

Enhancing Wildfire Detection using Transfer Learning-based Convolutional Neural Networks

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Abstract— Fires in forests are the most devastating natural hazards, resulting in substantial economic damages and fatalities across the globe. Millions of hectares are lost on an annual basis and experts caution that atmospheric changes will prompt wildfires to arise more repeatedly and with more intensity in the years ahead. For prompt reaction and mitigation actions, fire occurrences must be identified quickly and accurately. Preventing damage to persons and buildings, that are prone to fire, requires effective early fire detection. Many deep learning models were created to map and identify wild fires, assess their severity and forecast their spread in an effort to minimize these risks. This work presents a method for fire detection using four various pre-trained models: MobilenetV2, Inceptionv3, Resnet50 and VGG 16 to evaluate valuable features from input images and identify fire detection. Experimental results demonstrate Mobilenetv2 accuracy of 85.61%, Inception-v3 achieves an accuracy of 86.10%, Resnet50 obtain accuracy 95.34% and VGG16 accuracy of 93.32%. The results of these investigations demonstrate that, in comparison to other existing fire detection techniques, the suggested method (Resnet50) successfully identifies fire zones and attains good classification performance.

Index Terms— wildfire detection, MobilenetV2, InceptionV3 Resnet50 and VGG16.

I. INTRODUCTION

One of the world's most vital resources from nature is forests. In addition to providing the minerals and materials needed for industry, they also play a big part in preserving ecological balance, preventing sandstorms, and conserving water. Above 36% of India's forest place under cover is prone-fire as per the FSOI. The frequency and Size of forest fires are influenced by temperature, precipitation, vegetation, and moisture. In India, the months of November through June are regarded as the forest fire season. Due to the abundance of dry biomass available after winter and throughout the dominant summer season, there are more fire incidences reported in March, April, and May. According to FSI data, Mizoram - 3,748, Manipur -1,712, Assam 1,642, Meghalaya - 1,232 and Maharashtra -1,255 reported the most wildfires in March 2024. The major Causes include methods of agriculture, negligence, natural disasters, and intentional blazes started by residents. According to a government report, residents burn woods to promote the development of higher-quality grass, conceal unlawful tree-cutting and aid in poaching. The ecosystem, wildlife and human life are all equally harmed by forest fire. Everything in their path can be destroyed by wildfires as they spread swiftly.

The protection of forests from fire is a top priority for governments worldwide. Sensing devices including temperature, gas, smoke, and flame detectors are typically used to identify fires. Prevention The building of watch towers detection at early stages, the transportation of fire watchers, community involvement and the installation upkeep of blazes are some of the measures outlined by the MOEFCC to prevent and control blazes in forest. However, these detectors have some drawbacks, such as limited coverage areas, slow reaction times, and public availability problems [1]. Due to their low operating and maintenance costs, ease of deployment and improved access to difficult-to-reach places, UAV's and drones have become popular in a diversity of professions as a outcome of recent advancements in internet technology. A significant amount of surveillance-related data will be produced by the linked UAV networks, which can assist UAVs in strategically maximizing their performance. By continuously monitoring and promptly putting out the forest fire, UAVs with vision capabilities might greatly lower the risks of any big calamity. Furthermore, as examined in [16], the deployment of UAVs can be less expensive than the installation of several closed circuit television (CCTV) cameras for the same area's observation [2].

Our goal in this paper is to detect blaze fires by utilizing the most successful TL Deep Learning models includes MobileNetv2, Inceptionv3, Resnet50 and VGG16 to detect wildfire detection.

The main aim of this paper is:

- We present dataset which is publicly available from kaggle and pre-processing is done.
- We implement transfer learning models like Mobilenetv2, inceptionv3, Resnet50 and VGG16 to detect forest fire detection.
- Then we find Performance Measures include accuracy, Specificity, precession, F1-Score and recall.

II. LITERATURE REVIEW

Early wildfire exploration has been suggested using Deep pre-trained models. To predict early detection of wildfire authors proposed different TL models such as Mobile net v2, Res2net, CNN, VGG 16, Inceptionv3 and ResNet50, as well as different methods including U-net, YOLO V5, Smoke net Model and CBAM. Table I show the Contribution of Existing works on wildfire detection.

Huo, Y, et al. [13], utilized YOLO-Smoke and contrasted with the original YOLOv3 model by adding drop block layers as a regularization technique, switching the loss function to focal impairment to address the root cause of imbalanced class, and integrating with ECA. To prevent model over fitting, which is brought on by the public dataset's plain backgrounds, we employ mosaic data augmentation. Outcome of the test dataset demonstrated that without increasing image processing time, the suggested model increased YOLOv3mAP from 81.95% to 86.86%.

W. Cai, et al. [14] suggests a better framework based on YOLOv4 that uses spatial pyramid pooling and depth-wise separable convolutions with CSPdarknet53 serving as the backbone. This research proposed a multiscale object detection system for image-based smoke detection based on deep separable CNN. In order to expand the core network and enhances its ability to extract picture characteristics, we started by adding a convolution to the CSPdarknet53 network's convolution process. A SPP module was then introduced to improve the features of tiny destinations after the backbone network had output the feature layers. Lastly, network parameters were decreased using depth wise-separable convolution. In contrast to YOLOv4, which performed with an accuracy rate of 97.8% and a false rate of 1.7%, the proposed model outperformed YOLOv4, which had an accuracy value of 96.7% and an error rate of 3.0%.

Rahul, M., et al.[15] used CNN based image identification technique. In comparison to the previous SOTA techniques, such as VGG16 AND DenseNet121, we significantly improved the training and test outcomes by fine-tuning the Resnet50 framework by including few layers of convolutional with ReLu functions and a binary identification as output layer. With an accuracy of 92.27%, it outperformed VGG16 and DenseNet121 by 7.06% and 3.23%, respectively With the use of the Stochastic Gradient Descent, we were able to prevent the model from being under fit or over fit.

Dutta, S., et al. [16] paired an image processing method with a basic CNN to detect wildfires in aerial photos. Six convolutional, pooling (max), activations (Relu) and three regularization methods (L2 regularization, BN(batch normalization), dropout) are all included in the basic CNN. Both the HSV color space thresholding approach and the multi-channel binary thresholding method are used in the image processing procedure. Because of its simplicity, the suggested architecture requires less computing power. Even with fog and smoke present, a high sensitivity of 98.10% was attained using the FLAME dataset.

K Mohammed, R.et al [17] built own dataset includes 1,103 pictures of smoke and fire class, using a pretrained Inception ResNetv2 on the ImageNet dataset. F1-Score, specificity, recall, precision, and classification accuracy were 100%, 98.08%, 99.09%, and 98.30%, respectively.

TABLE I: CONTRIBUTION OF EXISTING WORKS ON WILDFIRE DETECTION

Author	Dataset	Methodology	Advantages	Limitations	Accuracy
Gao, S. H.,[3]	Wildfire Dataset	Res2Net	Res2Net increases the multi-scale feature extraction.	Substantial computational intricacy; situations with high-resolution inputs have an impact on inference speed.	85.20%
Liu, L.,[4]	BowFire Dataset	CNN+AGSO	Enhances accuracy by combining 2 datasets	Assess the methods resilience to weather and wind, among other environmental influences.	95.65%
Gao, X.,[5]	Landsat-8 dataset	CNN	Obtain high Accuracy	Need to improve the generalization and robustness of DAFDM.	93.21%
Hu, X.,[6]	FLAME dataset,	U-Net, HRNet, FCN, and OCRNet,	enhancing the object features and contextual representations	High computational complexity;	91.14%
Lv, C.,[7]	Fire Detection Dataset	YOLOv5	Introduces multi layer feature extraction	Low detection accuracy	94.8%
Woo, S., Park,[8]	MS COCO detection, and VOC 2007 detection datasets	CBAM	Improves classification and detection	Applied for small datasets	98.4%
Ba, R., Chen, C[9]	MODIS data with 6225 images	Smoke net Model	Achieves high accuracy	Lack of multispectral data with high resolutions	92.75%
Shamsoshoara, A.,[10]	FLAME dataset with 47992 images	Xception	Large dataset	Achieves less accuracy	76.23%
Zhang et al.[11]	FLAME Dataset	FT-ResNet50,	Better feature extraction with high performance	Limlited Label Samples	79.48%,
Guan et al.[12]	FLAME:8000images	DSA-ResNet	flexible structure and excellent performance	Not applicable for multimodel data	93.65%

This method has been implemented with camera-equipped Raspberry Pi . We scanned the video stream frames and predicted the likelihood of smoke or fire using the Open CV library for real-time detection. Five DL Techniques (Xception, LeNet5, VGG16, MobileNet v2, and ResNet18) were assessed by Chen et al. [18] for their ability to detect wildfires in aerial photos. An extensive learning dataset of 53,461 RGB images—(25,435) belongs to fire/smoke images, 14,327 belongs to fire/non-smoke images, and 13,710 non-fire/non-smoke photos—was used to test these models.

III. METHODOLOGY

This research workflow is used to identify Wildfire Detection using Deep Learning technique as shown in Fig. 1. First step is to collect a wildfire dataset. Second Step is to Performs pre-processing to remove noise data then normalization techniques is used. Then load pre-trained methods like Mobilenetv2, VGG16, Inceptionv3 and Resnet50 for wildfire Detection then models are fine tuned to improve accuracy. Finally, fine tune models identify fire on data.

A. Dataset Description

FCDNet Dataset is a thermal imaging dataset captured by UAV/drones. Which contain 3078 images, which is very large scale. Only thermal images — no paired RGB or multispectral data included. That limits fusion-type modeling. These pictures are classified into validating, training and testing. this data set is mainly used for object detection.

B. MobilenetV2

Mobile Net is a minimalist model made specifically for mobile devices with modest power consumption, quick execution, and minimal memory usage. In addition to incorporating novel design components that enhance its performance, non-linearity and application, this iteration of the Mobile Net series builds on the strengths of its predecessor Mobile NetV1

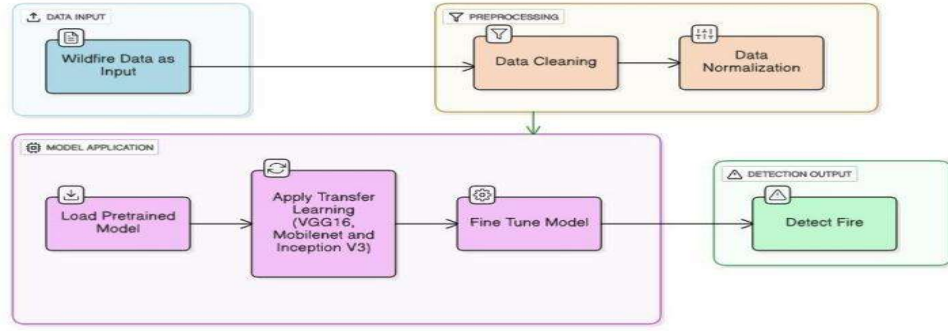


Figure 1: The proposed diagram for Wildfire Detection

The Inverted Residuals structure was introduced in Mobile Net V2. Reevaluating the conventional residual structure is at the heart of this approach, which makes the model more performance-focused and nonlinear. In addition to marking the ongoing development of the Mobile Net series, the release of Mobile Net V2 gives the deep learning community stronger tools to satisfy the expanding needs of apps[19].

C. Inception-v3

Google built the deep convolutional neural network known as Inception-v3 especially for computer vision picture categorization applications. Factorization techniques are also incorporated into this architecture, which lowers the number of parameters and increases overall efficiency. During training, Inception-v3 incorporates auxiliary classifiers to facilitate convergence and uses Global Average Pooling (GAP) in place of completely connected layers. Inception-v3 is a constituent of the Inception community, which also includes the Inception-v4 version, Inception-ResNet models and is the primary model for transfer learning.

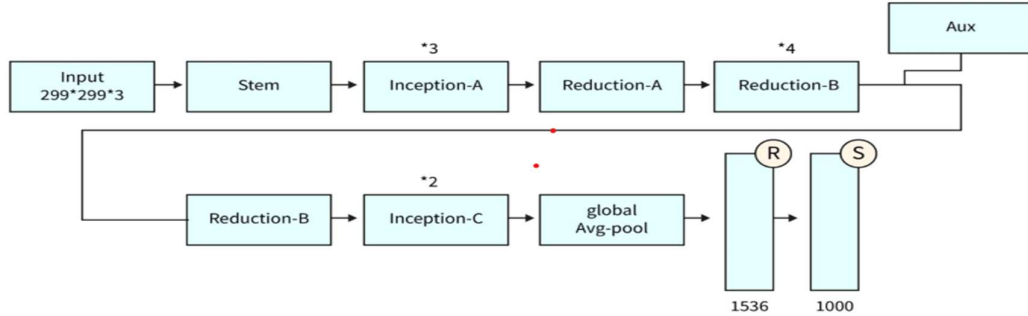


Fig 2: Architecture of Inception v3

The stem, the Inception blocks, and finishing layers are the three separate components that make up the architecture of Inception-v3. Reducing the input image's spatial resolution is the stem's goal, which is frequently accomplished using a sequence of convolutional layers. The Inception blocks are essential to the architecture and are crucial in deepening the network. The convolutions improve the network's depth, and the Inception modules help capture features at different scales. Usually, a global average pooling layer is combined with multiple convolutional layers to form these closing layers. The final categorization is achieved by processing the outcome from these last layers through FCL [20].

D. VGG16

The deep learning architecture was created especially for the image recognition challenge Image Net Large Scale by the Visual Geometry Group. The VGG16 is an essential part of the VGG family of NN structures, which Simonyan and Zisserman initially used for picture recognition. It consists of five layers of convolution, four deep layers, and a final fully interconnected layer [21]. Furthermore, 1x1 convolutions are incorporated into the convolutional layers of VGG16, which aid in managing network complexity. Learning linear combinations of successive feature maps is made possible by these 1x1 convolutions. Each convolution is followed by pooling layer with padding to preserve spatial resolution [22].

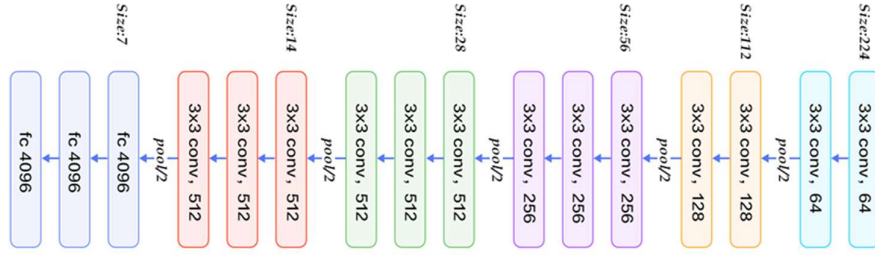


Fig 3: Architecture of VGG16

E. Resnet50

Kaiming and his colleagues developed ResNet, which made deeper network training practical. To make training deeper networks easier, they created a new learning framework called "residual learning". This model is termed "residual network" aims to minimize the difference between residual by allowing initial input knowledge to be straightly connected to successive neurons. Specifically, x was established as the network's initial input, while $H(x)$ was set as the desired output in the end. When the initial input z is sent straight to the network's tail as the first result, the learning objective in this case is $F(z)=H(z) z$. ResNet-50 consists of 49 convolution layers, including a 3×3 convolution layer, an (average)pool layer, and a fully linked layer(FLL). The back of each convolution layer in the bottleneck block is subjected to the rectify the nonlinearity by using activation function and the batch normalization (BN), whereas the fully connected layers of the classical (ResNet) model, which has 25.66 million parameters, are subjected to the Softmax function[23].

IV. EXPERIMENTAL RESULTS

This research work developed a model for analyzing, Wildfire Detection using the four pre-trained models Mobilenet2, InceptionV3, Resnet50 and VGG16. Performances metrics like Accuracy, F1Score, Precession, Specificity and Recall of Mobilenet2, InceptionV3, Resnet50 and vgg16 as shown in table2.

TABLE II: PERFORMANCE METRICS FOR TL MODELS OF PROPOSED SYSTEM

Metrics	Mobilenet	Inceptionv3	Resnet50	VGG16
Accuracy	85.61	86.10	95.34	93.32
F1score	85.6	86.4	95.4	93.3
Precession	85.3	84.8	94.7	92.7
Specificity	85.2	84.2	94.6	94.0
Recall	86.0	88.0	96.0	94.0

A. Mobilenet2

Below plot identifies Model accuracy and loss of training and validation of a deep learning with 10 epochs. It shows training Accuracy with 81.05% and validation accuracy with 79% and test accuracy is 85.61% which is comparatively higher than training accuracy is shown in figure 4.

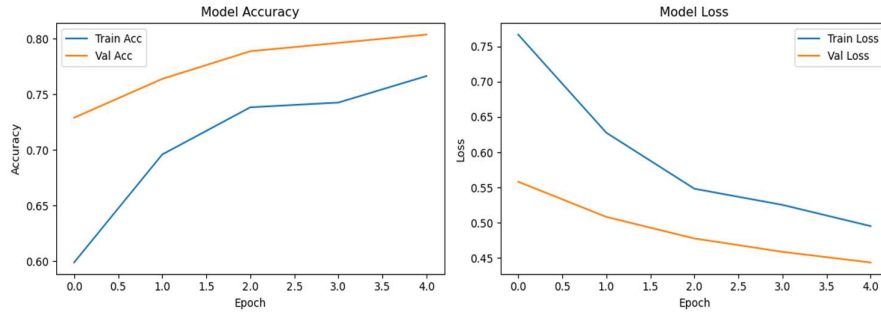


Figure 4: Accuracy and loss plot of Mobilenet2

These plots show strong improvement and there is a minimal over fitting ,performance indicate low error rate. The below confusion matrix is designed to detect fire or no fire .This model correctly predicted True positive has 115 instances ,false positive has 25 instances ,false negative 23 instances and true negative 228 instances .

B. Inceptionv3

This plot identifies Model accuracy and loss of training and validation of a Inception v3 with 8 epochs. It shows training Accuracy with 82.5% and validation accuracy with 81.5% and test accuracy is 86.10 %. Shown in figure 5. Below plot show good training process where the learning model is effective with minimal signs of over fitting.

The below confusion matrix is designed to detect fire or no fire .This model correctly predicted True positive has 114 instances ,false positive has 45 instances ,false negative 12 instances and true negative 239 instances.

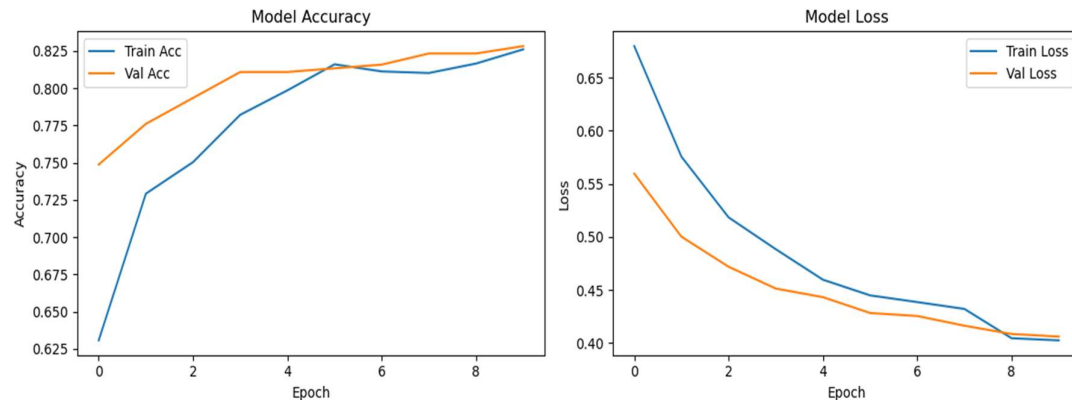


Figure 5: Accuracy and loss plot of Inception V3

C. Resnet50

This plot compare the performance of Model accuracy and loss of training and testing of a Resnet50 with 8 epochs. It shows training Accuracy with 95.2% and testing accuracy with 94.5% shown in figure 6. Below plot show sign of over fitting to train data which includes noise. In second figure training loss is low which reduce the minimized error and high test loss drop performance. To minimize over fitting some techniques like dropout, Regularization techniques are used.

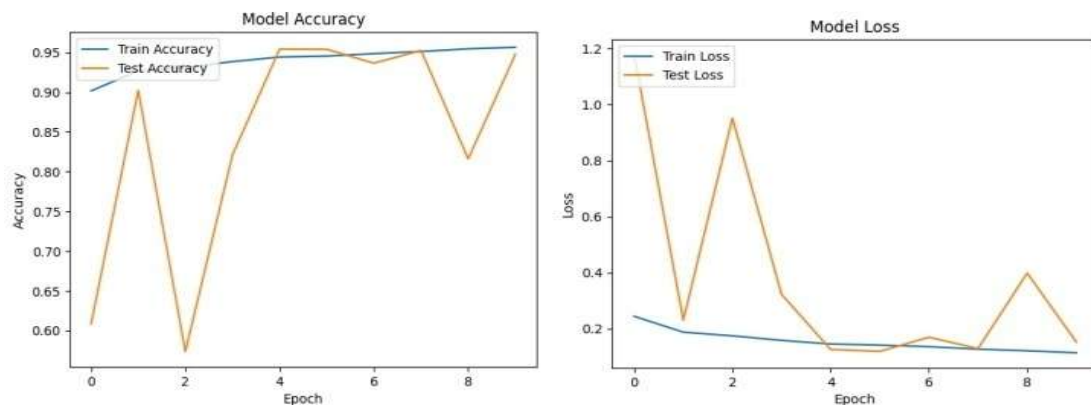


Figure 6: Accuracy and loss plot of Resnet50

D. VGG 16

This plot compare the performances of accuracy and loss of training and validation of a VGG16 with 8 epochs. It shows training Accuracy with 93.2% and validation accuracy with 87.5% is shown in figure 7. This model obtains high training accuracy compare to testing accuracy. it shows good sign of over fitting and generalization. these plots reduce the error rate with high accuracy and very reliable.

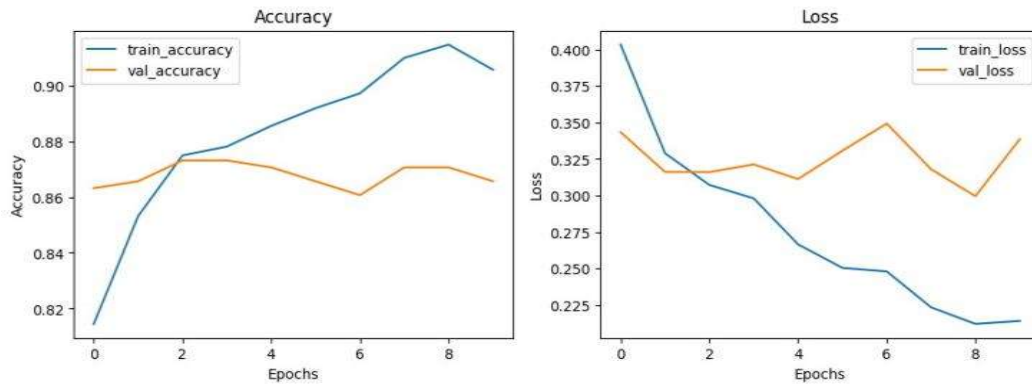


Figure 7: Accuracy and loss plot of VGG16

V. CONCLUSIONS

It is essential to use UAVs for wildfire detection and image analysis in order to put out fires early. Deep learning-based forest fire detection has been a promising field of study. This paper proposes Transfer Learning models Include MobileNetv2, Inceptionv3, Resnet50 and VGG16. we are taking FCDNetdataset which is taken from kaggle, first preprocessed dataset to remove noise .after preprocessing we apply TL methods for getting accuracy. compare models and finally identified Resnet50 method which gives best performance to detect wildfire detection. The proposed TL methods achieves an overall accuracy of 85.61%,86.10%, 95.34% and 93.32% .The Resnet50 method shows better Accuracy, Precision, F1-score, Specificity and Recall simulation results than existing techniques.

The problem of scarce labeled data can be effectively addressed by future research projects that use virtual reality frameworks and live surveillance to process wildfire extent and forecast spread.

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