Forest Fire and Smoke Detection using Deep Learning

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Abstract. The diverse plant and animal species that make up forests are essential components of ecosystems that have developed over time to co-exist. Wildfires, which may originate naturally, inadvertently by humans, or as a result of lightning strikes, frequently pose a threat to such ecosystems. Early wildfire detection is essential for preserving people, property, and resources. The approaches for localizing and categorizing images of forests under three varied domains of Fires, NoFire and Smoke using various data augmentation and pre-processing techniques are reviewed in this study. Additionally, this work makes use of employing the dataset for detecting wildfires in forests, or just the presence of smoke which resolves the classification issue of distinguishing between photographs with and without a fire. This work proposes an effectiveness study of various pre-trained deep learning (DL) neural networks namely Inceptionv3, VGG19, VGG16 and ResNet50. Inceptionv3 outshone all the other models, with regards to performance over datasets without CLAHE 95.12% with CLAHE 97.63% accuracy.

Keywords: CLAHE, Fire Detection, Forest Fires, Inception-v3, Smoke Detec- tion.

1 Introduction

Forests represent the world's largest land-based ecosystem system that carries great significance to the entire environment. They are particularly effective in controlling the climate and preserving the quality of the soil and water [1]. Natural ecosystems with animals together with human populations experience significant threats because of forest fires. Effective mitigation and response activities depend on the early detection of forest fires. By taking millions of lives and wreaking billions of dollars in damage, the recent forest fires in Australia served as a stark reminder to the entire globe of the destructive power of fire and the impending ecological catastrophe [2]. Wildfires have been increasingly destructive over the last few years. Mid-July 2021 saw the outbreak of wildfires in Algeria, Morocco and Tunisia, as well as in Italy along with Greece. The flames started by the arsonists destroyed thousands of acres of farmland while killing and hurting several others. The fires caused havoc on the local economies, destroying businesses and homes as well as causing serious agricultural damage. Many people postponed their holidays to the affected areas, which hurt the tourism industry. Despite the efforts of firemen and volunteers, the fires burned for weeks, leaving a path of destruction in their wake. Manual smoke detection is inefficient and time-consuming. Furthermore, one of the most difficult issues is that variations in the shape, texture, and colour of smoke are too complicated to detect in a single shot. Similarly, the majority of the research and proposed approaches in the literature attempt to detect and classify smoke areas in images, as the process necessitates unique and complex computations. Furthermore, control instruments (such as thermal cameras) are costly. Furthermore, many detection methods rely on human feature extraction, and the execution of classifiers based on these gathered features often results in false alarms [3]. In this study, we review the traditional and deep learning based methods for the purpose of forest fire detection with CNNs. The methodology includes a preprocessing, training and evaluation of ResNet50, InceptionV3, VGG16, and VGG19 using accuracy, precision, recall, and F1-score. Preliminary assessments of pre-trained model accuracies were conducted by using two unique pre-processed datasets that included either augmented data or corrected data coupled with CLAHE. Finally, strengths and weaknesses of the model are highlighted, and the key findings, the best performing model and potential future research are concluded.

2 Literature Review

Many nations seriously struggle with the detection and prevention of forest fires. Researchers have recommended multiple methods to observe fire events.. Due to the significant damage that forest fires may inflict to society and the environment, many experts have been emphasizing forest fire recognition during the past 10 years as a result of an increase in backcountry fire case reports from around the globe. Authorities utilized Fire Suppression and Detection Techniques which include controlled burning, watch towers, satellite-based systems, optical sensor imaging devices, and Wireless sensor Networks in the past to find forest fires [4]. To save individuals and assets, forest fires must be discovered earlier. Forest fire detection and prediction are challenging undertakings because wildfires can swiftly grow to be enormous and hazardous fires from small, are challenging to observe from far-away locations [3]. To tackle the problem, Wang et at. proposed an adaptive pooling strategy that combines traditional image processing techniques and convolutional neural networks. The candidate flame area of fire is split, and then the CNN is employed to complete fire flame recognition [5]. Pragati1 et al. worked in order to eliminate the static essence of WSN, presented a machine learning algorithm imbibed with WSN. They proposed a decision tree machine learning approach for detecting events [6]. Researchers Suhas et al. investigated into the identification of forest fires and discovered that Inception V3, Inception-ResNet-V2, and Inception-ResNet-V3 were suitable techniques for feature extraction because they produced favorable results with high accuracy. The best results were achieved using SVM and ResNet50 as the ML classifier and DL feature extraction models, respectively [2]. To enhance the efficiency of fire detection techniques through image, the author Pu et al. employed sophisticated object detection CNNs, R-FCN, Faster-RCNN, YOLO-v3 and SSD [7]. They suggested some algorithms that can extract complicated image fire properties automatically and reliably identify fire in a variety of scenarios. On the ImageNet dataset, Raghad et al. pioneered the usage of a pre-trained Inception-ResNet-v2 network. For real-time detection, the OpenCV library was used to scan the video feed frame by frame and forecast the likelihood of fire or smoke [8]. The researchers [9], suggested a GAN and CNN, DCNN algorithms, for smoke and fire detection. These techniques functioned well when combined with new and unique training examples. Bidirectional LSTM was additionally employed in the study. When contrasted with previous strategies, the Bi-LSTM framework achieves improved precision in early detection. The Bi-LSTM framework yield a detection rate of 97.5% and an accuracy rate of 97.8%. The authors research [3] was to identify wildfires before they grow out of control utilizing drones and DL algorithms like VGG16 and ResNet50, with ResNet50 outperforming the others in terms of accuracy. For detecting the forest fire, the author employed a unique ensemble learning algorithm using various settings. At first, Yolov5 & Efficient Net were added to complete the fire detection procedure. The Efficient Net system uses global knowledge accumulation to stop false positive identification processes. The proposed strategy improves the detection rate by 2.5% to 10.9% while decreasing errors in detection by 51.3% with no additional latency [10]. Numerous research methods exist to detect and identify forest fires according to previous studies. Inception v3, Faster-RCNN, Resnet50, YOLO v3, and R-FCN are the most well-known approaches utilized for forest fire detection in real-time scenarios out of all the paper reviews.

3 Dataset Overview

The dataset has 2,163 photos categorized into three classes: Fire, NoFire, and Smoke. The dataset is prepared by combining the images from various sites including the images of forest fire and Smoke Dataset from Kaggle [18][19][20]. Post augmentation, the dataset had a total count of 6,006 and each class had about 2,002 images. The sample image of each class, shown below in Fig. 1.

Fig. 1. Various Classes in the Dataset

4 Proposed Methodology

The study applied multiple pre-trained models through transfer learning methods to sort images into Fire, NoFire and Smoke categories. The images underwent a variety of preprocessing procedures before being provided to the models. For the preprocessing stage, image augmentation and the CLAHE technique was implemented. Further, the preprocessed images were classified among various classes using numerous models like, InceptionV3, VGG16, VGG19 and ResNet50. The proposed strategy is illustrated schematically in Fig. 2.

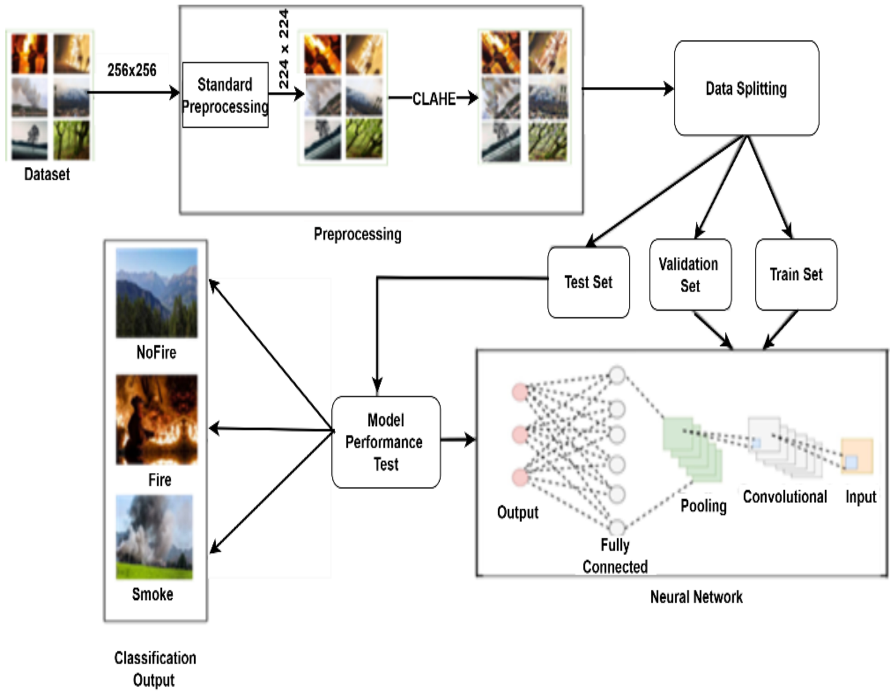


Fig. 2. Proposed Methodology

4.1 Image Resizing

This process reduces or enhances the dimensions of the image without removing any content from it. Image resizing provides an optimal display to the images [11]. In this study, the images were resized from a dimension of 256 X 256 (original) to 224 X 224 (resized). The resized images are more feasible and the time to train the image is reduced.

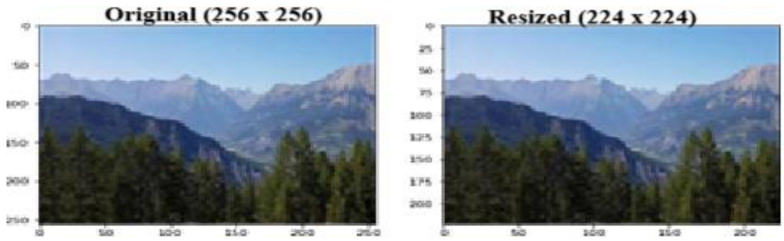


Fig. 3. (256x256) Original and (224x224) Rescaled image

4.2 Image Augmentation

Image data augmentation is a strategy to expand the diversity of an image accumulation through the generation of new transformed replicates of the original images. It performs a variety of alterations on the images to create new images. The modifications include translation, scaling, brightness and contrast adjustments, rotation, flipping, and other manipulations. Rotations and flipping of images have no effect on the semantic labels of the images [12].

4.3 CLAHE

CLAHE Contrast-Limited Adaptive Histogram Equalization or CLAHE [13], is an al- gorithm for image processing which enhances the microstructure of the image. Unlike other preprocessing techniques, it is applied only to a particular portion of the image rather than the whole one. It is used for the improvement of the image contrast. CLAHE seeks to avoid over-amplification by hindering contrast amplification [14].

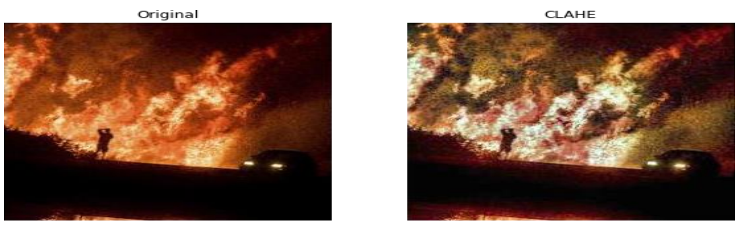


Fig. 4. Original and CLAHE Processed Image

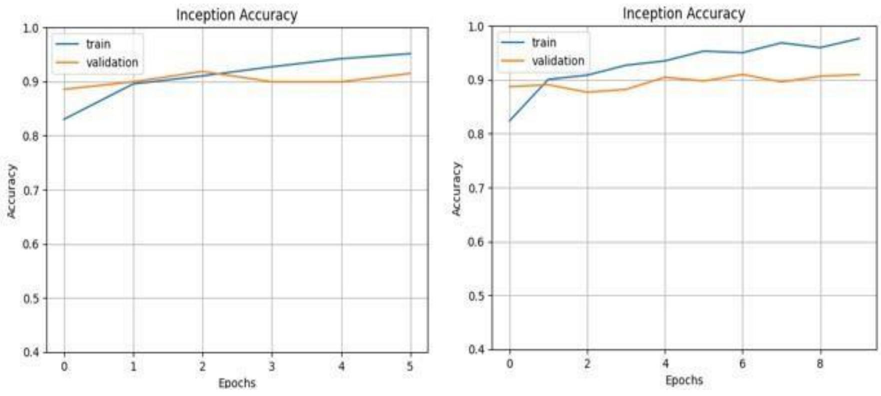
The inverse of the intensity image is also improved using this technique. When CLAHE is employed to a negative image, the visual aspects of the image are embellished, and the embel- lished image has more details. Fig. 4 shows the original and CLAHE image.

5 Experimental Setup

The entire experiment was performed on a system with the aforementioned characteristics: Google Collaboration with Intel Xeon CPU with 2 vCPUs and 13 GB of RAM and T4 GPU. The environment provides a more feasible workplace for faster computation for the implementation of the models. The implementation of the models is done using Python3. The models ResNet50, VGG16, VGG19, and Inception-v3 were employed in the experiment with a batch size of 32, epochs value of 30 using early stopping strategy.

5.1 Inception-v3

Inception-v3, a CNN architecture belonging to the inception family which consists of a 42-layers deep residual network [15].



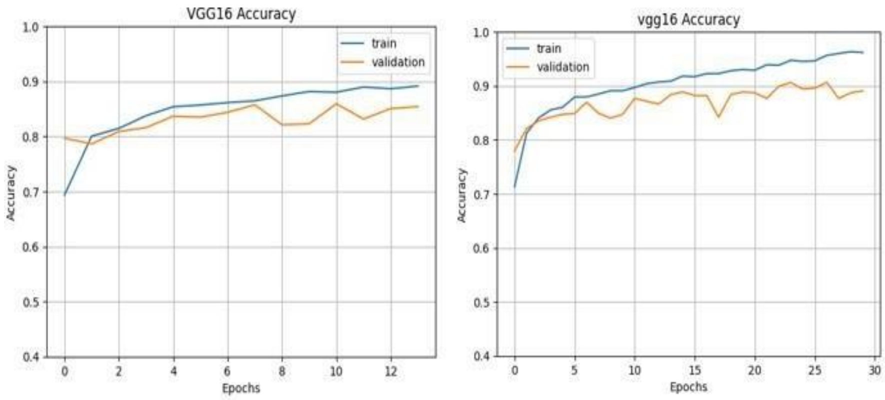
(a) Without-CLAHE (b) With-CLAHE

Fig. 5. Accuracy of Inception-v3

The rate of error of inception-v3 is low as compared to other predecessors of the family. On the ImageNet Dataset the accuracy attained by Inception-v3 architecture was greater than 78.1%. The model acquired 95.14% training set accuracy and 91.49% on validation set using transfer learning and the weights of ImageNet using standard preprocessing, 97.63% testing set and 90.97% on validate set accuracy using CLAHE technique. Fig. 5, illustrates the accuracy curve that was generated during model training and validation employing both strategies.

5.2 VGG16

VGG16 is an architecture of the VGG or Visual Geometry Group family which consists of 16-deep CNN layers [16]. The network design features thirteen convolutional layers with five Max Pooling layers alongside three traditional validating layers throughout its twenty-one levels where sixteen layers hold learnable features. On the ImageNet Dataset the accuracy attained by the model was 92.7%. The model acquired 89.15% train set, 85.42% validate accuracy using transfer learning and the weights of ImageNet using standard preprocessing and 96.19% on test and 89.06% on validate subset using CLAHE technique. Fig. 6, illustrates the accuracy curve that was generated during model training and validation employing both strategies.



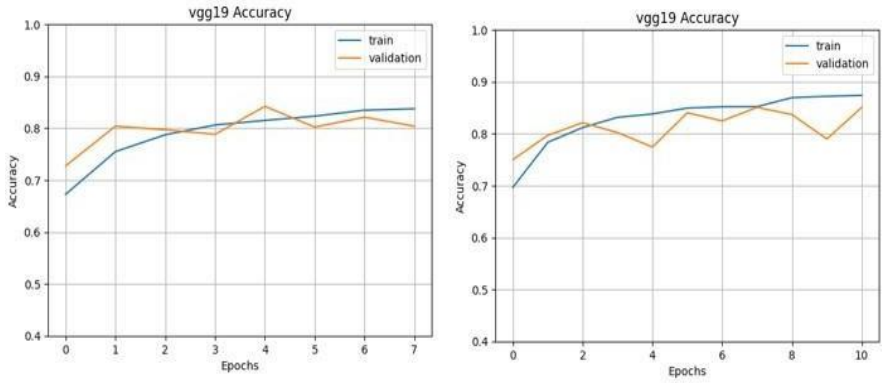
(a) Without-CLAHE (b) With-CLAHE

Fig. 6. Performance of VGG16

5.3 VGG19

VGG19 is a variant architecture of the VGG family which consists of a 19-deep Convolutional Neural Network [16]. The model consists of three fully connected layers together with sixteen convolutional layers. On ImageNet dataset, model attained 90.1% train accuracy. The model acquired 83.74% during training and 80.38% accuracy during validation using transfer learning and the weights of

ImageNet using standard preprocessing and 87.38% test subset and 85.07% validate subset efficiency using CLAHE technique. Fig. 7 illustrates the accuracy curve that was generated duringmodel training and validation employing both strategies.

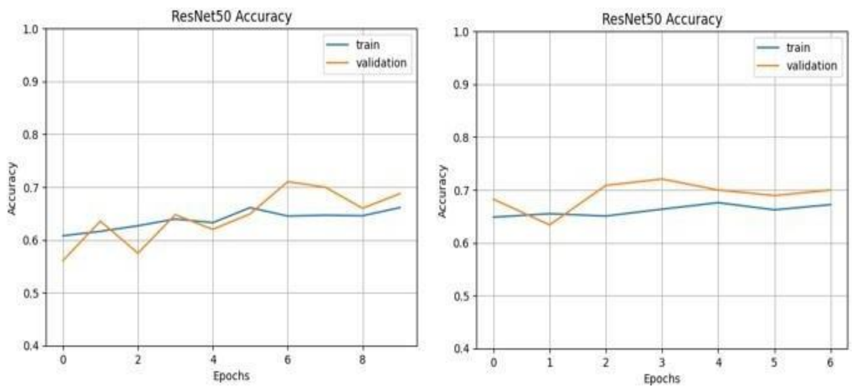


(a) Without-CLAHE (b) With-CLAHE

Fig. 7. Performance of VGG16

5.4 ResNet50

ResNet50 is an architecture of the Resnet or Residual Network family which consists of 50-deep CNN layers. Its layers are formed by 48 convolutional, average pool layer and 1 max-pool in which the network is formed by stacking residual blocks [17].



(a) Without-CLAHE (b) With-CLAHE

Fig.8. Accuracy of ResNet50

The implementation acquired 66.09% train subset and 68.75% validate subset accuracy using transfer learning and the weights of ImageNet using standard preprocessing and 67.20% test subset and 69.97% validate subset accuracy using CLAHE technique. Fig. 8 illustrates the accuracy curve that was generated during model training and validation employing both strategies.

6 Result and Discussion

T4-GPU processing on Google Colab provided the computing power throughout the investigation. Each testing dataset was evaluated multiple times through models using a batch size value of 32 as the specified hyperparameter. The models following Inception-v3 trailed with 90.80% accuracy and minimum loss at 23.69% belonged to VGG16 (85.76%), VGG19 (80.73%) and ResNet50 (68.06%). The obtained results proved that each model successfully distinguished photos into their corresponding categories of Fire, NoFire and Smoke. However, a drastic growth in the value of accuracy is observed after applying CLAHE on the standard preprocessing techniques for all the models. After employing CLAHE the highest accuracy is attained by the Inception-v3 model of 92.01% with a minimum loss value of 22.79% on the testing set of data. The VGG16 model followed the Inception-v3 model by the accuracy value of 89.93% with a loss value of 28.50%. Further, VGG19 model performed better followed by ResNet50 model with the value of accuracy 86.28% and 73.44% respectively. In accordance with accuracy and loss values, the Inception-v3 model outperformed every other model among the two approaches. Analyses highlight that Inception-v3 delivers superior performance than competing models when identifying categorized images. All three models successfully recognized the three dataset classes using the optimizer Adam at 0.001 rate of learning. The indicators of performance in this experimental investigation comprises accuracy, F1-Score, precision, and recall. The Table1 and Table2 represent the performance metrices of various model on various model. Fig. 9 shows the confusion matrix of various models using CLAHE visualizing the correct prediction of images in various classes.

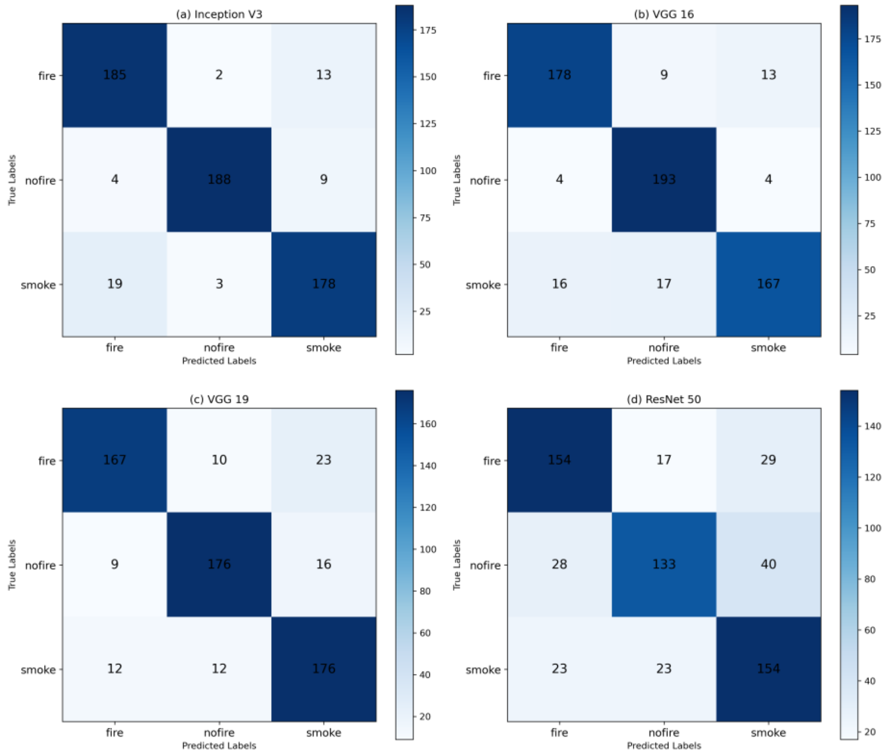


Fig. 9. Confusion matrix for: a) Inception-v3-model b) VGG16-model c) VGG19-model and d) ResNet50-model

Table 1: Performance evaluation on external testing dataset without CLAHE

Category	*Perfor-mance Metrics*	*Incep-tion- v3*	*VGG16*	*VGG19*	**ResNet50**
Fire	F1	**0.91**	0.85	0.82	0.74
	Pr	0.87	0.77	0.97	0.76
	Rc	0.95	0.95	0.71	0.71
NoFire	F1	**0.94**	0.90	0.84	0.63
	Pr	0.97	0.90	0.87	0.83
	Rc	0.91	0.90	0.81	0.50
Smoke	F1	**0.87**	0.81	0.78	0.69
	Pr	0.88	0.93	0.69	0.58
	Rc	0.86	0.71	0.92	0.84

Table 2: Performance evaluation on external testing dataset CLAHE

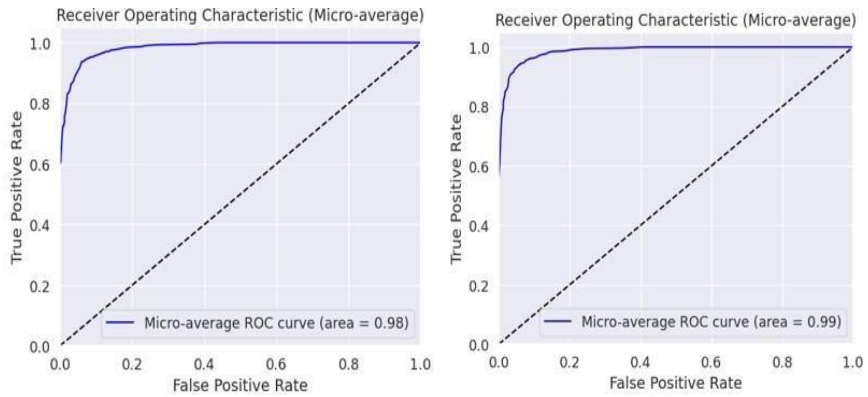
Category	*Perfor- mance Metrics*	*Incep- tion- v3*	*VGG16*	*VGG19*	**ResNet50**
Fire	F1	**0.91**	0.89	0.86	0.76
	Pr	0.89	0.90	0.89	0.75
	Rc	0.93	0.89	0.83	0.77
NoFire	F1	**0.95**	0.92	0.88	0.71
	Pr	0.97	0.88	0.89	0.77
	Rc	0.94	0.96	0.88	0.66
Smoke	F1	**0.89**	0.87	0.85	0.73
	Pr	0.89	0.91	0.82	0.69
	Rc	0.89	0.83	0.88	0.77

The indicators of performance in this experiential investigation comprises accu- racy, F1-value(F1), precision(Pr), and recall(Rc). The Table 1 and Table 2 represent the perfor- mance metrics of various model on various model.

7 Conclusion

In Real-time recognition of the fire or smoke necessitates a reliable technique for detecting forest fires. We demonstrated certain techniques that use a deep neural network and the idea of transfer learning to categorise images into thethree classes of Fire, NoFire, and Smoke after doing numerous experiments. The dataset utilised throughout the experiment had 6,006 images which were split into three classes. To tackle the issue of disparities in classes and avoid data leakage, dataaugmentation techniques were utilised. When the model underwent training on CLAHE preprocessed images in contrast to traditional preprocessing techniques, the performance of every single model had illustrated a significant improvement in accu- racy. All the models involved in the experiment, such as Inception-v3, VGG16, VGG19 and ResNet50 showed an excellent performance on the dataset to classify the image into respective type. Among all the models Inception-v3 outperformed all the models in accuracy followed by VGG16, VGG19 then ResNet50. For the standard prepro- cessing technique and CLAHE, respectively, Inception-v3's ultimate accuracy values were 95.14% and 97.63%, whichillustrates a remarkable increase in the value of accuracy. This demonstrates how effectively the Inception-v3 model recognises the patterns in the images and accurately assigns them to the relevant categories. The high value of theAUC-ROC curve also suggests the effectiveness of the Inception-v3 on both the ap- proaches. Fig. 10 illustrates the

AUC-ROC curve that was generated without and with CLAHE preprocessing technique. It can be inferred that adopting CLAHE preprocessing in contrast to traditional preprocessing methodology leads to a significant enhancement in accuracy value.



(a) Without-CLAHE (b) With-CLAHE

Fig. 10. AUC-ROC Curve for Inception-v3

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