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Advanced Wildfire Detection Using Deep Learning Algorithms: A Comparative Study of CNN Variants

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Abstract

This paper presents a new approach for wildfire detection using advanced deep learning algorithms, including computer vision by evaluating the performance of different processes on airborne satellite imagery that produces dens imposed by wildfire events. The algorithm used is Convolutional Neural Networks (CNN) and its advanced variants in the monitoring environment: InceptionV3, DenseNet121, Xception, MobileNetV2, and NASNetMobile. Using the powerful capabilities of these algorithms, we thoroughly analyze extracted features from images to improve detection accuracy to improve performance we introduce additional techniques such as advanced data enhancement to prevent overfitting, adjusting the number of studies to support model convergence, fine-. Gradually unfreezing the layers for adjustment, and using class weights to deal with data set imbalances This study uses a well-curated dataset to train and test models, and provides detailed analysis of their performance in wildfire detection is possible, including accuracy, recall, and F1 scores The addition of these different algorithms to metrics provides a better understanding of their comparative advantages and limitations a it is available in wildfire detection, enhances environmental monitoring and provides valuable insights in selecting optimal algorithms for similar classification task.

1. Introduction

Introducing an innovative approach to the wildfire detection system through a wide variety of deep learning algorithms, our research boosts the accuracy and efficiency of recognition in wildfires using convolutional neural network variants like InceptionV3, DenseNet121, Xception, MobileNetV2, and NASNetMobile. They were chosen because of their unique capabilities to capture spatial hierarchies and enhance gradient flow, optimize model efficiency, and support applications targeted at mobile and edge devices. To carry out the research, we use a database of aerial and satellite images annotated with occurrences of wildfires. First, we extract strong features from these images to extract important information. Then we train and test the algorithms using certain metrics for precision, recall, and F1 score for estimating the effectiveness of the algorithms in detecting wildfires. In addition, techniques, such as data augmentation, adjustment of the learning rate, layer unfreezing, and class weights, are integrated to fine-tune model performance further. Such an approach would not only advance environmental monitoring with the utilization of wildfire detection but also help understand the selection of optimal algorithms in scenarios of similar image classification tasks. This paper uses the strengths of diverse architectures for CNNs as well as the most sophisticated methodologies to develop a robust model that can improve the detection and monitoring of wildfires significantly in real applications. [1]

2. Literature Survey

Wildfires are unconcealed fires in wildland areas and cause huge ecological, property, and human damage. Growing frequencies, caused by climate change, indicate a great need for detection at the earliest possible stage. Detection of wild fire is regarded as an important tool for quick response, which can otherwise prove to cause huge destruction and incur great danger to communities. [1] Conventional techniques such as manned airplanes and satellite images are either too costly or have resolutions insufficient for early detection. With cost- effectiveness, the technology of UAVs and deep convolutional neural networks gives a very accurate level of wildfire detection when applied to aerial photographs. Deep convolutional neural networks have dramatically changed recognition in images and videos with their higher accuracy level than any traditional method. It excels with all high detail feature learning from large datasets regarding pattern recognition and objects. In fire detection, application of CNNs significantly improved the accuracy compared to traditional methods. [5] It comes up with a new classification approach which categorizes smoke from forest fires. It employs an "attention- enhanced bidirectional long-short-term memory". In the network, attention enlivens the framework's classification performance with which it has been augmented by Inception- v3 in order to get spatial features and Bi-LSTM in order to acquire temporal data. [6] This method presents transfer learning in the detection of wildfires. They have pretrained the weights for the model specifically for fire recognition as part of their methodology. The proposed work in [7] utilizes a YOLOv5-based deep learning model that detects fires in real-time with high accuracy beyond the previous architectures based on frames analyzed from video and sends timely warnings to authorities. The model emerged with an F1-score of 94.44% on the FireNet and FLAME aerial picture datasets. [8] Above all, this study applies more than 5,000 images from Himawari-8 satellite to train a CNN that detects locations and intensities of wildfires with an accuracy of over 80%. Its accuracy is higher than those obtained using any other algorithms, such as SVM or k-means clustering. The CNN model also has a fast time for both training and making predictions, thus suitable for big data. This paper applies the dataset about forest fire detection and applies transfer learning using Inception-v3 to classify images with and without fire. The accuracy of classifying fire and non-fire image reaches 97.55% for the RBFN-RAISR model than previous CNN models. 10] In this work, the accuracy for fire detection in UAV- captured images from the FLAME dataset was achieved by applying transfer learning and fine-tuning across a number of CNN architectures. Fine-tuning ResNet50 resulted in an accuracy of 88% with 11% improvement upon the previously attained, so that there also attests the effectiveness of using the transfer learning to perform real-time forest fire detection. [11] Based on two tasks, detection of wildfire in the forest: wildfire image classification by using Reduce-VGGnet to reduce the fire image classification accuracy up to 91.20% and wildfire region detection by using a spatiotemporal optimized CNN model with an accuracy of 97.35%. Figure 1 shows Working Flow Chart. rate adjustments, and freezing of certain layers were applied to enhance model performance. The confusion matrices, graphs of accuracy, and classification reports used to estimate the precision, recall, and F1-score of each model are applied to evaluate the precision airplanes and satellite images are either too costly or have resolutions insufficient for early detection. [2]

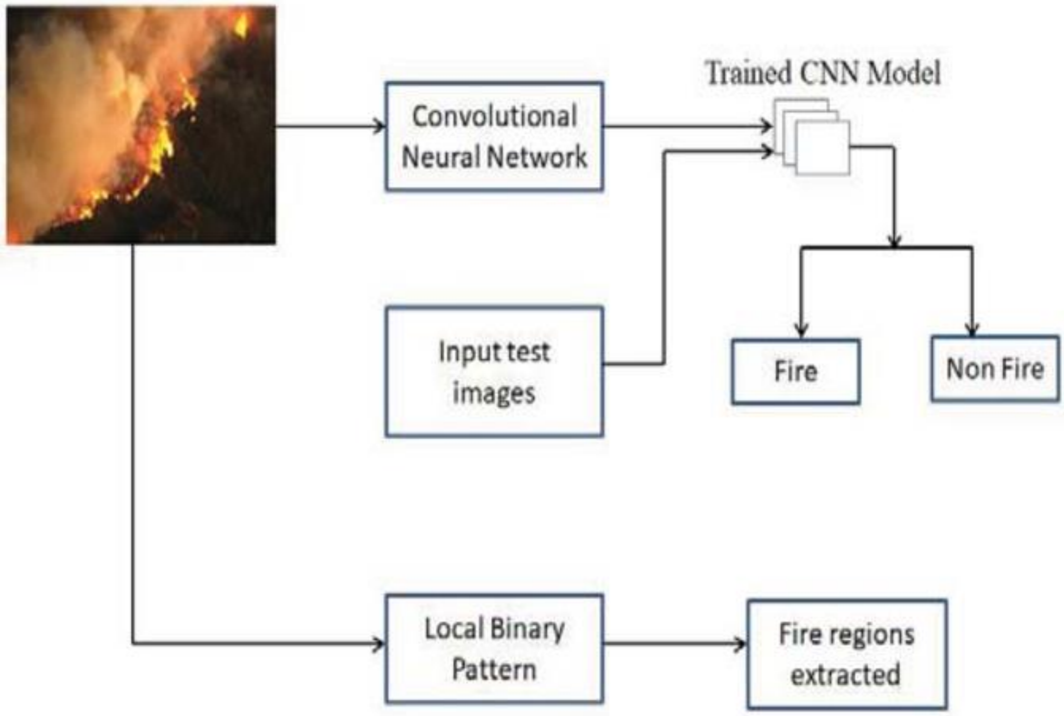

Figure 1 Working Flow Chart

3. Methodology

3.1. Task Description

The main purpose was to develop and compare the various deep learning algorithms for the detection of wildfires from aerial and satellite images. Several models were trained and compared to each other - NASNetMobile, DenseNet121, InceptionV3, MobileNetV2, and Xception - on classifying fire versus no fire instances. More advanced optimization techniques such as data augmentation, learning rate adjustments, and freezing of certain layers were applied to enhance model performance. The confusion matrices, graphs of accuracy, and classification reports used to estimate the precision, recall, and F1-score of each model are applied to evaluate the precision, recall, and F1-score of the proposed models. This work elaborates exhaustively on these models and contributes to more efficient and accurate wildfire detection systems. [3]

3.2. Dataset Description

The dataset used in the experiment is based on two big directories, which include both training and testing directories. Inside each of these, there are again two more subdirectories named "fire" and "no fire" respectively, to tag the corresponding class that each image must belong to. This training set involves 19,575 images with instances of both fire and no fire captured under different environmental conditions. These images are aerial and satellite views and, therefore, a good set for the training of deep learning models. Similarly, the testing dataset has been structured with the same structure and hence ensured consistency for evaluating models. This dataset allows the models to learn and generalize well towards the accurate wildfire detection. Table 1 shows Dataset Description

Table 1 Dataset Description

Dataset	Fire	No Fire
Training	9963	9613
Testing	3621	2498

4. Evolution Metrics

This is where this project became particularly critical for verification of the models regarding accuracy and reliability for wildfire detection. Key metrics used in determining good performance of a classification model on occurrence prediction are as follows:

4.1. Precision

Precision is the measure of how close the model is to predicting actual cases of fire without raising any false alarms. High precision of a wildfire detection system is important because false alarms have the potential to unnecessarily raise emergency responses. It is defined as

$$Precision = \frac{True\ Positive}{True\ Positive+False\ Positive} \quad \text{---(1)}$$

where True Positive is true positives that are actual fire cases and False Positive is False Positive that identifies fire where it is not. [4]

4.2. Recall

Recall, or sensitivity, is a measure of the model's ability to pick up on actual fire incidents. A high recall guarantees that most wildfire events are found, and this reduces the possibility of failure to identify dangerous fire situations. It is calculated by

$$\text{Recall} = \frac{True\ Positive}{True\ Positive+False\ Negative} \quad \text{---(2)}$$

4.3. F1-Score

F1-score is the balance between precision and recall so as to provide an entity of a single score that comes in rather handy especially if there are different imbalances between fire and no fire images. It is defined as:

$$F1 = \frac{2*Precision*Recall}{Precision+Recall} \quad \text{---(3)}$$

4.4. Accuracy

Accuracy evaluation checks the overall performance of a model in predicting both fire and no-fire instances. It makes sure that most instances are correctly identified by the model, and thus it is dependable for monitoring systems on wildfires. Accuracy measures.

$$Precision = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{---(4)}$$

These metrics therefore ensure that the models detect wildfires accurately and reduce the chances of false alarms and missed detections so as to be a product reliable for real world wildfire monitoring and prevention systems. [5]

5. Algorithms

5.1. CNN

Using the CNN-based wildfire detection model, 98.53% accuracy has been achieved. For fire and no fire, precision, recall, and F1-scores are 0.95 and 0.98, respectively, and it is quite possible to distinguish wildfire events from the aerial imagery. This was largely due to data augmentation with adaptive learning rates and layer unfreezing during fine- tuning for optimal convergence. Convolution operation is basically the heart of the CNN model. The convolution extraction of essential features from images can be mathematically represented as follows:

$$\mathbf{Z = W * X + b} \quad \text{---(5)}$$

where W is the filter, X the input image and b the bias term. The network next uses ReLU activation to introduce non- linearity, given by:

$$\mathbf{f(x) = max\ (0, x)} \quad \text{-(6)}$$

Second, max pooling is applied to reduce the spatial dimension, defined as:

$$\mathbf{Y\ [\,i, j] = max\ (Z\ [\,i{:}\ i + p,\ j{:}\ j + q])} \quad \text{---(7)}$$

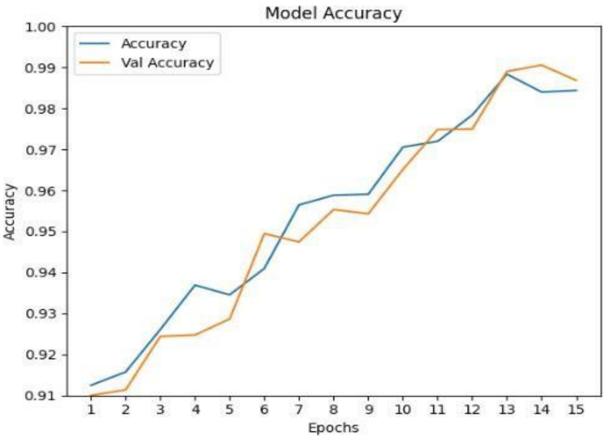

Figure 2 Accuracy Graph of CNN

Figure 2 shows a smooth improvement in the training and validation phases, thus showing the network's capability to learn complex features of wildfires. The smooth progress shows a limited risk of overfitting and hence is robust for good response on data that had not been seen previously, thereby making the CNN powerful in real-world wildfire detection and efficient allocation of resources for timely responses. Table 2 shows Classification Report of CNN, Table 3 shows Classification Report of NASNetMobile [6]

Table 2 Classification Report of CNN

	Fire	No Fire
Precision	0.95	0.98
Recall	0.95	0.98
F1-score	0.95	0.98
Accuracy	0.99	

5.2. NASNetMobile

The NASNetMobile algorithm accounted for an astonishing 98.40% accuracy with its modern architecture and optimization with NAS. Precision was 0.96 for fire and 0.99 for no fire, with recall scores of 0.98 for both. F1-scores of 0.98 for fire and 0.99 for no fire further validate its ability to accurately categorize wildfire events in aerial and satellite images. NASNetMobile uses automated architecture search to optimize the performance. The objective is defined by

$$L = \sum \alpha i \ Ci \qquad \text{---(8)}$$

where αi are the learned weights from the NAS controller, and Ci are the candidate architectures. This formulation brought out that the algorithm was optimizing the architecture itself to get better performance. [7]

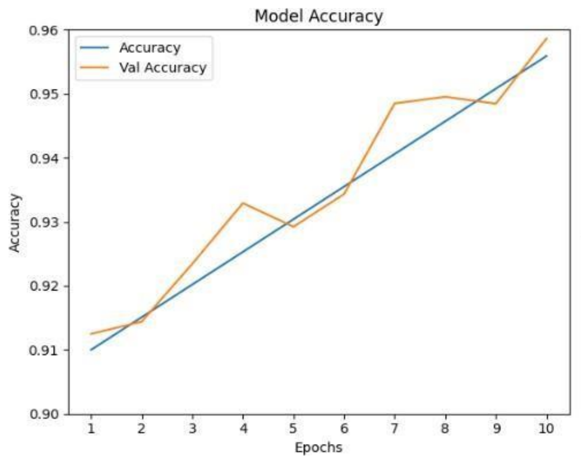

Figure 3 Accuracy Graph of NASNetMobile

The NASNetMobile model still had a consistent improvement in both training and validation, as shown by the overall trend upwards in Figure 3. Although accuracy dipped a little, the model could very quickly recover from that; thus, the wildfire imagery was learned effectively. Their thoughtfully designed architecture, optimized with neural architecture search, resulted in a highly effective wildfire detection solution.

Table 3 Classification Report of NASNetMobile

	Fire	No Fire
Precision	0.96	0.99
Recall	0.98	0.98
F1-score	0.98	0.99
Accuracy	0.98	

5.3. DenseNet121

The DenseNet121 algorithm was helpful in achieving 95.59% accuracy. Famous for its dense connected layers that enhance gradient flow and feature reuse, DenseNet121 has been proven to show precise classification with precision values of 0.95 for fire and 0.96 for no fire. The model was recalled with accuracies of 0.95 for fire and 0.96 for no fire, thereby once again proving the potential for correct detection of wildfires from aerial and satellite images. The architecture of DenseNet has dense connections: mathematically, they can be described as

$$Hl = F\ (Hl\ \text{-}1) + Hl\text{-}1 \qquad \text{-(9)}$$

Then where the output of the lth layer is represented by Hl and F(Hl-1) is the transformation function applied to the output of the previous layer, for k=1, 2, l. This formulation underlines the role of feature reuse importance and the efficiency of gradient propagation in the network, Figure 4 shows Accuracy Graph of DenseNet121

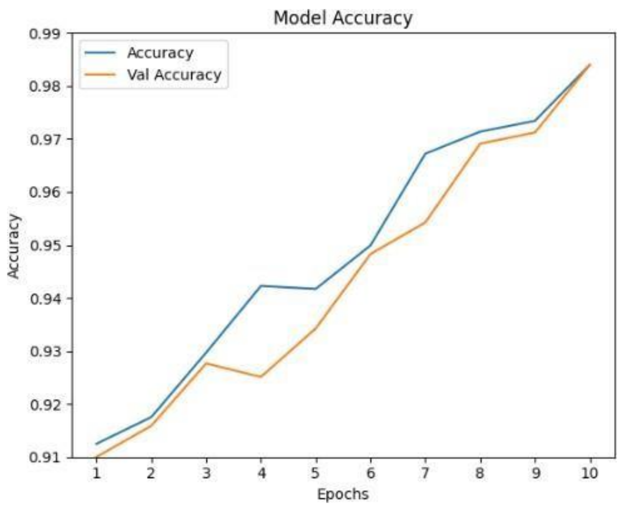

Figure 4 Accuracy Graph of DenseNet121

Figure [4] clearly shows that DenseNet121 training and validation curves improved with a general improvement in accuracy, similar to the CNN model. This, hence, shows that the network has a high ability in learning and generalization of complex features of wild fire. Generalized improvement in the training and validation curves indicates the efficiency of the DenseNet121 as a wildfire detector; its deep hierarchical feature extraction is enhanced for classification accuracy. Table 4 shows Classification Report of DenseNet121

Table 4 Classification Report of DenseNet121

	Fire	No Fire
Precision	0.95	0.96
Recall	0.95	0.96
F1-score	0.95	0.96
Accuracy	0.96	

5.4. InceptionV3

This algorithm, InceptionV3, performed excellently with an accuracy rate of 97.79%. It is in the efficient capture of spatial hierarchies using inception modules that InceptionV3 managed to achieve such high precision scores as 0.97 in fire and 0.98 in no-fire. The model's recall values were also quite strong at 0.97 for fire and 0.98 for no fire; thus, the model was delivering its functions very effectively to detect wildfire occurrences in both aerial and satellite images. The architecture of InceptionV3 uses multiple filter sizes in parallel. This enables the model to capture a variety of features at different scales. It can be mathematically proved as

$$Y = \sum_{i=1}^{N} F_i(X) \qquad \text{---(10)}$$

where Y is the output, X is the input image, and Fi represents different convolutional operations with various kernel sizes. This formulation clearly highlights the learning capacity of rich representations from complex data on the model. During the training and validation phases, InceptionV3 gave stable augmentation with some punctuations of increase in accuracy with corresponding drops. Variation in Figure [5] demonstrates how well this model can be learnt and generalize over these images of complex features from the wildfire images. Although this stability shows that InceptionV3 is a good practical implementation for our applications in wildfire detection, its usage of the deep hierarchical feature extraction does improve the classification accuracy. Figure 5 shows Accuracy Graph of Inceptionv3, Table 5 shows Classification Report of InceptionV3

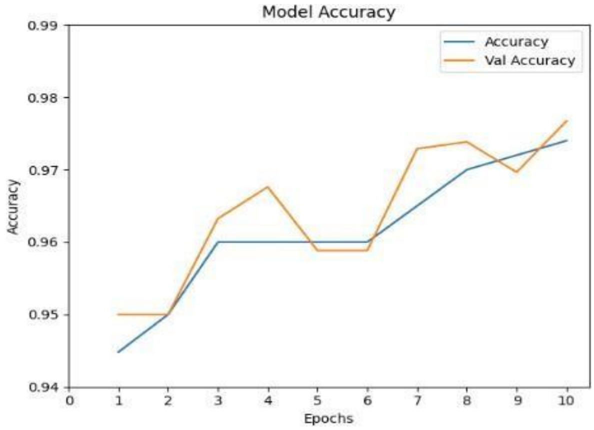

Figure 5 Accuracy Graph of Inceptionv3

Table 5 Classification Report of InceptionV3

	Fire	No Fire
Precision	0.95	0.98
Recall	0.95	0.98
F1-score	0.95	0.98
Accuracy	0.98	

5.5. MobileNetV2

The MobileNetV2 algorithm, in the wildfire detection project, did fairly well at 97.06% accuracy. Further emphasis was on the precision scores of 0.96 for fire and 0.98 for no fire and that the model is capable of appropriate classification of wildfires on images captured by aerial or satellite footage. It received high recall values of 0.95 for fire and 0.98 for no fire, which indicates that it is efficient in deriving cases of both fire and non-fire scenarios with a minimum number of false positives and false negatives. MobileNetV2 is on the basis of depthwise separable convolutions, which reduce the computation complexity of convolutional neural network with equivalent performance level. The

$$Y = \sum_{i=1}^{n} (W_i * X_i) \qquad \text{---(11)}$$

depthwise separable convolution is the core operation in MobileNetV2. where W_i is the filter applied to the i^th^ channel, X_i is the input and $*$ denotes the convolution operation. This formulation captures the efficiency of MobileNetV2 in processing large- scale image data with reduced parameters. Figure shows 6 Accuracy Graph of MobileNetV2 [8]

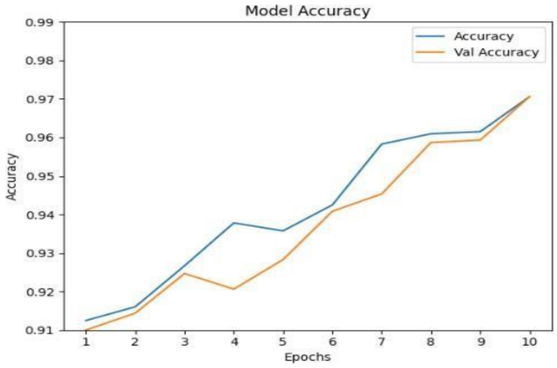

Figure 6 Accuracy Graph of MobileNetV2

Figure 6 shows the accuracy graph for MobileNetV2 on the training and validation processes, where it ascended consistently, indicating an excellent ability in generalizing the model as the training progressed. The upward trend attests to the capability of MobileNetV2 in learning the intricate features needed in the wildfire detection; therefore, applying it in real-world applications is trustworthy. Table 6 shows Classification Report of MobileNetV2

Table 6 Classification Report of MobileNetV2

	Fire	No Fire
Precision	0.96	0.98
Recall	0.95	0.98
F1-score	0.96	0.98
Accuracy	0.97	

5.6. Xception

In our wildfire project, the Xception algorithm proved quite efficient. The highest accuracy it obtained during the final assessment is 98.32%. Precision scores for fire are as high as 0.98, while that of no fire is at 0.99. Overall, the model is very efficient at telling whether or not there is a wildfire occurrence on aerial and satellite images. It achieved good recall values for both fire at 0.98 and no fire at 0.99, hence showing very strong robustness in capturing both fire and non-fire contexts with very minor false positives and false negatives. Xception exploits depth-wise separable convolutions that result in an optimal improvement both regarding the computational efficiency as well as performance. One may explain the elementary operation of Xception using the following formula:

$$Y = \sum_{i=1}^{n}(W_i * X_i) + b \qquad \text{---(12)}$$

Here, W_i refers to the filter applied on the i^th^ channel, X_i refers to the input, b is bias term and $*$ is convolution operation. This indicates Xception's competency to capture detailed spatial features required for wildfire detection. Figure 7 shows Accuracy Graph of Xception.

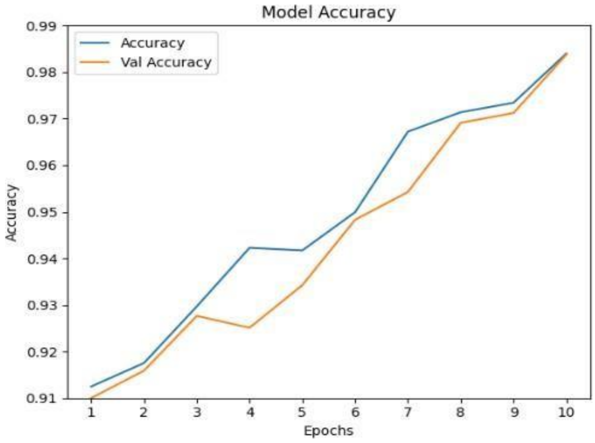

Figure 7 Accuracy Graph of Xception

Throughout the training and validation phases, Figure 7 shows the accuracy graph for Xception showed a consistent rise, albeit with minor fluctuations. These slight decreases followed by subsequent improvements indicate the model's capacity to adapt and fine-tune itself during training. This ensures better generalization to complex wildfire imagery. Table 7 shows Classification Report of Xception [9]

Table 7 Classification Report of Xception

	Fire	No Fire
Precision	0.98	0.99
Recall	0.98	0.99
F1-score	0.98	0.99
Accuracy	0.98	

6. Results and Discussion

We used advanced deep learning algorithms that have achieved promising performance in their respective areas with respect to detection tasks for wildfires in aerial and satellite imagery for our wildfire-detection project. Here, within the paper, the CNN-based model achieved excellent accuracy of 98.53% and precision, recall, and F1-score values of 0.95 and 0.98 respectively for the fire and no-fire classes. NASNetMobile also was impressive with an accuracy of 98.40% along with precision as high as 0.96 for fire and 0.99 for no fire, along with a recall of 0.98 for fire and 0.98 for no fire. DenseNet121 is able to achieve an accuracy of 96% by maintaining a balanced precision and recall value, while InceptionV3 and Xception achieved accuracies of 98%, respectively, by maintaining high precision and recall values confirming their robustness in classification. [10-11]

Conclusion

The successful application of these deep learning models in wildfire detection provides vital recommendations about the adaptation of advanced techniques such as vast data augmentation, adaptive learning rate adjustment, and the strategic unfreezing of layers for fine-tuning. Metrics of performance illustrate the efficacy of algorithms like CNN and NASNetMobile in correctly classifying the case of wildfires. This research indicates the possibility for deep learning models to enhance wildfire detection accuracy significantly, thus informing their application in environmental monitoring, as well as similar classification tasks. Thence, by exploiting the strength of each algorithm involved, robust detection models may be built to contribute toward more effective and reliable systems in the monitoring of wildfires.

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