Wildfire Detection and Aerosol Identification Using Satellite Imagery

MSc Research Project
Data Analytics

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Wildfire Detection and Aerosol Identification Using Satellite Imagery

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Abstract

Wildfires are one of the most frequent events occurring all over the world and they became the major concerning factor in the climate changes for the past decade. Early Detection of these wildfires and smoke plumes through satellite imagery is crucial since they are not easily extinguishable which may lead to catastrophic consequences for both wildlife and forest ecosystems. In this study, we propose a Convolutional neural network (CNN) model from scratch which helps in detecting the smoke plumes and identifying aerosols, the other classes of the smoke plumes emanating in the atmosphere such as haze and dust as they are very similar to smoke. Also, EfficientNet, MobileNetV3 and Inception V3 models are employed, which are popular deep learning approaches and transfer learning models applied on the same dataset. compare the performance and output parameters of the state-of-the-art models that are most recent models in rise for image classification with faster training times and enables the better accuracies. Hyper-parameter tuning has been performed for more accurate results and the critically evaluated metrics in this research are accuracy, precision, recall and f1- score. This comprehensive analysis aims to identify the best transfer learning model and the model that closely aligns with the performance of the CNN built. This study provides the valuable insights into the potential of Transfer learning models and CNN proposed in Early wildfire detection by identifying the smoke plumes and helps in reducing the false fire alarms.

1 Introduction

Forests play the most crucial role in sustaining life on Earth and contribute significantly to the well-being of both environment and human societies by providing various natural resources. They almost cover over 31 percent of the land area on the earth, the escalation of wildfires, exacerbated by the effects of climate change, has become a critical global concern by their cataclysmic impact on the forests and the wildlife. The frequency of these wildfires has been major concern during the last decade. These wildfires may occur anywhere from the forests and impact on climate change by affecting various sustainable natural resources, and wildlife. Climate change is responsible for the exacerbating droughts and the heatwaves all over the planet and the flames emerging all over the forests by increasing the total area where a little flame or spark is lighting up and resulting in parched vegetation by generating uncontrollable devouring flames.

1.1. Background and Motivation

The fires in Spain incident have been one of the major examples for the destruction of entire wildlife and emission of 1.3 million tons of the carbon within the small duration around one month. Also, the smoke that has been released from this incident has led to the cause of thousands of premature deaths in that duration where satellite imagery is used for this assessment for taking the environmental protection measures against the incident. There are many such incidents which are affecting the planet by causing various ecological impacts by affecting Biodiversity hotspots, air quality, natural resources, affecting the rainfall patterns, and wildlife. Which is prompting the need for advanced technologies to address the solution for wildfire detection in early stage by identifying the smoke plumes through satellite imagery and predicting the actual locations without misleading by false fire alarms.

Various researches has been conducted to address the solutions for this issue using Artificial Intelligence and Machine Learning (ML) techniques which are mostly used for detecting the wildfires R. Shanmuga Priya et. Al (2019) as early as possible. In the last few decades, deep learning approaches has been the major problem-solving methods and gained attention in detecting the smoke plumes from satellite imagery because of thier ability in representing the complicated structures of data related to multiple images and does self-learning by rapidly processing the complex data.

In the recent years, the rapid advancement of the Artificial Intelligence (AI) technology and the computer vision has been accelerated significantly. Deep learning approaches have enabled the Convolution neural networks (CNNs) to achieve the state-of-the-art such as the best performance on the various computer vision tasks related to image classification and the object detection. In contrast the standard approaches like deep learning techniques may learn sophisticated interpretations or predictions from various image datasets. This study analyses the wildfires using USTC-smoke dataset, where such datasets are quite difficult to find and there are quite less datasets with different classes of images such as aerosols including in satellite imagery. Hence MODIS which is Moderate Resolution Imaging Spectroradiometer is used Akbari Asanjan, A. (2023), where the image data is collected from different regions related to six different classes such as cloud, dust, haze, land, seaside and smoke.

1.2 Research objectives

Below steps are the major research objectives carried out in this study.

1. We have proposed a CNN from scratch, where the images in the dataset are classified into six different classes by mainly focusing on the images similar to the smoke such as haze and dust which are indistinguishable from satellite imagery in different weather conditions.
2. State-of-the-art transfer learning models such as EfficientNet, MobileNetV3 and Inception V3 has been proposed and these models are applied on the same dataset with respect to the six classes of images from the dataset, these Transfer Learning models are utilised to build classification models.
3. Major Pre-processing steps such as Image-Processing, Image smoothening, Normalization and Data-Augmentation techniques are carried-out on different classes of images from the dataset in respective proposed models. Hyper-parameter tuning is

performed with respect to the model building procedure which helps in fine-tuning the corresponding base models. Therefore, a better model is selected based on the evaluation metrics and the performance measures of the proposed models.

Research Question of this study is outlined and described below.

How well does a Deep Convolutional Neural Network (CNN) model perform in detecting smoke and aerosol identification using satellite imagery during wildfire incidents. In relation to other cutting-edge best image-processing models such as transfer learning models, how does its performance differ with respect to accuracy, parameter efficiency such as precision, recall, and f1-score, and discovery of pattern?

2 Related Work

2.1 Wildfire Detection using CNN Models and Machine Learning Algorithms.

Deep learning methods has been the major problem-solving methods used during this wildfire detection procedure. Convolutional neural networks have been used frequently in this deep learning approaches for forest fire detection. CNN-based fires detection method is presented by Zhang (2016). This study involved in training the full image as well as fine grained patch fore classifier in the joined Deep CNN models. They have tested the full image in terms of the global level of images and then if the respective results are positive for the fire detection, the fine-grained patch classifier is processed next to identify the corresponding location of the patches related to fire. Their research has approached with the idea of patch-level annotations with great accuracies related to the patch detection. But the major drawback that has been observed in this research is the usage of the normal images or standard images which results in identifying only the objects which are nearer rather than the larger area detection.

A convolutional neural network for automated wildfire is proposed by Vladimir Khryashchev et. Al (2020) where two datasets has been used in having satellite RGB-images with different spatial resolutions around 1457 images and high-resolution images about 393 images. Adaptive moment estimation algorithm has been used in this study for training process optimization. They have developed this algorithm which contains the special metrics such as Sorensen-Dice co-efficient other than precision, recall, f1-score. In their research they have also used IoU value, which gives the developed model's quality. In the process of enlarging the respective training and test sets which are generated by data windowing various techniques of data augmentation has been followed. Here U-Net neural network is used following with the encoder as RestNet34 and the datasets results worked satisfactorily.

Due to the lack of Availability of datasets related to smoke images, smoke plumes were directly inserted into an image to create the smoke image sequences to research on these wildfires, Labati et al (2011) has experimented this technique of inserting smoke plumes as smoke image sequences. R-CNN has been trained in this study to detect the smoke by implementing the deep domain adaption method in the early wildfire detection process. Although the results and the performance of the model has been increased but the visuals are not as realistic as they have followed the insertion process for the analysis.

Above research's have performed better coming to their performance, but they have implemented on few parameters without following the augmentation techniques. In our study, we have performed image augmentation with respect to the satellite imagery dataset with different aerosol classes in the dataset which helps in reducing false fire alarms. then we feed these respective images for our CNN model that has been built from scratch where normalization and drop out layers are aided at various locations in improving the performance coming to the Identification of smoke in each image as the size of the image is reduced only to the required area after all these steps.

Rabeb Kaabi et al (2018) proposed a model using Machine learning techniques and introduced a deep belief the network which is used as a technique for the restricted Boltzmann machine having stacked layers in that network. In this research the smoke detection methods have used various dynamic features such as colour, energy and their motion, depth and amplitude of frames with respect to blocks. Also flicker disorder is also one of the most important features in their study. They have compared their deep belief network designed with other proposed models proposed by Zhao et al (2015) which achieved around 94% accuracy I the early smoke detection. Toreyin et al (2006) where the respective built model achieved accuracy around 85%. Although these methods have gained good accuracies the drawback faced in these proposed models is the size of the image with respect to frames may cause the divergence if appropriate size is exceeded size of the image frame. Their future work is to include the CNN with their deep belief network for improving the results for early detection.

Above studies have major drawbacks without addressing proper batch sizes in their analysis, where our study already addressed them. Our CNN is built with respective batch sizes, dropping rates, and learning rates by improving the image quality by smoothening the images and reducing their size. By cropping the unwanted pixels of the image, all the data from the dataset is taken in the same format. Hyper parameter tuning results in fine tuning the parameters in each model and gives the best model output parameters. Following these steps will show impact on model's performance as well as better results.

2.2 Wildfire Detection using CNN Models and without using Transfer-Learning Models.

Classification of images using Artificial neural networks (ANNs), this research has been proposed by Nabi (2023) where their work is different from existing researches in terms of training several different ANN architectures in terms of classifying the images related to forest fires and they have compared those models with each other. They have created two CNNs for this detection in terms of classification and segmentation. Their study has shown that better results related to fire detection can be achieved using 3 channels without using all the channels. CNN's and hyper spectral data analysis has been performed for accelerating the hardware performance in terms of edge computing for the wildfires of real-time alerts is proposed by Thangavel K. (2023) on considering the three distinct hardware accelerators like the Intel Movidius Myraid 2, the Nvidia Jetson Nano, and the Nvidia Jetson TX2 to show the respective accelerators have the onboard application which is practicable for upcoming or future space missions which helps in improving the services as well as establishing and managing the space to ground data flow by providing the data related to real-time. Where TASO is the trusted autonomous satellite operation which gets enabled in this procedure for real time disaster management. Here, thier future work is to introduce few transfer learning models for wildfire detection and manage other missions related to such disasters.

Deep CNN "MultiScale-Net" has been proposed by Rostami et al. (2022) for AFD where the Landsat-8 imagery datasets has been used at the pixel level. For improving the performance if this AFI is added to the network as their inputs has SWIR2, SWIR1, and blue bands were also aided. IoU scores were also obtained in this research along with highest precision and sensitivity and f1-score. This research involves in testing the fire samples along with the cloud samples as well. Their qualitative investigations have revealed that the usage of the multi-size kernels make their model more robust comparing to the changes in the size of the fires or active fires in the images. Their future studies will be based on the sentinel-2 data for the AFD which will have higher temporal and spatial resolution.

Almeida Pereira et al. (2022) also used the same dataset landsat-8 satellite imagery where 146,214 image patches has been extracted and these image patches have been split into two parts containing the spectral images with 10-band. Where the results have been generated with respect to 3 hand crafted algorithms and then they have combined these model's outputs for better output parameters and performance. Their future work is to focus on the alternative methods for active wildfire identification and apply on different satellite image samples for exploring the better trained models over the samples and combine the results according to their spatial resolutions of the multiple satellites.

In our research, we have also proposed the pre-trained models which are transfer learning models along with the CNN built from scratch and we have leveraged the computation power of the respective transfer learning models to predict smoke plumes accurately and reduce the fire alarms by detecting them early. From the above research's they have proposed their model along with hand crafted algorithms which a bit complicated in terms of obtaining the True positives and more chances of getting false positives which impacts the model's performance. Where in our study we have used the deep learning approaches with transfer learning models by executing them with heavy GPUs with the help of Google Collaboratory and the classification results has been obtained in terms of the output parameters if model's accuracy, precision, recall, and the f1-score.

2.3 Wildfire Detection using CNN models, Transfer-Learning Models, and Machine Learning Algorithms.

Fire Luminosity airborne-based ML evaluation dataset having the images of forest fire which is obtained using the unmanned aerial vehicle has been proposed by Reis et al. (2023). In this research they have used deep learning algorithms such as ResNet50V2, DenseNet121, Inception V3, and VGG-19. As these transfer learning models can obtain better results comparing to the models that are built from scratch. Gated recurrent unit, Bidirectional Long Short-Term Memory, support vector machine, Random Forest algorithms. Accuracy of the DenseNet121 model with random weights is obtained around 97.95%. where DenseNet121 model with ImageNet weights from the dataset has achieved accuracy around 99.32%. Their future work studies will be based on the segmentation methods for automatic detection of forest fire areas and EfficientNet and RegNetX architecture will be explored. They have also said that feature selection techniques will be used in future work to know the dominating feature results where the training times will be shortened and size of the images with respect to the dataset will be reduced in this process.

Images using AI-based computer vision techniques followed by Sathishkumar et al. (2023) involves implementing transfer learning models such as VGG16, Xception, and Inception V3. This study has also shown that LwF can be the successfully categorized novel and the datasets that are unseen datasets with major differences in the performance of the models.

Xception gave accuracy around 79.23% without LwF on Bow Fire dataset whereas 91.41% using LwF by reducing the computational complexity and outperforms in the feature extraction. In their future work they want to apply new CNNs to identify the fire incidents with low false positives and explore more on LwF with multitask learning.

Maria et al. (2020) proposed the transfer learning model approach based on Inception V3 which gained the accuracy around 93%. This research involved in combining the data Augmentation techniques which have been tested under the tenfold cross-validation scheme. Almost 35 real fire events have been covered by featuring these images from open-source dataset. Similarly, transfer learning model, Inception V3 has utilised by Shanmugapriya et al. (2019) and CNN based Inception V3 which can extract the images automatically by categorizing the image into two sets such as fire images and the non-fire images. Where in this particular research they have used only one transfer learning model along with hand crafted algorithm. Mazzoni et al. (2019) proposed a SVM (support vector Machine) which helps in identifying the smoke plumes with respect to the fire hotspots. The major drawback in this study where the descriptive features must be preselected, or feature engineering is need by the SVM approach.

Our study focuses on exploring three important and three different algorithms which are helpful to predict the smoke plumes easily with their best performances. We have used EfficientNet, MobileNetV3 and Inception V3 and implemented through TensorFlow Framework. Also, we have built a model from the scratch which is CNN model by including more layers and building blocks in the architecture with Normalization and drop-out layers. The major difference in our study compared to other research's shows addressing the aerosol classes by performing the analysis on the six different classes and involving analysis with both transfer learning models and CNN model together for better analysis along with hyper-parameter tuning where the models are fine-tuned by reducing the processing times. Later the output performance of the newly built CNN, and the state-of-art transfer learning models are compared between them to study which model is the best model through the evaluation metrics.

3 Research Methodology

The Research was aimed on the building the New CNN model from scratch where CNNs are the best models for dealing with complex images and will be comparing this model to three different cutting-edge Transfer-learning models on the dataset with satellite imagery.

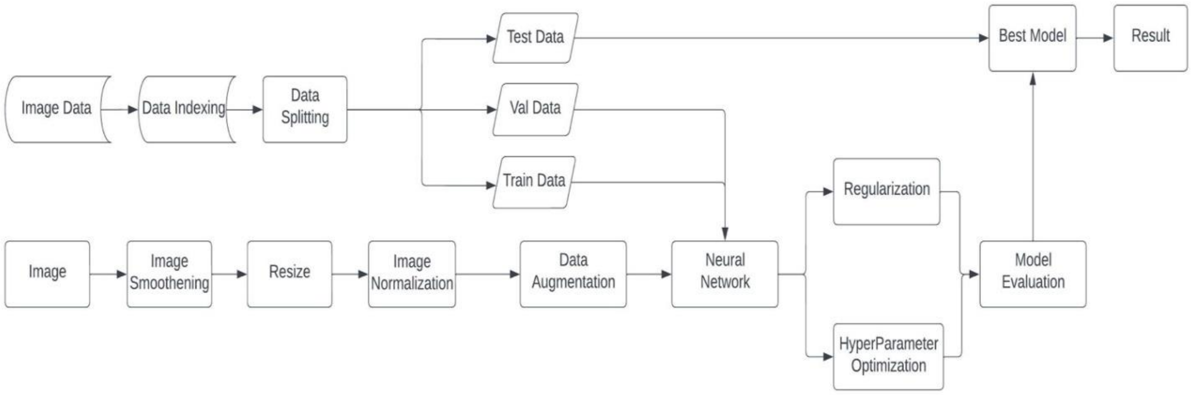

Figure 1: Implementation Pipeline

3.1 Data Collection

Only Few open datasets are available related to the satellite imagery with multiple classes of images, USTC-Smoke Dataset, where the data is extracted from the MODIS sensor which has been installed on the Tera and Aqua satellites that are used extensively for the Wildfire detection. This satellite overpasses 4 times in a day and revisits every 1-2 days. The data has six different classes of images about 6225 RBG images relevant to wildfires. The six categories such as Smoke, Dust, Haze, Land, Cloud, and Seaside on other side we also know them as aerosols and these six directories in the dataset contains files related to 1164 Cloud Images, 1009 Dust images, 1002 Haze images, 1027 Land images, 1007 Seaside images, and 1016 Smoke images. This Dataset has been obtained from the Kaggle Website and the below source link has the dataset used in this Research Project.

https://www.kaggle.com/datasets/horton1314/ustssmoker

3.2 Data Preparation

Due to some comparable spectral and the feature textures Cloud, Dust and Haze are identified as one of the most similar classes in the dataset. Where Land and water images have been included to differentiate various terrains. Hence the extracted dataset is geometrically corrected, where channels ,3,4 are employed to obtain the RGB images from the satellite Xie et al. (2007). The data has been gathered from events that occurred throughout the twenty years where the MODIS/Terra and Aqua Thermal anomalies are helpful in identifying fire-related smoke, hence all these images are used for training. Ba et al. (2019) have briefed in their research how the images are manually acquired and labelled. Sample images related to this are as shown below.

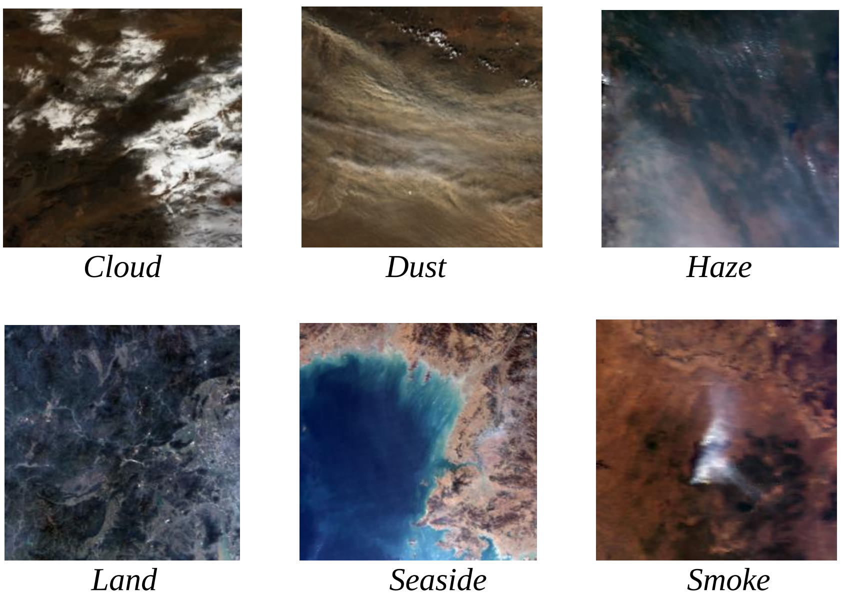

Figure 2: Six Classes of Aerosols in the Satellite imagery Dataset

3.3 Data Pre-Processing and Transformation

It is critical to integrate the Image processing steps and to consider the models capable of distinguishing even the very smallest patterns or details. Convolutional neural networks are the best models to deal with such kind of data which has complex images. So, we have implemented the CNN from scratch and compared it to the number advanced or cutting-edge models that is Transfer learning models on the dataset. Also, Image Smoothening has been performed to eliminate or remove the disturbances that occur in such high-resolution images such as Noise, Clutter, and Sharpness from an image. This process results in giving the smooth and blended effect on each image. Using the power of OpenCV and python various smoothening effects can be created. After the application of smoothening effects, it identifies the edges having the disturbances and removes the unnecessary noise. Below image shows the result after the smoothening and removing unwanted noise.

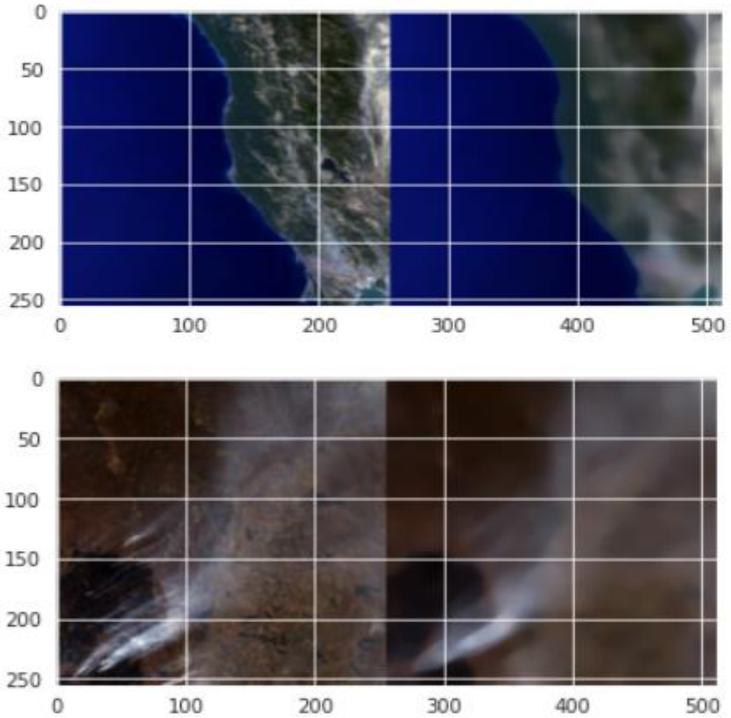

Figure 3: Image-Smoothening Process

Original images have been resized to smaller image sizes for making the model perform better and faster. Initially, In the training phase, the size of the images is about 256*256 and then images were downsized to 224*224 which is taken as the most suitable and recommended size for the pre-trained models. Later in CNN, the images size has been reduced to 150*150 and 120*120 to observe the impact on the model performance. Normalization is performed to converge this model with its best optimal parameters. Later Image-Augmentation is performed for converting the available images into various forms. Edge detection, Image recognition factors can be performed using the linear transformations techniques Miao et al. (2016). Below is the image after the application of the linear transformation where smoke and cloud can be distinguished as the cloud is more distributed and the smoke starts with a point where it has some shape of a tail.

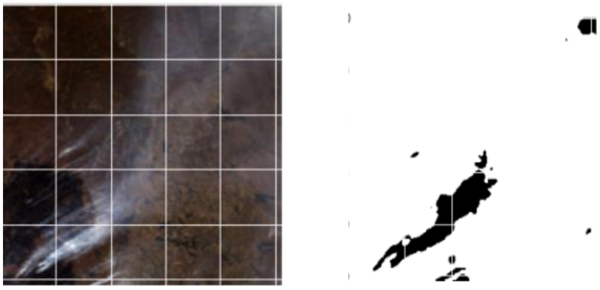

Figure 4: Linear-Transformation

4 Design Specification

4.1 Convolutional Neural Network (CNN) Model

To build a sequential Convolutional neural network from scratch, Mechanism such as continuous Spatial and Channel attention are required. Here, all input channels are integrated as one matrix for spatial attention. This matrix has been generated using element-wise multiplication. Where the channel attention is responsible for the construction of a single scalar from every pixel to pay respective attention to each channel. Our CNN has been built to transfer the data or corresponding information from each layer to the final layer. As we progress around the network, this results in conveying better data in terms of providing information and with less trainable parameters. To prevent over fitting, Batch Normalization and Drop out layers are inserted. This new CNN architecture was developed to be an effective and efficient one considering its output parameters and performance at each stage with the resources that are available.

Layer Name	Output Shape
Zero Padding + Conv 2 * 2	120*120*3
Batch Normalisation + ReLu + Zero padding + conv 2d (Conv2D)+ Dropout + Block Concatenate	120*120*32
Batch Normalisation + ReLu + Zero padding + Conv 2 * 2 + Dropout + Block Concatenate	120*120*64
Batch Normalisation + ReLu + Conv2D+ Dropout	120*120*60
Average Pooling	60*60*60
Batch Normalisation + ReLu + Zero padding + Conv 2 * 2+Dropout + Block Concatenate	60*60*108
Batch Normalisation + ReLu + Zero padding + conv2d (Conv2D)+ Dropout + Block Concatenate	60*60*172
Batch Normalisation + ReLu + Conv2D+ dropout	60*60*30
Average Pooling	30*30*30
Batch Normalisation + ReLu + Zero padding + Conv 2 * 2 + Dropout + Block Concatenate	30*30*110
Batch Normalisation + ReLu + Zero padding + Conv 2 * 2 + Dropout + Block Concatenate	30*30*206
Batch Normalisation + ReLu + Conv2D+ dropout	30*30*15
Average Pooling	15*15
Global Average Pooling	None,15

Figure 4: Proposed Model Architecture

Above Figure 4 shows the proposed model architecture. On aiding the Keras Tuner, the initial parameters required, and the hyper-parameter tuning has been performed to train the CNN with different output parameters such as learning rates and drop-out rates in order to obtain the best optimal values for the dataset.

4.2 Modelling Techniques

4.2.1 Transfer Learning Models

These models are the pre-trained models used to resolve various problems related to classification. Currently, these models are very popular through the deep learning approaches as they can train deep neural networks and also used for training the new models by loading these models and on evaluating these models, we can obtain the best model. Where large amounts of the standard data which has very high and good computational power shows the trade between the performance and speed. In this research, some pre-trained models such as transfer learning models based on their performance and speed are taken which are as follows:

A. **EfficientNet:** EfficientNet is the architecture, which is used majorly in recent times, on application of this model with the benchmark datasets we can obtain significant results when it is compared to the other transfer learning models. Compound coefficient is the technique utilized by this architecture that maintains the compound coefficient to make sure that the width and depth are scaled uniformly and proved that their efficiency to reduce various parameters and corresponding floating-point operations for each second.

B. **MobileNet:** In this architecture, we have used MobileNetV3Large where the Depth-wise separable convolution has been introduced, it is a Convolution Layer which is a new kind. These Convolutions with the depth-wise separable layers that are more efficient compared to the standard 2D convolution operations. Where Filtering and combining activities are performed sequentially in this layer. Filtering consists of separating or splitting the data into distinct channels and performing the kernel operation independently whereas Output Channels will be stacked in this combining process. MobileNet models are significantly faster and take very less time by making the size which is small which makes them easily accessible from the mobile app applications.

C. **InceptionV3:** The Inception-v3 model is based on the database related to ImageNet, where the main theme behind this model is to utilize all the corresponding operations in a particular single layer. This implies that instead of separate layers for max-pooling and convolution operations, we can have the two operations in each layer. This makes the model different from other models as well.

4.2.2 AUC-ROC CURVE

AUC-ROC Curves are used in classification-related problems to measure their performance. Here AUC is known for separability and the ROC stands for Curve Probability. We have used this AUC-ROC curve to understand how better the models are differentiating the various classes of aerosols that have been considered in this research. We will obtain the plots related to each class of images regarding the model’s performances and these plots are between True Positive Rate and False Positive Rate. The analysis with these AUC-ROC curve's gives us better understanding of all the models proposed in this study such as the new CNN model and the other Transfer Learning models. Hence all these models are implemented with this AUC-ROC Curve feature in the end results.

5 Implementation

5.1 Setup

The Image Data Has been indexed with respective path and the corresponding label by allowing us to feed our images to any type of Convolution Neural Network this makes it simple. 6225 images from the dataset are further divided into the subsets of three such as training data, the validation data, and the test data. Where the training data is slightly imbalanced. Therefore, by deleting or removing the excessive images the data is balanced equally. Once the CNN design is finished these images are given as input and various batch sizes, learning rates, and the growth rates were considered in testing. Similarly, the best hyper parameters will be tuned in the model to obtain the optimal performance with the model.

5.2 Data Handling

Satellite Imagery dataset has been mounted from the Google Drive to Google Collaboratory. Under the data folder we have six different folders related to six different classes or categories of aerosols such as Cloud, Dust, Haze, Land, Seaside and Smoke. The dataset contains 6225 RGB images, Python programming language is used for performing the Pre-processing which includes all the Image processing, Smoothening, Normalization, Data Indexing, and Data Augumentation steps are performed. Hyper-parameter tuning has been carried-out in the models to obtain best output parameters for the respective models. Keras and TensorFlow libraries have been used accordingly.

In terms of Learning rate values, we have taken various values between 0.01 and 0.0001 and tested them for the hyperparameter selection. The model has fine-tuned for each dropout rate and growth rate. Ideally high values of the learning rates led to overfitting and low values have led to model accuracy becoming stationary. Therefore, we have set the learning rate for 0.00075 to avoid this overfitting issue. ADAM optimizer is used for optimising or to converge the respective models. Initially, same parameters as optimization strategy, cost function have been followed. We have performed around 20 epochs to get better and a consistent accuracy for CNN and 25 epochs each for all the transfer learning models. Where initially each model involved in training on the trained data for the model to make it understand the data better, Validation on validation data for mearing the performance of the model. Also, in this step we decide about the final parameters while validating the data. The training parameters which have been gained the highest validation accuracy for the model are taken as the best optimal parameters and the model is considered as the best model.

6 Evaluation

In this Section, we have provided thorough examination of all models proposed in this research such as Transfer-Learning models and newly built CNN model. Various evaluation metrics has been taken in terms of confusion matrix which involves accuracy, precision, recall, and f1-score. Here we have also presented the respective AUC-ROC Curves for all the trained models. The number of the images that have been predicted correct by the model which occurs for true is called as the Accuracy rate (P). on increasing this value, the dependability of the model's output also increases. We also have an equation where TP stands for the True Positive values and FP is False Positive Values, below is that equation for the precision.

$$Precision = \frac{TP}{TP + FP} * 100$$

The Recall rate has been described where the number of the images in original data which is predicted accurately by the model. Also, fewer the model can be misclassified when this value is greater. Below is the equation for calculating Recall rate.

$$Recall = \frac{TP}{TP + FN} * 100$$

Also, F-measure is responsible for the model's effectiveness when it is assessed thoroughly. This F1-score is taken as the respective harmonic means of precision and recall.

$$F1\ Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

6.1 Inception V3

Inception V3 has achieved very poor accuracy compared to other models, it is unable to distinguish between the aerosols accurately such as haze and smoke, Edge detection has been poor. The f1-score for the model in each category helps us to understand that model has failed to classify between Haze, Land, and Smoke.

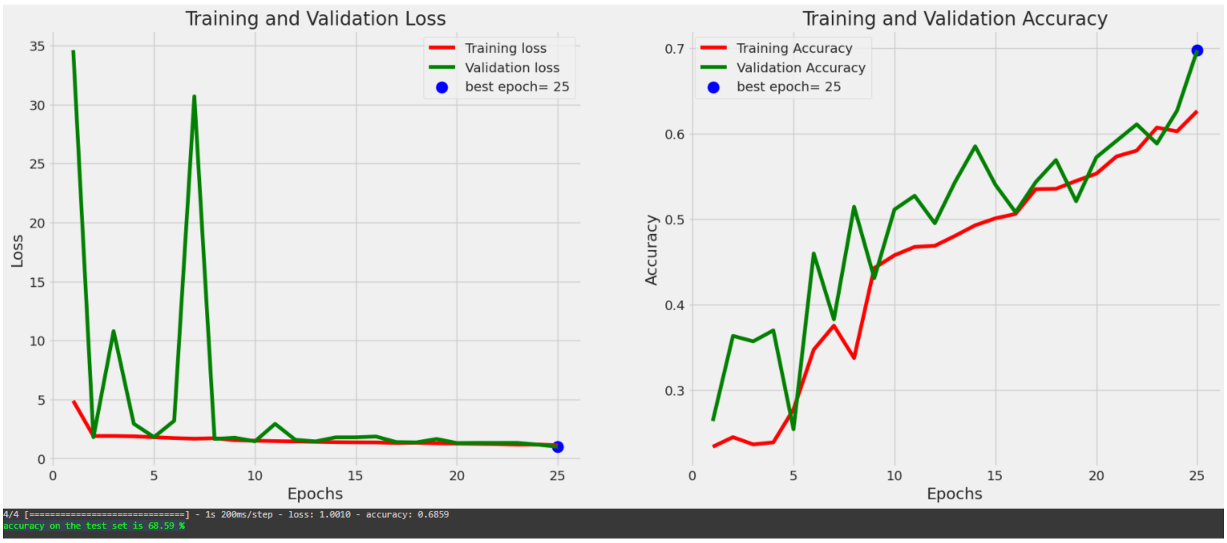

Figure 5: InceptionV3 Model Validation and Testing accuracies Plot

From the above Figure 5, There were different epoch values tested with respect to the model for the smoke dataset we used in the project and at epoch= 25 we have achieved the better accuracy. The loss for this model was settled at 1.0010. Coming to the test set accuracy, the InceptionV3 model achieved around 68.59%.

	Precision	Recall	F1-Score	Support
Cloud	0.81	0.79	0.80	58
Dust	0.61	0.82	0.70	57
Haze	0.58	0.46	0.51	48
Land	0.56	0.84	0.67	49
Seaside	1.00	0.82	0.90	51
Smoke	0.64	0.33	0.43	49
Accuracy				312
Macro Avg.	0.70	0.68	0.67	312
Weighted Avg.	0.70	0.69	0.68	312

Table 1- Classification Report for InceptionV3 Model

In the above is Table 1, output parameters for the Inception V3 model with respect to all the aerosol classes can be observed with respective evaluation metrics.

AUC-ROC Curves

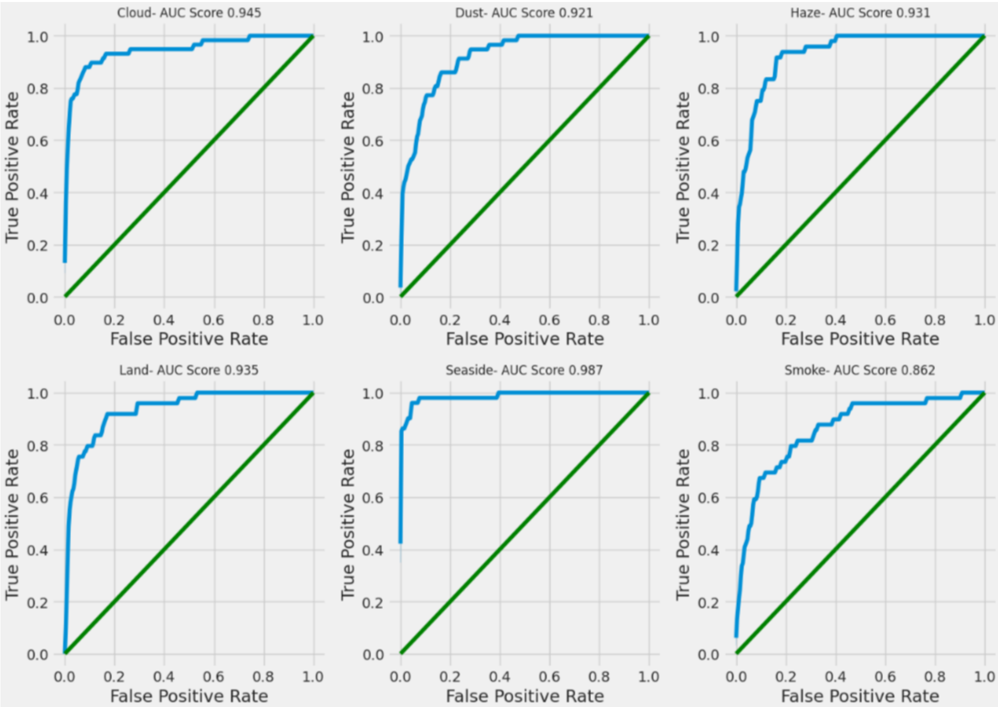

Figure 6: AUC-ROC Curves for InceptionV3 Model

The more the area lies under the respective curve, the better the respective performance is measured in these AUC_ROC curves. Unfortunately, Inception V3 accuracy is low particularly in the case of Dust, Haze, and Smoke.

6.2 MobileNetV3Large

Mobilenet is one of the best architectures that uses depth-wise separable convolution layer. It has outperformed at its best compared to Inception V3 model by efficiently distinguishing all the aerosols comparatively. This model has distinguished all the aerosols accurately and was able to identify the Smoke class with the f1-score of 91%. This the model which has fewer parameters with faster training rates that obtained most accurate results on all the classes.

	Precision	Recall	F1-Score	Support
Cloud	0.92	0.98	0.95	58
Dust	0.91	0.89	0.90	57
Haze	0.94	0.96	0.95	48
Land	0.94	0.94	0.94	49
Seaside	0.98	0.96	0.97	51
Smoke	0.93	0.88	0.91	49
Accuracy				312
Macro Avg.	0.94	0.94	0.94	312
Weighted Avg.	0.94	0.94	0.94	312

Table 2- Classification Report for MobileNetV3Large Model

From the above Table 2, Classification report for MobileNetV3Large model was determined, where we can observe that the model has achieved accuracy around 94% by outperforming the InceptionV3 transfer learning model.

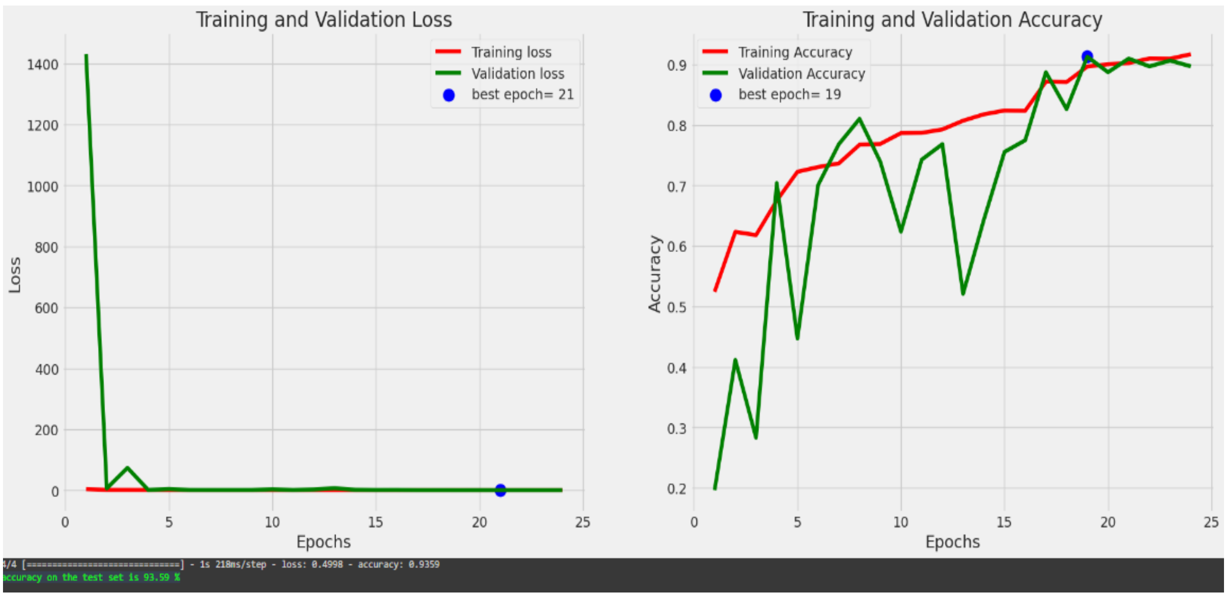

Figure 7: MobileNetV3Large Model Validation and Testing accuracies Plot

The given Figure 7 illustrates the plot between the training loss and validation loss which has been executed for 25 epochs for the model. The best output parameters were obtained at epoch =21 Whereas the second plot is between Model's Training accuracy and Validation accuracy where the best accuracy has been obtained at epoch=19. Here in this model, the accuracy on the test set has been obtained around 93.59% with the loss settling at 0.4998.

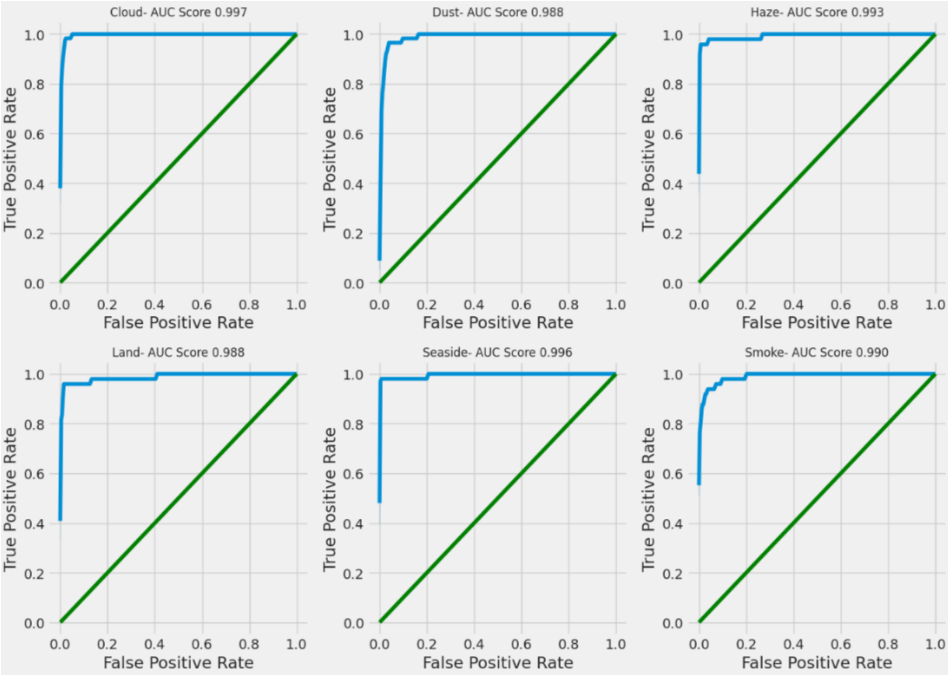

Figure 8: AUC-ROC Curves for MobileNetV3Large Model

By observing the curves from Figure 8, the transfer learning model has performed absolutely good by predicting all aerosol classes accurately as we can see the AUC-ROC curves related to each class have more area under the curve.

6.3 EfficientNet Evaluation

This model is one of the best and the efficient models, which has the most efficient architectures till date as it uses the advanced mathematical techniques such as compound coefficient. In terms of the performance, EfficientNet have outperformed all the other models which we have proposed in this research and the accuracy of both the training and testing datasets is high. From the below Figure 9, we can observe that the test set accuracy is about 95.19% with the loss setting at 0.3944.

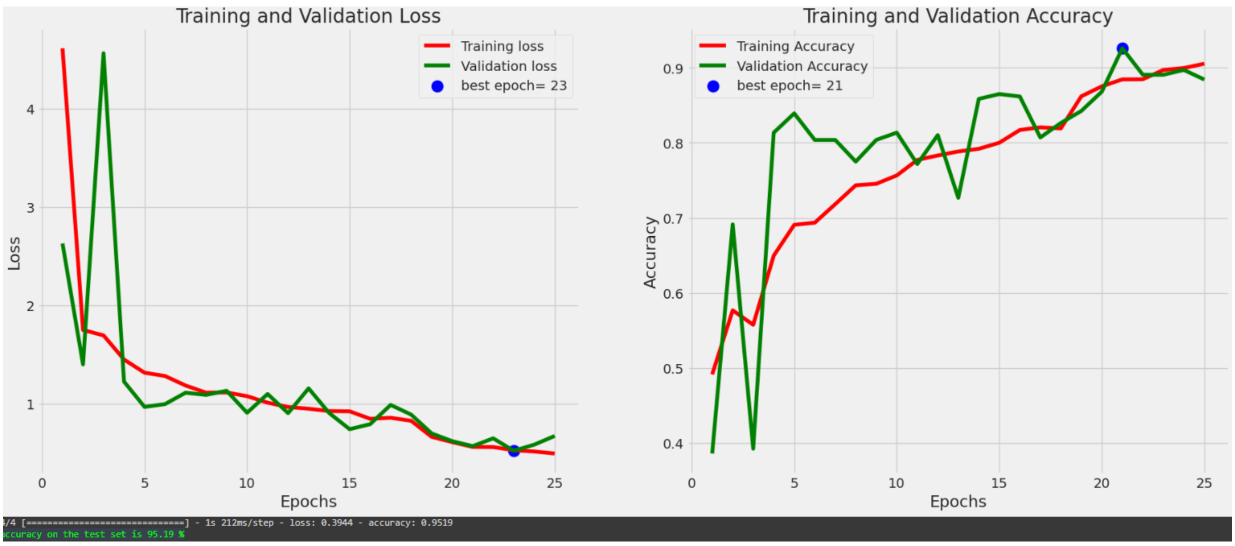

Figure 9: EfficientNet Model Validation and Testing accuracies Plot

The major difference between the MobileNetV3 and EfficientNet is that the former was not able to identify the difference between Smoke and the Haze clearly and few errors were seen in confusion matrix results, while classifying the respective aerosol classes such as smoke and haze images.

	Precision	Recall	F1-Score	Support
Cloud	0.97	0.98	0.97	58
Dust	0.90	0.98	0.94	57
Haze	0.92	0.94	0.93	48
Land	0.96	0.90	0.93	49
Seaside	1.00	0.96	0.98	51
Smoke	0.98	0.94	0.96	49
Accuracy				312
Macro Avg.	0.95	0.95	0.95	312
Weighted Avg.	0.95	0.95	0.95	312

Table 3- Classification Report for EfficientNet Model

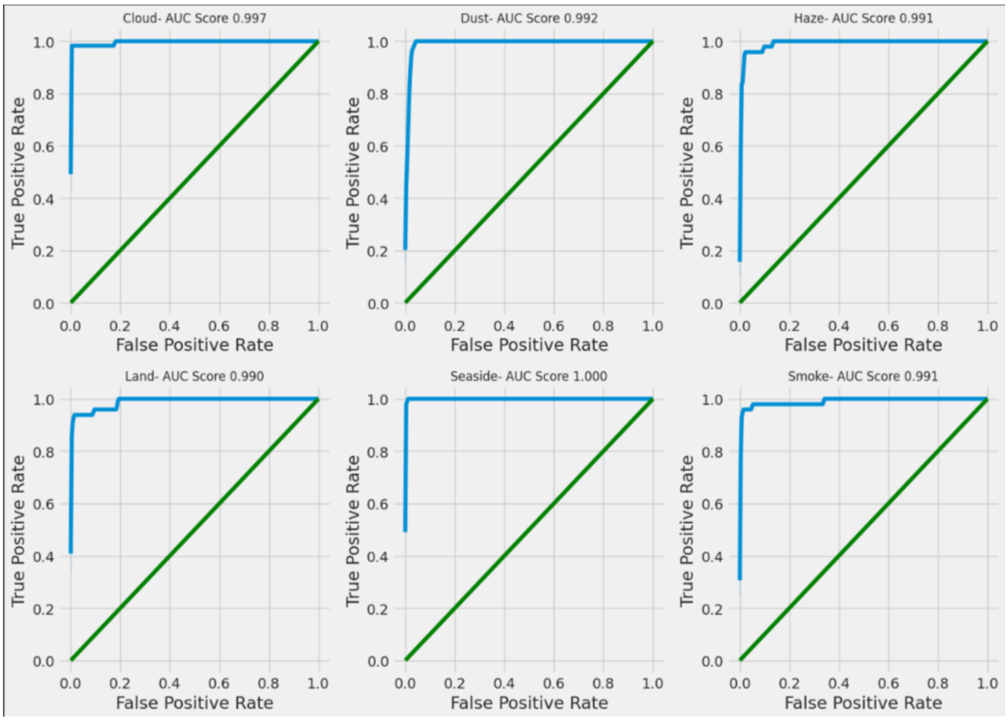

Figure 9: AUC-ROC Curves for EfficientNet Model

Here in the above Figure 9, we can see that the area under the curves is maximum for almost all the classes which is also observed similar in MobileNetV3 model curves.

6.4 New Convolutional Neural Network Model

CNN has been built from scratch to achieve the results in predicting the aerosol classes accurately like other transfer learning models which are pr-trained. Similarly, we have used heavy GPU’s from google Collab to obtain best accurate results with respect to our New CNN proposed.

Below are the output parameters for this model that we can observe in the Figure 10 and Figure 11, where the training, and validation results has been obtained. At epoch=16 we have obtained better accuracy with the loss settling around 0.80.

Figure 10: New CNN Model Validation and Testing accuracies Plot

	Precision	Recall	F1-Score	Support
Cloud	0.87	0.81	0.84	58
Dust	0.83	0.79	0.81	57
Haze	0.74	0.67	0.70	48
Land	0.62	0.84	0.71	49
Seaside	0.95	0.75	0.84	51
Smoke	0.69	0.78	0.73	49
Accuracy				312
Macro Avg.	0.79	0.77	0.77	312
Weighted Avg.	0.79	0.77	0.78	312

Table 4- Classification Report for the New CNN Model

From the above Table 4, details that the newly Built CNN model has almost predicted all the classes almost equally by classifying all the aerosol class images from the dataset. Here in the above classification report, the f1-score of the model says that land and haze classes are predicted less compared to the other classes whereas cloud, dust, seaside, and smoke are predicted almost accurately.

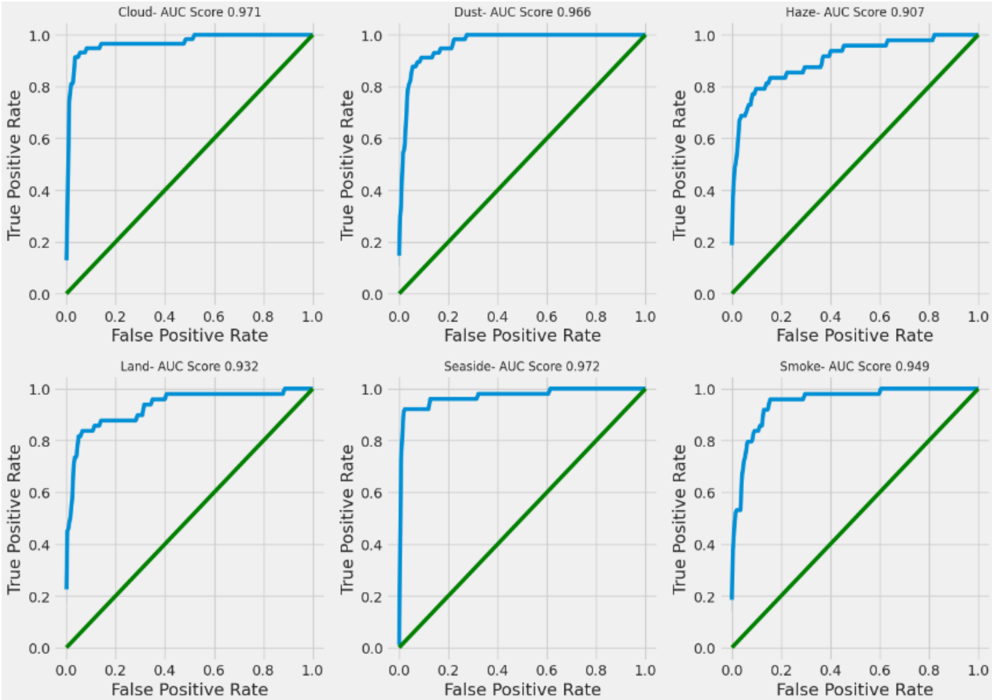

Figure 11: AUC-ROC Curves for the New CNN Model

Above AUC-ROC curves, shows the best performance in terms of the area under the curve for our CNN model compared to the AUC-ROC Curve results that has been obtained for InceptionV3 model. Here, the model has decently predicted all the aerosol classes successfully by having the AUC-ROC score that is obtained between the True Positive Rate and the False Positive Rate in each class which is more than 0.90 where haze and land has the less score with less area under the curve compared to other classes curves like cloud, dust, seaside, and smoke.

6.5 Discussion

This study aims to improve the wildfire detection and to reduce the false fire alarms that are detected when such incidents occur by shortening the time-period without wasting time in identifying wrong incidents through satellite imagery. By avoiding these false alarms, we can aid the precautionary measures on time for such incidents occurred at forests by taking immediate action.

Model	Accuracy	Precision	Recall	F1-Score
InceptionV3	0.69	0.70	0.69	0.68
MobileNetV3Large	0.94	0.94	0.94	0.94
EfficientNet	0.95	0.95	0.95	0.95
New CNN	0.77	0.79	0.77	0.77

Table 5 – Model Comparison

From the above Table 5, the model comparison results says that EfficientNet which is the latest Transfer-Learning model in the present deep learning approaches has outperformed all the other models by achieving the accuracy around 95% Whereas MobileNetV3Large have also performed almost similar to the EfficientNet. In this research, we have been able to build the new CNN architecture successfully which has performed decently good and is able to outperform one of the most powerful transfer learning models we have chosen to research in this project that is InceptionV3.

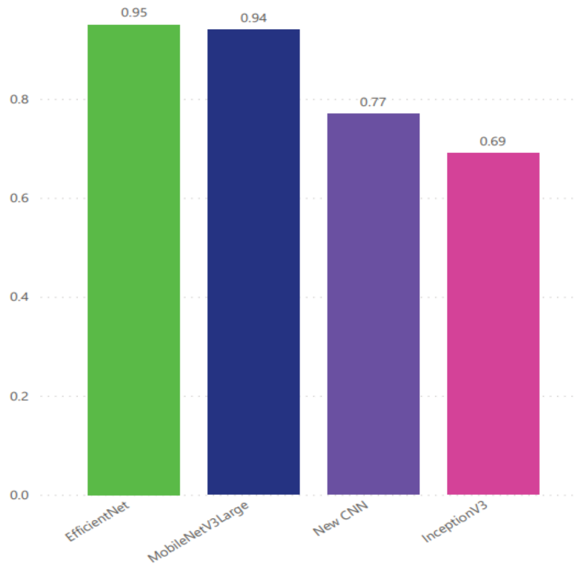

Figure 12: Accuracy by Proposed Models

We have used the Combination of the various batch sizes, learning rates and the image sizes for achieving the high-quality classification results. We have observed that reducing the size of the image has decreased the model running time as well as increased the precision for both Mobile Net models as well as the New CNN. But it was the opposite for the Efficient Net, the model with the larger images as its inputs performed better. In the New CNN, convoluted layers with the MaxPooling method have led the model with low accuracy compared to the best performed transfer learning models. Using the Average Pooling method led to better results and satisfactory classification.

7 Conclusion and Future Work

In this research, we have only pertained to specific spatial resolution. In future, if we extend the application to different spatial resolutions then there will be more room for our proposed models to make them understand the data more effectively. Since the data is satellite imagery, it can be better done by using multispectral data to detect the smoke, taking images in different frequencies and wavelengths enables to achieve better performances in real-time situations. Using different kinds of feature maps with respect to images for our dataset to know which feature map is more efficient for identifying the Aerosol classes in satellite imagery and in detecting the smoke. Although the dataset's quality is considerable, it is preferable to have more images in each category to identify smoke from other Aerosols in the open environment that helps in enhancing or boosting the performance.

One of the most dangerous risks for wildlife and ecosystems is an active fire. Deep-Learning approaches have made the significant advances in computer vision and in Image-processing steps which enables the processing of a large number of images and finding patterns. This study proposes a deep CNN model for sensing smoke through satellite imagery and also compares its performance with various state-of-the-art image processing models such as the transfer learning models. The integration of multiple blocks connected enables for transfer of additional information within the network and aid in the discovery of complex patterns in this CNN. This CNN requires a relatively small number of parameters, which speeds up training. When it is compared to previous transfer learning models like Inception V3, our newly built CNN performs satisfactorily. Therefore, this research can be used to find the corresponding comparable aerosol classes present in the atmosphere and in addition spotting the wildfires.

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