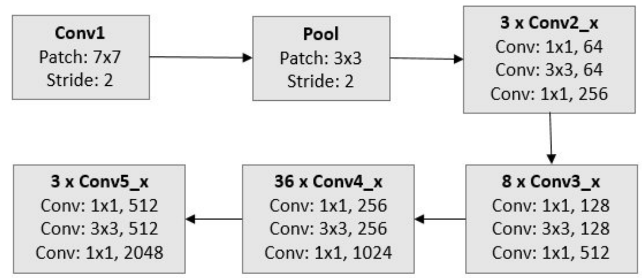

Fig. 4. Block Diagram of basic architecture of ResNet152 [40]

Since the fire discovery is a binary characterization task (Fire/No Fire), the activation function for the output layer is a Sigmoid function. The equalization for the Sigmoid capacity is appeared in (1),

$$P(label = Fire) = \sigma(label = Fire|\zeta(\theta)) = \frac{1}{1 + e^{-\zeta(\theta)}}, \tag{3}$$

where $\zeta(\theta)$ is the value of the output layer which is cited dependent on the input frames and the RGB value of every pixel and every weight across the hidden network. θ is the weights for the last layer of the network. The output value of the Sigmoid function is the possibility of fire discovery dependent on the imported frames into the network. As the issue in this part is a binary characterization, the considered loss function is a binary cross-entropy described as,

$$L(y, \hat{y}) = \sum_{i=1}^{N} (y_i * \log(p(\hat{y}_i)) + (1 - y_i) * \log(1 - p(\hat{y}_i)), \tag{4}$$

where N is the number of total units in each batch used to modernize the loss function for every epoch. y is the ground truth label for the frames of types fire (y = 1) and no-fire (y = 0) depend on training data. p($\hat{y}$) is the predicted probability of a frame relating to the fire class. Then, the Adam optimizer is utilized to reduce loss function and track down the weights during the learning method. Train the network with the training data. Later, evaluation is performed using test data.

IV. Results

Here, I have used a total of 39,375 images which includes 25,018 images of type "fire" and 14,357 images of type "non-fire". The training dataset further divided into 80% training and 20% validation datasets. I have added seed and shuffle so all images shuffle before adding to the network. Additionally, add augmentation methods for example horizontal flipping and random rotation 0.2 are used to create new frames and address the issue of bias for an unbalanced number of samples in the two "fire" and "non-fire" classes. I have run 12 epochs for training and the learning rate for the Adam optimizer is set to 0.00001 which stays unchanged throughout the training phase.

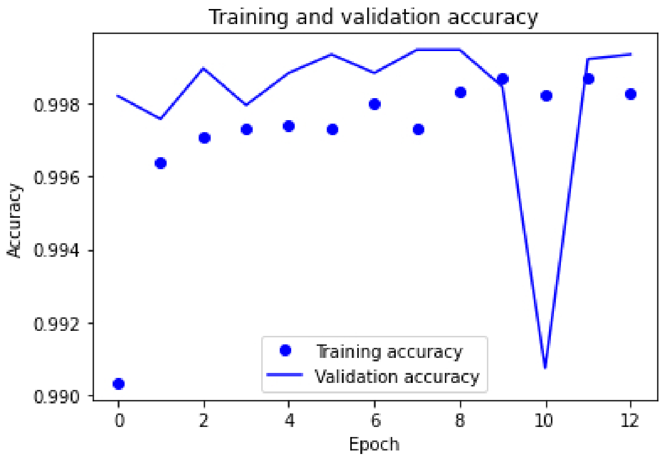

Fig. 5. Block diagram of training and validation accuracy

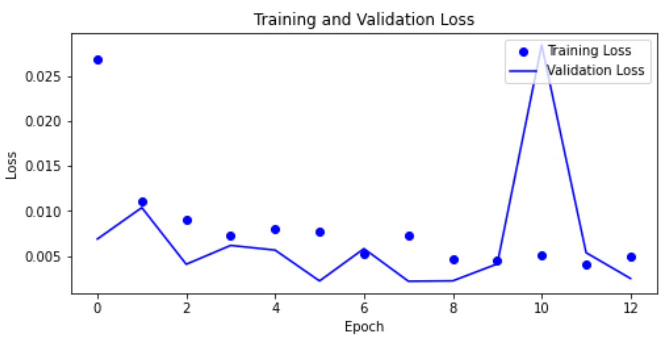

Fig. 6. Block diagram of training and validation loss

Additionally, the batch size of 32 is used to fit the model in the training phase. To assess the accuracy and loss on the testing dataset, images are added to the pre-trained networks.

The accuracy and loss for the training dataset were 99.85% and 0.0045 after 12 epochs. The accuracy and loss for the validation dataset were 99.95% and 0.0022 after 12 epochs. Fig. 5 and Fig. 6 shows the accuracy and loss of train and validation dataset in 12 epochs. I got 83.78% accuracy and 0.4269 loss in the test dataset. All simulations for the training, validation, and testing phases, are performed on Kaggle with GPU. Fig. 7 shows that ResNet152 pre-trained model with additional Dense layer.

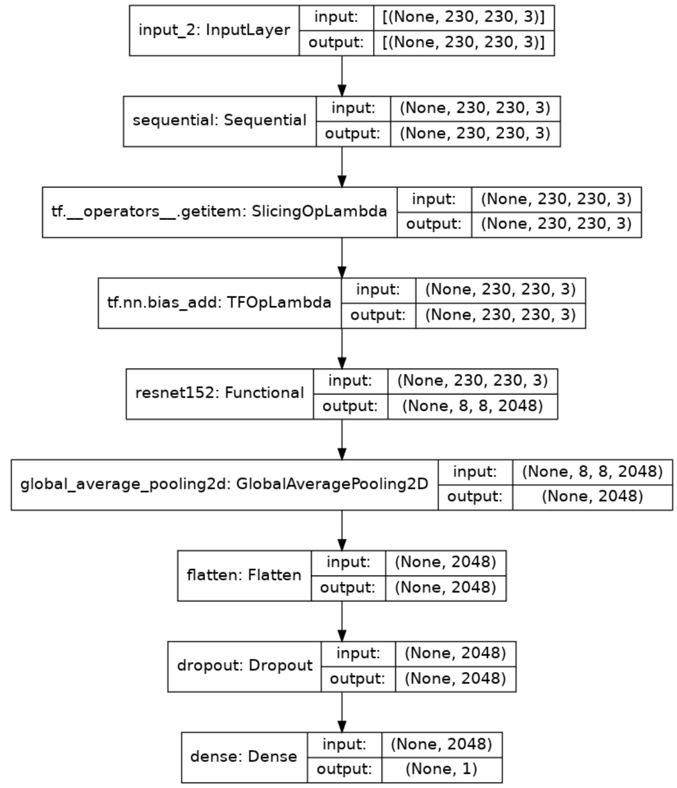

Fig. 7. Block diagram of ResNet152 pre-trained model with Dense layer

Model	Training Accuracy	Test Accuracy
CNN	99.53	60.07
VGG16	99.85	68.21
VGG19	99.85	71.44
ResNet50	99.88	72.58
ResNet101	99.86	79.67
ResNet152	99.85	83.78

Fig. 8. Block diagram of different model accuracy

V. Discussion and Conclusion

In the beginning I have faced problem because I have low configuration laptop without GPU. I have tried Google Colab but facing same problem so I have tried Kaggle notebook and it's work for me. I have tried different model to find out best test accuracy. After that I have started train my model with different method. I have tried CNN model, VGG16, VGG19, ResNet50, ResNet101 and ResNet152. Fig. 8 shows the results of the all model which I have tried to get better accuracy. Deep learning model take more time to train model then others. So it's preferred to use GPU rather than CPU for training deep learning model. From the above result I conclude that deep learning pre-trained model give better result than other. ResNet152 model gives better test accuracy for pile fire detection with FLAME dataset. I think still I can improve accuracy with some changes like seed, data augmentation parameter like random crop, random contrast, random zoom and other thing like weights. I will try to improve accuracy in future.

VI. Plan

Project plan is Fig. 9 in the form of gantt chart.

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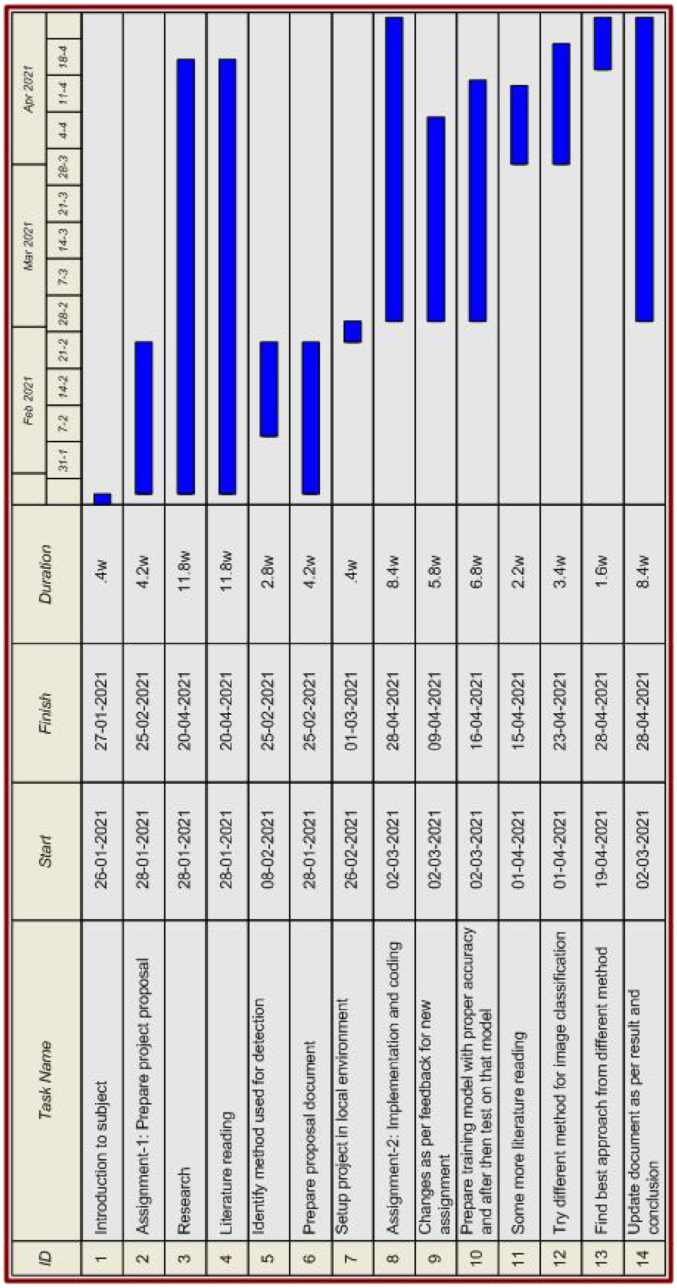

Fig. 9. The Gantt Chart

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