Image Analysis for Classifying Forest Fire using Deep Learning

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project/internship titled **"Image Analysis for Classifying Forest Fire using Deep Learning"**, submitted by Sabrina Saba, ID No: 191-15-2342, and Sazzad Hossain, ID No: 191-15-2459 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *30/01/2023*.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Mushfiqur Rahman, Senior Lecturer, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

80% of all living things on earth depend on forests as part of their ecosystem for food and shelter. For most of their existence, Homo humans lived in forests. Forests are at risk from forest fires. Because woods exist, there will always be forest fires. Uncontrolled forest fires occur in foliage that is taller than 1.8 meters (6 feet). Researchers' interest in the topic of fire detection in pictures using computer vision and image processing techniques has significantly increased during the last few years. This study compares various deep learning-based algorithms for detecting forest fires. The dataset is classified using five different DL methods: VGG 16, Inception V3, VGG19, MobileNetV2, and DenseNet201. The dataset, which includes 18,344 images divided into four groups (fire, nonfire, smoke, and fog). Forest fire forecasts are more accurate, according to the experimental investigation, with DenseNet201 having the highest accuracy (96.40%).

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CHAPTER 1
Introduction

1.1 Introduction

Forests are significant natural assets that serve important ecological and economic purposes, such as providing goods and livelihoods, protecting biodiversity, controlling water flow, preventing soil erosion and degradation, and regulating the climate by capturing carbon that might have contributed to CO_2 emissions. 3,9 billion ha, or 30% of the world's land surface, was reported to be covered in forests in 2000 [1], with natural forests making up roughly 95% of those and planted forests making up the remaining 5%. Globally, natural forests were down to 93 percent of total land area by 2015, or around 3.7 billion hectares [2]. Global calls for legally established native forest protected areas have been prompted by the extent and speed with which natural forests around the world are being destroyed by resource extraction and other human activities like agriculture, industrialization, and urbanization [3][4]. A forest fire is the most serious uncontrolled danger in the woods. They totally destroy forest richness and disrupt the balance of fauna and flora, biodiversity, ecology, and the environment. These massive flames may quickly spread and alter direction from their origins. In every nation, forest fire prevention is a crucial aspect of the development of land use and living standards. Raw lumber and trees and bushes are destroyed by forest fires. Fires deteriorate forest properties like soil protection and water conservation; Buildings and, in some cases, entire settlements are destroyed, as are animal populations. A forest fire also offers a significant risk to residents and agricultural animals [5]. Deep learning can help predict the condition of a forest fire using responsive image collections by analyzing many variables and evaluating the intensity of the fire. Statistics and predictive modeling are also covered in data science, which also includes deep learning. It is especially helpful for data scientists who are in charge of collecting, analyzing, and interpreting a lot of data; This procedure is sped up and made simpler by deep learning. Scientific advances now make it possible to identify forest fires automatically using a variety of approaches. And the goal of this research is to find the best model for identifying a forest fire from an image. Researchers' interest in the topic of fire detection in pictures using computer vision and image processing techniques has significantly increased during the last few years. This study compares various deep learning-based algorithms for classifying forest fires. The dataset is classified using five different DL methods: VGG16, InceptionV3, VGG19, MobileNetV2, and DenseNet201. The dataset, which includes 18,344 images divided into four classes (fire, nonfire, smoke, fog). Forest fire forecasts are more accurate, according to the experimental investigation, with DenseNet201 having the highest accuracy (96.40%).

The following are the research's overall contributions:

- This research has Collected different types of images (fire, nonfire, fog, smoke in a fire)
- Here has worked to pre-process the dataset through several procedures such as, managing unbalanced data, augmentation, zoom, flip, resize etc
- The method has predicted the forest fire using deep learning models.
- This study also carried out a comparison of all popular available methods for solving the same problem ((i.e., VGG16, DenseNet201, VGG19, MobileNetv2, inceptionv3)

The balance of this study's material is as follows. Detailed and critical analyses of prior research are presented in Section 2. Section 3 presents the experiment's proposed strategy and describes the experiment's dataset. The results and discussions of the experiment are presented in Section 4, and the effects on society and the environment are discussed in Section 5. The section's conclusion with some future scope is presented in Section 6.

1.2 Motivation

Around the world, forest fire presents a risk to the survival of people, animals, and plants. Quick responsiveness and an enormous identification region are not pertinent in the regular ways to recognizing fire [6]. Generally, the forest has a complex ecology, is home to numerous living organisms, provides a variety of resources, and regulates the generation of CO_2. Wildfires are an unpredictable risk in forests and they create tragedies [7, 8]. Forest fires annually result in the loss of nearly 85% of the world's trees, resulting in severe climatic changes and global warming. The motion, texture, and size of a forest fire are what distinguish it from other types. After cutting, forest fires are the second major global cause of forest area degradation. Thousands of hectares of forestland are damaged and lost each year due to fires, despite constant prevention efforts aimed at maintaining forests. Wildfires and volcanic activity impacted 6.2 million people worldwide between 1998 and 2017, resulting in 2400 deaths from suffocation, injuries, and burns. However, wildfire size and frequency are rising as a result of climate change. The resulting air pollution could lead to health issues like heart and respiratory problems. Another important aspect of health is how wildfires affect mental health and psychosocial well-being [9]. After reading various research papers, it is understood that every year due to forest fires, the environment is damaged as well as the economy. So, we decide to work on forest fires and collect different types of images and use different deep learning models to determine their accuracy. And from here we get motivated.

1.3 Rationale of the Study

We study many of papers about forest fire prediction. The research papers we are reading discuss a variety of tasks such as digital processing for forest fire mapping and inventory, remote sensing processing, surface fuel model mapping, long-time interval satellite image analysis, deep learning, etc. has been. There are a little number of research papers to work on deep learning for fire prediction. And that research doesn't work using multiple classes and multiple models. So, to achieve the best result and use multiple classes we are motivated and finally found the best accuracy most of all in our using Method.

1.4 Research Questions

- What are the key features of this database?
- How does the algorithm work in this research?
- How can you predict forest fires?
- What will the success rate of accuracy of image detection be?

1.5 Expected Output

In this study, we work for classifying forest fire. We hope, our system will accurately and consistently identify fires. Through this system, it can get the idea from images of whether a place is at risk and take the necessary steps. For example, it can be detected that the forest is on fire by seeing the smoke of the fire.

1.6 Project Management and Finance

Project management is the use of procedures, techniques, skills, knowledge, and experience to achieve specific project goals in accordance with predetermined guidelines.

The goal of project management is to properly plan and monitor a project to achieve its stated goals and deliverables. It requires risk assessment and management, wise resource allocation, savvy budgeting, and open communication between teams and stakeholders. Project management includes scheduling and planning meetings, facilitating the entire study, and entering data into databases. Study progress was recorded via the timely release of meeting agendas and minutes outlining progress and action items. These resources accumulated throughout time to create an archive that is centrally accessible via the Madcaps communication platform. A comprehensive essay that incorporates the elements of investigation, source assessment, analysis, critical thought, organization, and composition is a finance research paper. Below is a diagram of Research Management and Finance through Figure 1.1.

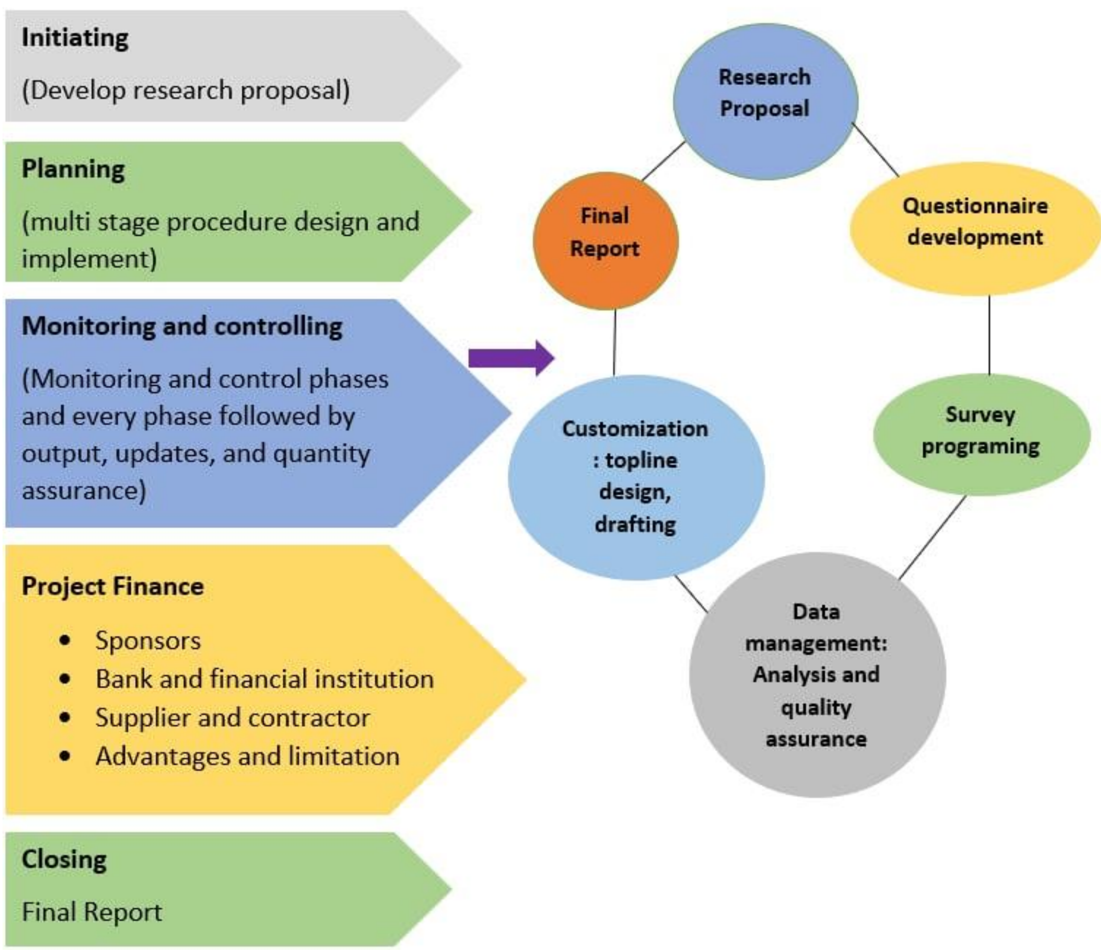


Figure 1.1: Research management and finance

1.7 Report Layout

- Chapter 1 covered the main ideas of "Deep Learning Image Analysis for Classifying Forest Fires,". Besides about our study's purpose, goal, and outcomes.
- In chapter2 section, the brief summary, problem, and outcomes are discussed from previous related research works.
- The research methodology is covered in Chapter 3.
- The details of the experimental findings are detailed in Chapter 4.
- Chapter 5 describes our social impact on environmental effects, etc.
- Chapter 5 describes Summary, Conclusion, Recommendation, and Implication for Future in this research.
- Reference

CHAPTER 2

Background

2.1 Preliminaries

A wildfire, also called as a wildland fire, forest fire, or rural fire, is an uncontrolled, unplanned, and unexpected fire that begins in both urban and rural locations in an area of burning vegetation. In their native form, several forest ecosystems rely on wildfire. Smoke from wildfires can have a number of negative effects on a person's health, from irritation of the eyes and respiratory system to more serious conditions like bronchitis, asthma attacks, heart failure, and even early death. Various researchers have worked on different topics related to machine learning algorithms or IoT for forest fire detection. Currently recognized as popular technologies, artificial intelligence and eep learning are widely utilized to identify a variety of issues. While several other pre-trained models have also been utilized by researchers, the deep learning method is the best model for detecting forest fires.

2.2 Related Works

For the purpose of detecting forest fires, several strategies and methodologies have been used. Every technique has benefits and drawbacks of its own. The following provides a detailed explanation of the overview of forest fire detection techniques.

Ruchkin, V. et al. [10] examined experimental and technical efforts on the topic of fire monitoring. The authors provide methods for analyzing satellite images to detect fires, identify fire seats, model fires, ascertain their spread, and monitor them. The method is put into practice by creating intelligent communication systems based on neuro-processing systems NM640X that can adapt to changing circumstances.

Gomes, P. et al. [11] offered a vision-based approach for distinguishing fire utilizing fixed savvy surveillance cameras. They estimated the expected object's size in the image plane, produced geo-referenced alarms, and considered the category and behavior of each moving object when making decisions to reduce the number of false alarms caused by the presence of moving objects with a fire-colored hue. Finally, a GPS-based calibration process was used to approximate the camera-world mapping. The proposed strategy can effectively recognize fires with a typical achievement pace of 93.1% at a handling pace of 10 Hz, which is regularly enough for genuine applications, as indicated by exploratory information.

Horng, W. B. et al. [12] A neural network is used to extract fire characteristics from the HSI color model, resulting in the picture's fire area. Fire area segmentation is the next step, in which false fire areas like fire shadows and fire-like objects are removed through image difference and the fire regions are broadly divided into sections. The fire's burning intensity, which can be categorized as small, medium, or large, is then assessed by utilizing the white pixel ratio and the difference between the contour images. The experiments demonstrate that the method can fairly accurately identify a variety of fire scenarios.

Bragilevsky, L. et al. [13] entered the competition, the algorithm's results, and suggestions for enhancements. The best model (ResNet50) achieved an F2 score of 92.886% by utilizing a combination of a deep custom Convolutional Neural Network (CNN) model and several other CNN architectures to address the satellite image labeling issue. The deep CNN model was inspired by the well-known VGG network architecture.

Vani, K. et al. [14] worked convolutional neural network-based Inception-v3 based on transfer learning is designed to improve fire detection accuracy. It trains satellite images and divides datasets into the fire and nonfire images to generate a confusion matrix that specifies the framework's efficiency. It also uses a local binary pattern to extract the fire-occurred region in the satellite image, lowering false detection rates.

Sharma, J. et al. [15] performed a standard CNN quite poorly when tested against the benchmark dataset with a more realistic balance. Therefore, they suggested that for fire identification in photos, even deeper convolutional neural networks be used, which would then be improved by fine-tuning based on a fully connected layer. Here was employed two pretrained cutting-edge Resnet50, Deep CNNs, and VGG16, to build our fire detection system and had built an unbalanced dataset to represent real-world circumstances, and we test the Deep CNNs on it. On a more difficult dataset, they discovered that our deeper CNNs work well, with Resnet50, marginally beating VGG16. Thus, these findings could influence the development of more effective fire detection technologies.

Chopde, A. et al. [16] proposed deep learning-based forest fire detection model and a large-scale monitoring system called RCNN. This system can identify forest fires using video frames taken by UAV drones. They propose a broad reconnaissance framework and a model for distinguishing woods fires in view of the profound discovery that can recognize flares from video outlines taken by UAV drones. 97.29% of the time, the proposed CNN model correctly and reliably identifies forest fires.

Jiao, Z. et al. [17] used the YOLOv3 model-based learning strategy for real-time UAV-based forest fire detection with the goal of increasing the efficiency and accuracy of UAV-based fire detection and achieved an accuracy of 98%.

Muhammad, K. et al. [18] proposed a CNN architecture for cost-effective fire detection for surveillance videos. In light of GoogleNet's reasonable computational complexity and suitability for the intended problem in comparison to other computationally expensive networks like AlexNet, the model is based on GoogleNet architecture. This study's accuracy rate is 94.43%.

Foggia, P. et al. [19] proposed a technique for analyzing surveillance camera footage to identify fires. There were two main new features. A multi-expert system first combined complementary information based on color, shape variation, and motion analysis. The fact that the system's overall performance significantly improves with relatively little effort from the designer is this method's primary benefit. Second, a novel descriptor for representing motion that is based on a bag-of-words approach has been proposed. A very large dataset of fire videos from real-world and online sources has been used to test the proposed method. Without sacrificing accuracy or the ability to run the system on embedded platforms, the obtained result confirms a consistent reduction in the number of false positives.

Habiboğlu, Y. H. et al. [20] proposed a color, spatial, and temporal information-based video-based fire detection system. The system used covariance-based features extracted from spatial-temporal blocks in the video to detect fire. They got 90.32% accuracy from their study.

Rafiee, A. et al. [21] offered a strategy for making use of fire and smoke's dynamic and static characteristics. Static property is the two-dimensional wavelet analysis. By monitoring shifts in the energy of two-dimensional wavelets, it was utilized for the purpose of determining the color and motion properties. Additionally, one of the dynamic characteristics utilized in the proposed method is the disorderly nature of smoke and fire. Chen, T. H. et al. [22] presented an early video processing-based method for raising fire alarms. With RCB and HSI color models, they achieved an accuracy of 87.10%.

2.3 Comparative Analysis and Summary

Table 2.1. shows a comparative analysis of previous research works.

Table 2.1: Comparative analysis of previous research works

SL No	Title	Model	Accuracy
1	Bragilevsky, L. et al. [13]	VGG network architecture, ResNet50	F2 score of 92.886% (ResNet50)
2	Vani, K. et al. [14]	Inception-v3	98% (Inception v3)
3	Sharma, J. et al. [15]	VGG16, ResNet50	92.15% (ResNet50)
4	Chopde, A. et al. [16]	RCNN	97.29% (RCNN)
5	Jiao, Z. et al. [17]	YOLOv3	98% (YOLOv3)
6	Muhammad, K. et al. [18]	CNN architecture	94.43% (CNN)
7	Foggia, P. et al. [19]	MES classifier (CE+ME+SV)	93.55%
8	Habiboğlu, Y. H. et al. [20]	Covariance matrix-based detection algorithm, SVM model	90.32%
9	Rafiee, A. et al. [21]	YUV, RGB color model	87.10% (YUV)

10	Chen, T. H. et al. [22]	RCB, HSI color model	87.10%
11	This study	VGG16, DenseNet201, VGG19, MobileNetv2, Inception v3	96% (DenseNet201)

2.4 Scope of the Problem

The research paper deals with forest fire classify. This work is done through a deep learning algorithm. First, we have to collect images for forest fire detection, here we have collected 4586 images including fire images, non-fire, smoke on fire, fog images. The researchers that we have read have worked with the RGB color model or have worked on various topics. We have done our project by deep learning; we have found some research papers where that have worked only with fire and non-fire. However, we found that non-fire and fog detection is complicated by non-fire images which contain only smoke. Some of these images we took from Kaggle and some were collected by ourselves, which became a challenge for us to collect.

2.5 Challenges

- Collect image data
- Data selection
- Data cleaning
- Data resize
- Select models
- Data augmentation
- Data train

CHAPTER-3

Research Methodology

3.1 Research Subject and Instrumentation

An instrumentation system's main goal is to provide the user with a numerical number that corresponds to the variable being monitored. The platform Google Collaborator uses Python to implement all of the experiments. It enables the writing and execution of any Python code using a web browser. Colab requires no setup. Colab lets users import an image dataset, train an image classifier on it, and evaluate the model in just a few lines of code. No matter how powerful the computer, Colab laptops may use the hardware power of Google, including GPUs and TPUs, because they run code on Google's cloud servers.

3.2 Data Collection Procedure

The information for model preparation, testing, and approval was assembled utilizing Kaggle [24], other social media, and online sources. While analyzing a total of 4586 images of forests, this study classified forest fire, non-fire, fog, and fire smoke into four categories. The image's pre-processing, which included cropping and reducing their size to 224 x 224 pixels,, was also taken into consideration when creating the training and testing data. The sample of four specific image kinds used in the study is shown in Figure 3.1.

Figure 3.1: Sample of data

985 images of fire, 1257 images of non-fire, 1247 images of fog, and 1097 images of fire smoke are included in the dataset.

3.3 Statistical Analysis

Figure 3.2 shows the number of images of fire, non-fire, smoke, and fog. And figure 3.3 Shows the number of train, test, and validation images.

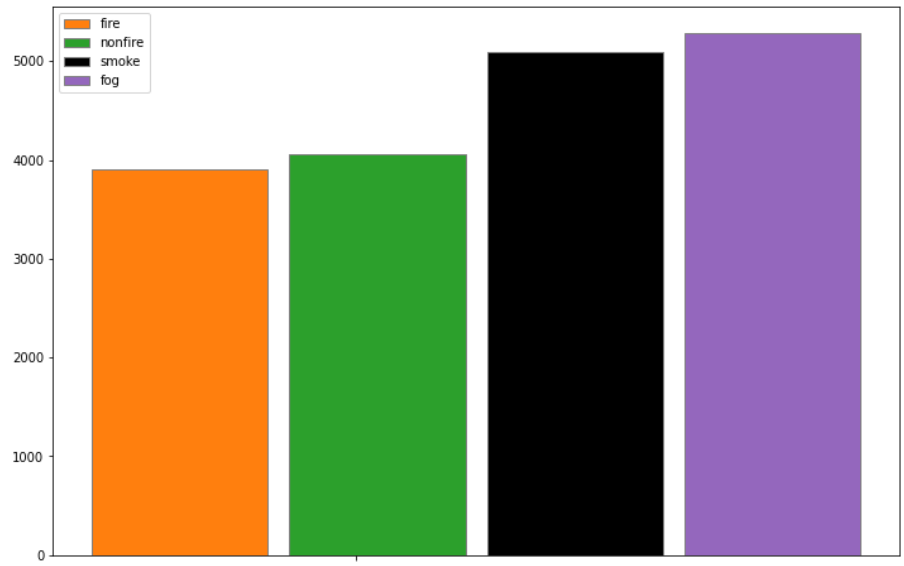


Figure 3.2: The quantity of fire, non-fire, smoke, and fog images

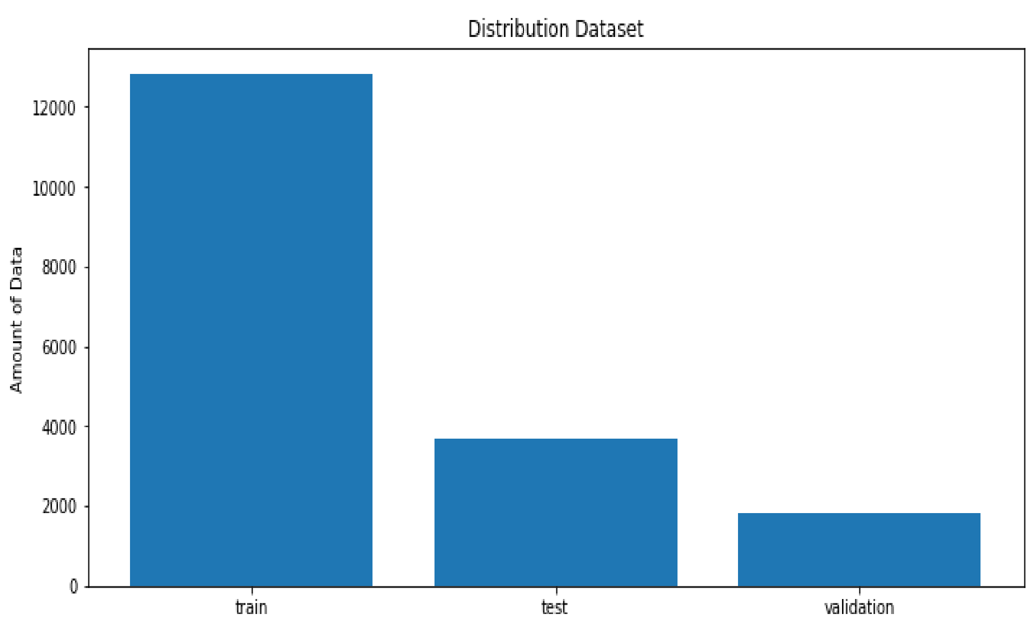


Figure 3.3: The number of images trained, tested, validation

3.4 Proposed Methodology

The final objective of this project is to offer a useful model for identifying forest fires. So, many working procedures are used in this study. The relevant information is collected from "Kaggle', social media, and the internet. The present method consists of different steps which are data collection, dataset labeling, and pre-processing. In this present study, we use different 4 algorithms VGG16, DenseNet201, VGG19, Inception v3, and MobileNetv2. Where the best accuracy is in DenseNet201 at 96.40%. The study's overall workflow is depicted in Figure 3.4

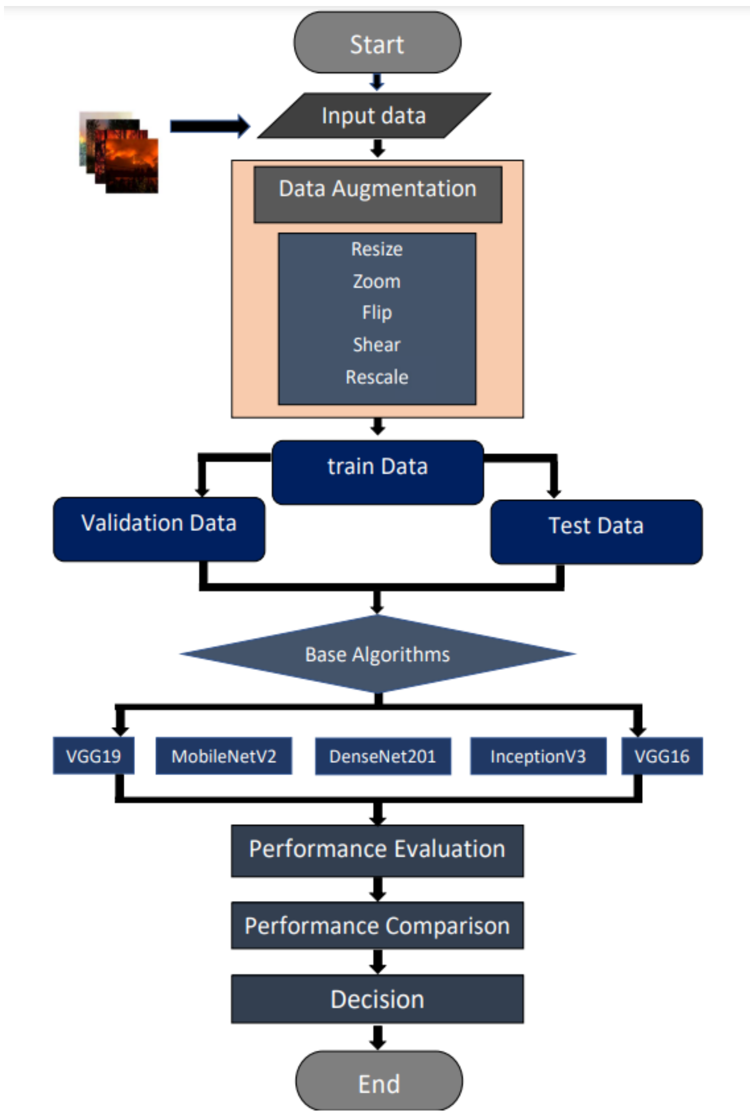


Figure 3.4: Process for executing this study's system

3.4.1 Pre-processing

To clean the data and get it ready for a deep-learning model, data preprocessing is necessary. This makes the model more accurate and effective. Preprocessing data is a typical first step in the deep learning workflow to prepare raw data in a way that the network can accept. To manage a sizable collection of photographs that won't all fit in memory, use an image Datastore object. Deep learning applications sometimes need training on thousands of annotated pictures and also include large datasets of photos. Usually, these images are stored in a folder with subfolders that contain images for each and every class. Data that is gathered from several sources may arrive in a variety of forms. Despite the fact that the primary goal of the entire procedure is to prepare data for machines, the process must nonetheless start with similarly structured data. While maintaining the same training/testing/validation ratio (70/20/10), the image's pre-processing, which included cropping to 224 x 224 pixels, was also taken into consideration when developing the testing and training data. In this study, the primary purpose of using data augmentation is to train deep learning models on more data. By adding slightly altered data to already existing data, data augmentation techniques can add to the insufficient amount of training data.Flipping, shifting, cropping, scaling, rotation, and translation are some of the most common methods for enhancing data.We used a variety of data augmentation techniques in our work, including shifting, rotating, shearing, flipping, and reflecting on our initial dataset.The images were rotated with a random angle of 0.8 set.Through arguments about the width and height range, the images were moved by 20% along the X-axis and Y-axis.Furthermore, 2% range of the images were sheared.We set it horizontally for flipping.We have gathered 4586 forest image data from the ground.We now have 18344 images in total after expanding the data.We have apportioned this dataset into train, validation, and test set. 20% of the data have been kept for testing. 10% of the remaining data were used to validate the models, and the remaining 70% data were used to train the models. The dataset consists of 3908 images of fire, 4060 images of non-fire, 5288 images of fog, and 5088 images of the smoke of the fire. Table 3.1 displays the amount of train, test, and valid data.

Table 3.1: Information of dataset images

Categories	Num of total data	Num of train data	Num of test data	Num of validation
Fire	3908	2735	782	391
Nonfire	4060	2842	812	406
Fog	5288	3701	1058	529
Smoke in fire	5088	3561	1018	509
Total	18344	12839	3670	1835

3.4.2 Performance Measures

Our datasets have been used to determine the recall, precision, and F1-score, which provide as measures of the architecture's efficiency and accuracy. TP stands for "true positives" (the classifier identifies fire in the flame-filled region of the image.); FP for "false positives" (the classifier identifies fire in the area of the image where there are no flames.); and FN for "false negatives" (classifier does not find fire in the area of the image with flames) [11]. Based on our datasets, fire detection accuracy is 96.40%.

precision= $\frac{TP}{TP+FP}$ ………………..…… . (i)

Recall= $\frac{TP}{TP+FN}$ ……………………….………. (ii)

F1score=2× $\frac{precision \times Recall}{precision + Recall}$ ..………... (iii)

3.5 Implementation Requirements

In this study, the datasets were classified using deep learning-based classifiers such as VGG19, DenseNet201, VGG16, Inceptionv3, and MobileNetv2.

3.5.1 VGG16

The most remarkable part of VGG16 is that it reliably utilized a similar cushioning and max pool layer of 2x2 channels with a step 2 and inclined toward having convolution layers of 3x3 channels with a step 1. Convolution and max pool layers are set up similarly across the entire plan. Two completely associated layers (FC) and a SoftMax for yield are utilized as its decision. The number 16 in VGG16 represents the 16 layers with loads. VGG16 figure 3.5 is shown below:

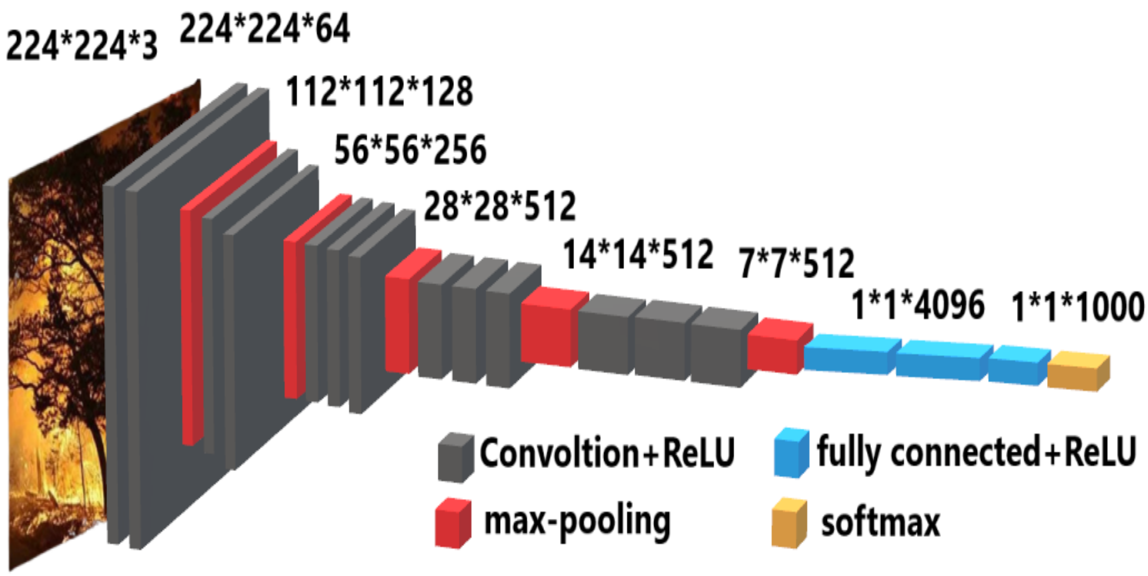


Figure 3.5: The architecture of VGG16

3.5.2 VGG 19

A 19-layer CNN termed VGG-19 is used to classify pictures. Photos are manually organized and thrown into different files after being acquired. The only preprocessing step that was carried out was the calculation of the mean RGB value for each pixel across the entirety of the training set. Use the function to extract all of the features and labels from the test, training, and validation datasets. The image was then categorized using a final layer. Figure 3.6 depicts the sequence convolutional layer of the VGG19 model.

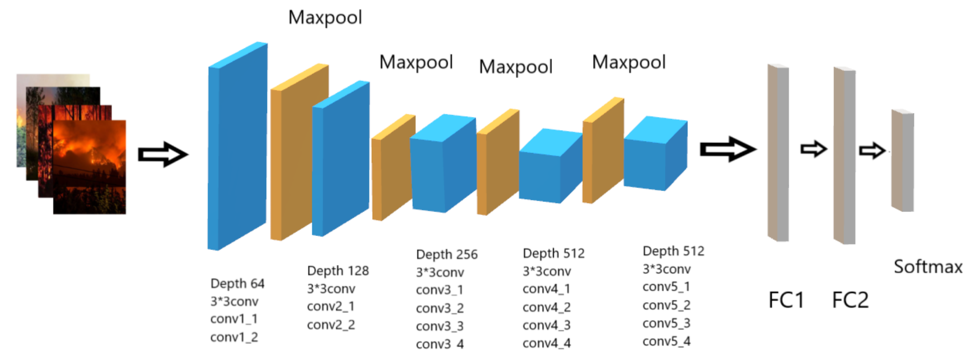


Figure 3.6: The architecture of VGG 19

3.5.3 MobileNetv2

MobileNetV2, a convolutional neural network design, cases to perform well on portable stages. The bottleneck layers are associated with remaining associations, and it is built on a modified lingering structure. The middle of the road extension layer involves lightweight profundity-wise convolutions as a wellspring of non-linearity to channel highlights. A 32-channel beginning completely convolution layer and 19 extra bottleneck layers are likewise remembered for the MobileNetV2 design. Figure 3.7 shows the MobileNetv2 model schema.

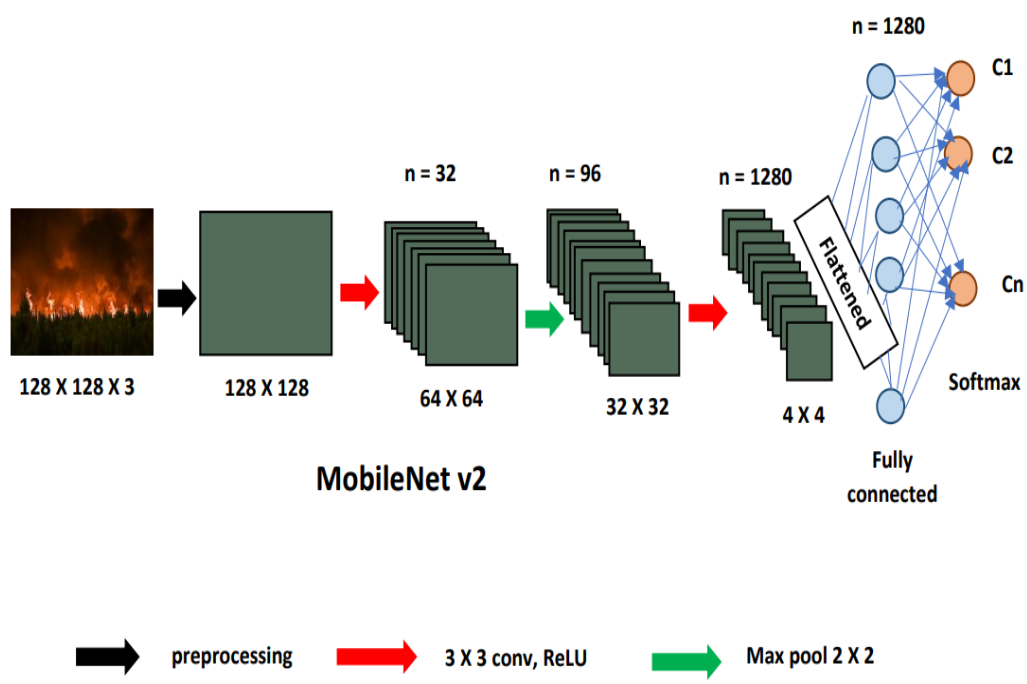


Figure 3.7: The architecture of MobileNetv2

3.5.4 Inceptionv3

Convolutional neural networks are used in Inception v3, a Google net module that guides in object recognizable proof and picture examination. The third variant of the Google Beginning Convolutional Brain Organization was at first shown during the ImageNet Acknowledgment Challenge. The Origin V3 model enhanced the organization involving different procedures for better model variation. It has a more profound organization than the Initiation V1 and V2 models, yet its speed is unaffected. Figure costs are lower. It involves helper Classifiers as regularizes. Figure 3.8 is given the Inception v3 model architecture.

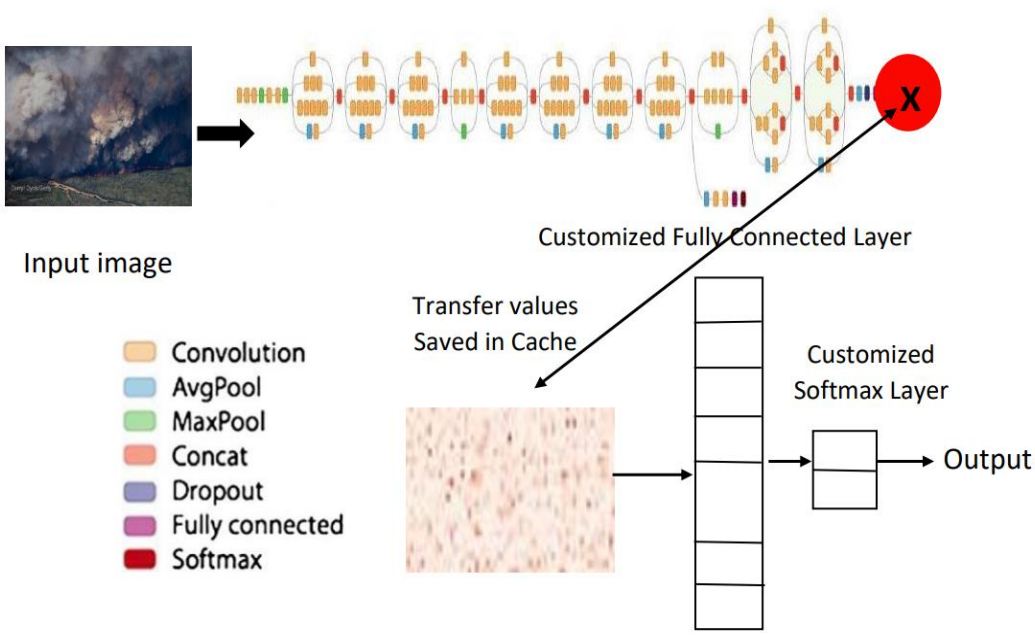


Figure 3.8: The architecture of Inception v3

3.5.5 DenseNet201

A convolutional neural network with 201 layers is called DenseNet-201. Thick Blocks, which link all levels, are used to create dense connections between the layers. Here, you can load a network that has been trained with more than a million images from the ImageNet database. Among other appealing advantages, they dramatically reduce the number of parameters, alleviate the vanishing-gradient problem, promote feature reuse, and improve feature propagation. Figure 3.9 shows the DenseNet201 model schema.

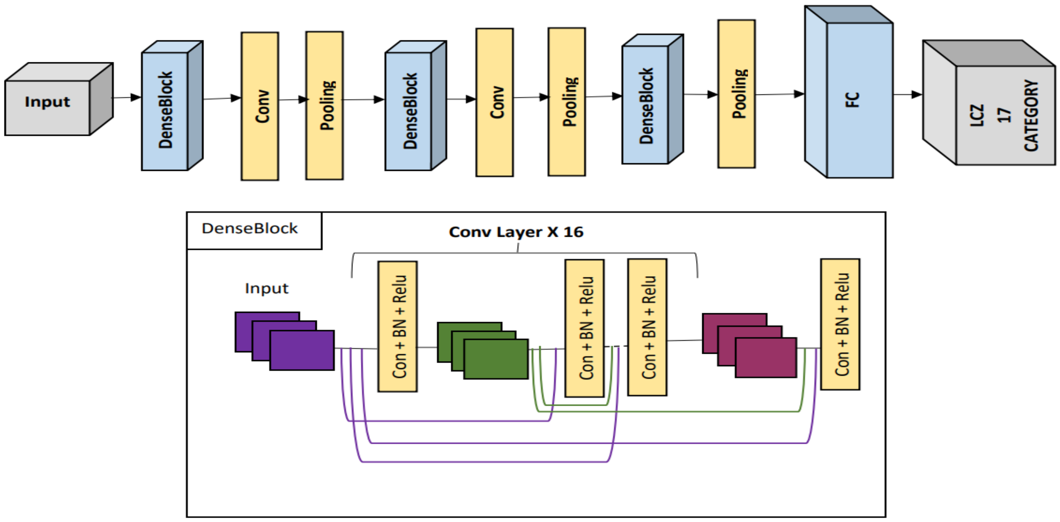


Figure 3.9: The architecture of DenseNet201

CHAPTER 4

Experimental Results and Discussion

4.1 Experimental Setup

In this study, firstly we collect the fire, non-fire, fog, and smoke images. We work in Google Colab. We do to create a new notebook, go to Colab and click on New Notebook (select either Python 2 or 3). It automatically creates a Colab Notebook on your Google Drive. Because it is a Google Drive document, we can share and transfer it around just like any other Drive document.

4.2 Experimental Results & Analysis

A comparative analysis based on the experimental results of the evaluation measures for the forest dataset's deep learning models must be carried out in this section. First, we pre-processed our dataset to evaluate how ensemble classifiers performed. Consequently, utilizing the VGG16, DenseNet201, VGG19, MobileNetv2, and Inception v3 models, various results have been seen here. The outcomes of these five models are shown in Table 4.1

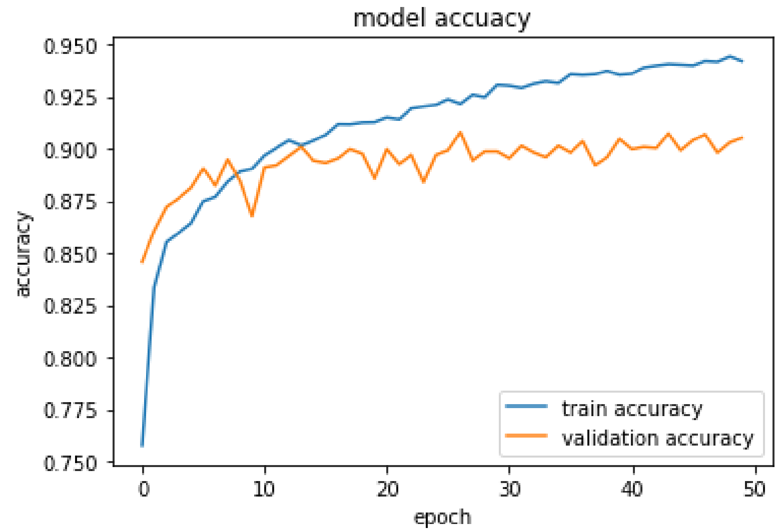
Table 4.1: The performance of accuracy and loss function

Model	**Accuracy**	**Loss function**
DenseNet 201	96.40%	17.61%
MobileNetv2	93.81%	46.85%
Inception v3	93.67%	27.91%
VGG 16	90.76%	30.59%
VGG 19	88.55%	34.32%

4.2.1 VGG 16 Accuracy and Loss function

In figure 4.1 the loss function and train and validation accuracy of VGG 16 are displayed in the graph. The training accuracy represented by the blue line in model accuracy is roughly between 0.751 and 0.945. Additionally, the validation accuracy represented by the orange line is roughly between 0.845 and 0.885.

The training loss that is moving in the range of less than 0.7 in the model loss is represented by the blue line. Additionally, the validation loss that is moving in the range of less than 0.5 is represented by the orange line.



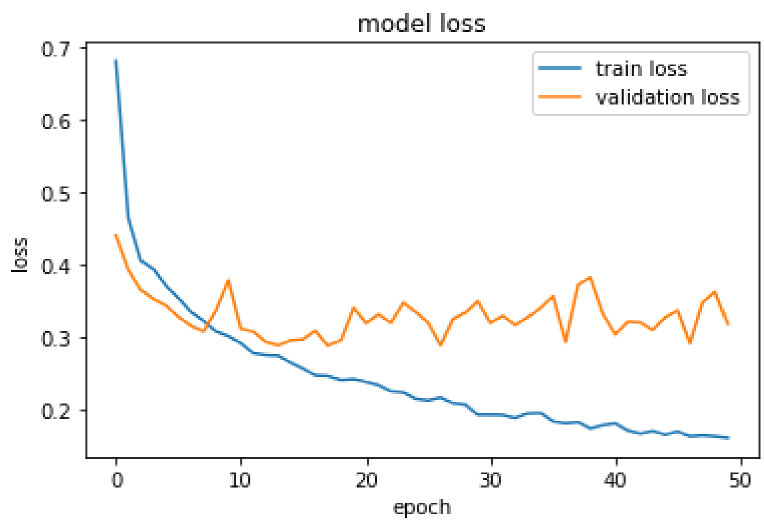


Figure 4.1: Accuracy and Loss performance of validation and training for VGG 16

4.2.2 VGG 19 Accuracy and Loss function

In figure 4.2 VGG 19's train and approval exactness and misfortune capability are available in the diagram. The training accuracy represented by the blue line in model accuracy is approximately up to 0.900. Additionally, the validation accuracy represented by the orange line is roughly between 0.810 and 0.85. The training loss represented by the blue line in the model loss is moving in the range of 0.8. Additionally, the validation loss represented by the orange line is approximately 0.4 to 0.5.

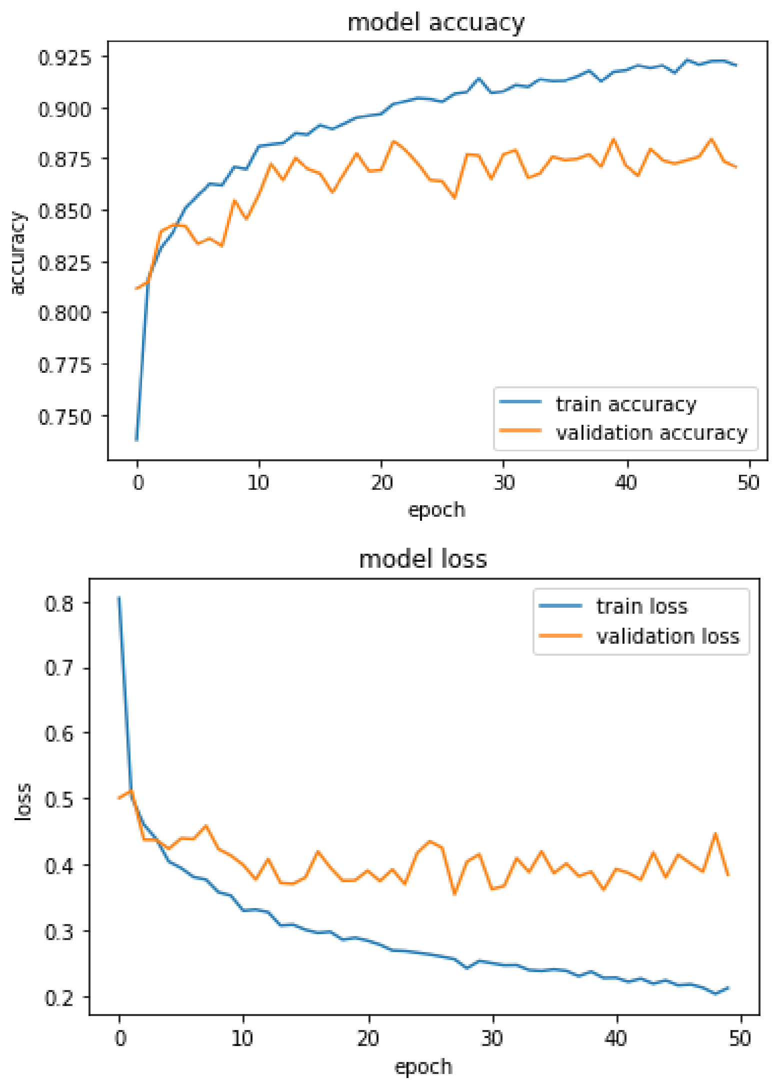


Figure 4.2: Accuracy and Loss performance of validation and training for VGG 19

4.2.3 MobileNetv2 Accuracy and Loss function

In figure 4.3 the loss function and accuracy of MobileNetv2's train and validation are displayed in the graph. The training accuracy represented by the blue line was as high as 0.98, and the validation accuracy represented by the orange line was somewhere between 0.91 and 0.92.

The training loss that reaches 0.8 is depicted by the blue line in the model loss. Additionally, the validation loss represented by the orange line is less than or equal to 0.5.

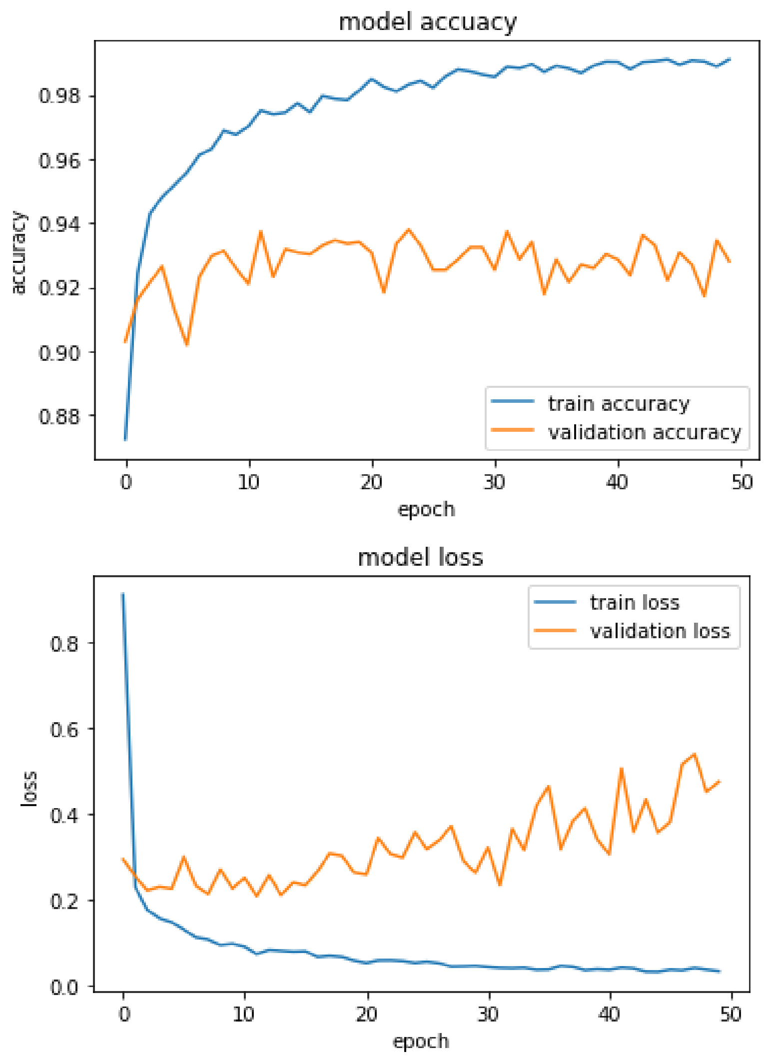


Figure 4.3: Accuracy and Loss performance of validation and training for MobileNetv2

4.2.4 Inception v3 Accuracy and Loss function

In figure. 4.4 the loss function and train and validation accuracy of Inception v3 are visible in the graph. The training accuracy represented by the blue line in model accuracy is roughly between 0.85 and 0.98. Additionally, validation accuracy that falls below 0.96 is represented by the orange line.

The training loss that is approximately 0.8 above the model loss is represented by the blue line. Additionally, the orange line indicates a validation loss of approximately 0.2 to 0.4.

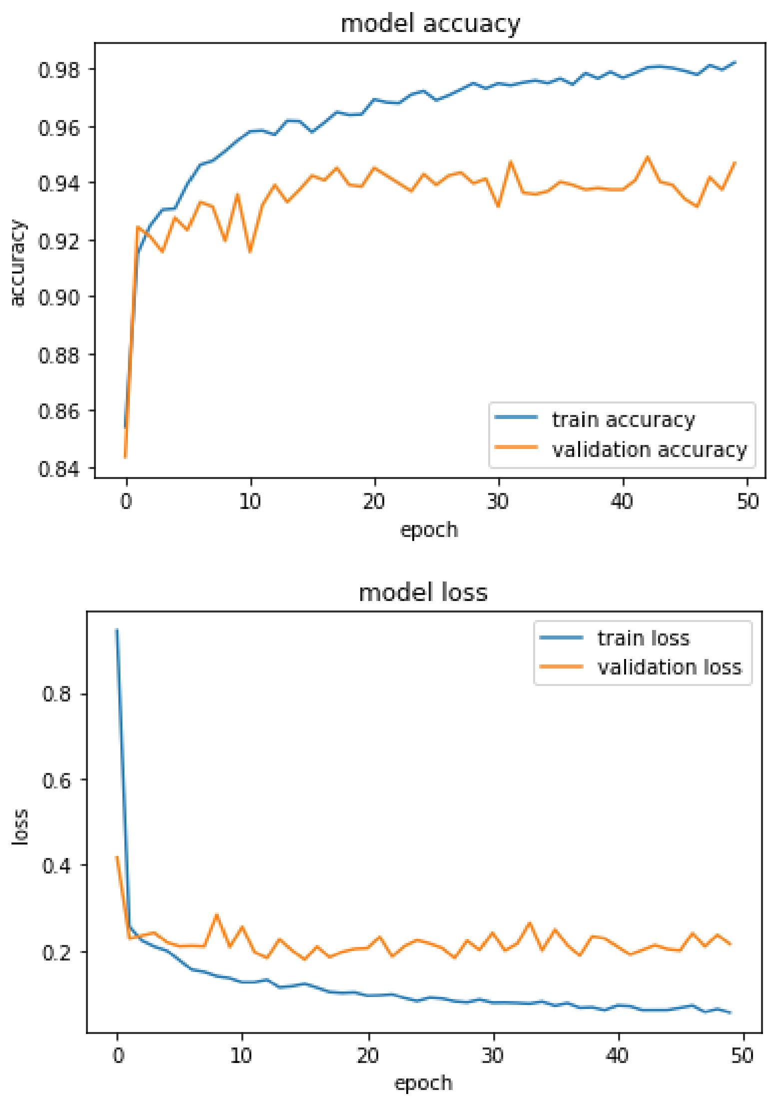


Figure 4.4: Accuracy and Loss performance of validation and training for Inception v3

4.2.5 DenseNet201 Accuracy and Loss function

In figure 4.5 the loss function and accuracy of DenseNet201's train and validation are shown in the graph. The training accuracy represented by the blue line in model accuracy is approximately 0.98 above. Additionally, validation accuracy that falls below 0.96 is represented by the orange line.

The training loss that is less than 0.6 is represented by the blue line in model loss, and the validation loss that is between 0.15 and 0.55 is represented by the orange line.

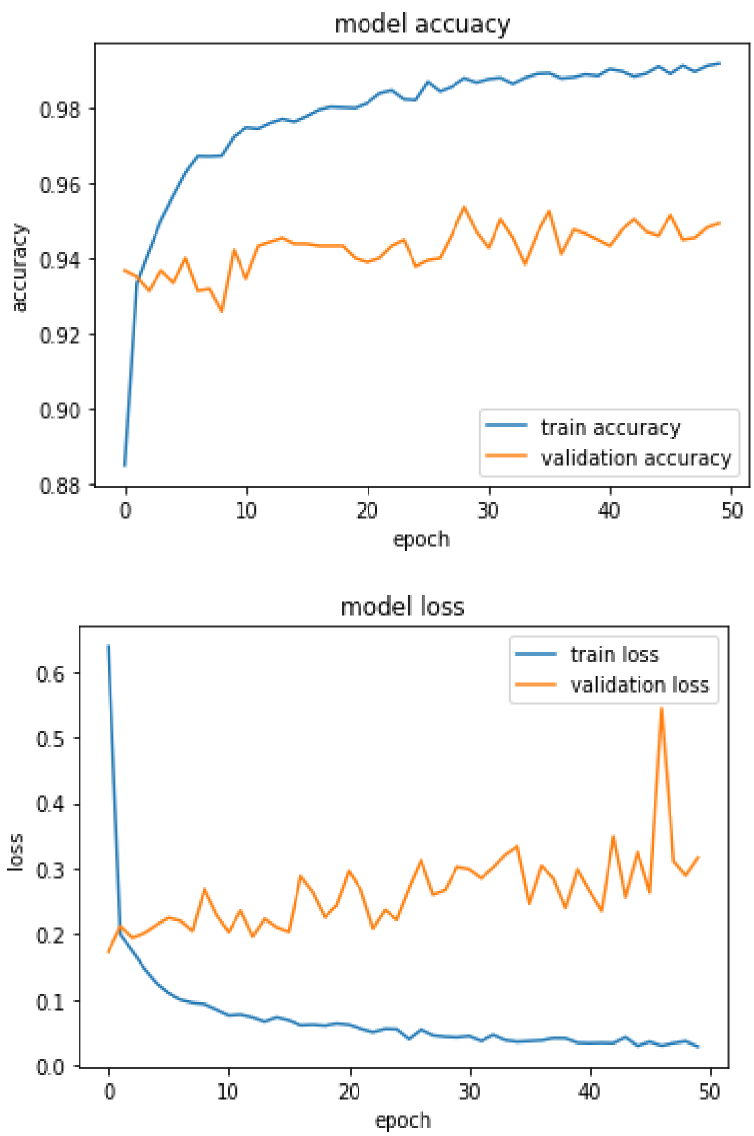


Figure 4.5: Accuracy and Loss performance of validation and training for DenseNet201

4.2.6 Performance

Here, the lowest accuracy is obtained from the VGG 19 model which is 88.55% and loss function 0.34. The highest accuracy is obtained from the DenseNet201 model which is 96.40% and has a loss function of 0.17. The total performance is assessed by analyzing the model's recall, precision, and f1 score. The model's performance is shown in Table 4.2

Table 4.2: Performance of model's precision, recall, f1 score

Categories	**Classes**	**Model**				
		VGG19	***VGG 16***	***Inception v3***	***MobileNet v2***	***DenseNet 201***
Fire	Precision	0.89	0.93	0.97	0.95	0.98
	Recall	0.88	0.88	0.91	0.97	0.96
	F1 score	0.88	0.91	0.94	0.96	0.97
Non fire	Precision	0.89	0.90	0.93	0.97	0.96
	Recall	0.90	0.93	0.96	0.96	0.97
	F1 score	0.90	0.91	0.95	0.97	0.96
Fog	Precision	0.92	0.93	0.93	0.87	0.96
	Recall	0.87	0.90	0.92	0.97	0.96
	F1 score	0.90	0.92	0.93	0.92	0.96

Smoke	Precision	0.85	0.88	0.93	0.98	0.96
	Recall	0.89	0.92	0.95	0.86	0.97
	F1 score	0.87	0.89	0.94	0.92	0.96

With a precision of 96.40%, the DenseNet201 model is the most accurate. Forward connections between each layer are fed by the Dense Convolutional Network (DenseNet). The vanishing gradient problem is solved, feature propagation is improved, feature reuse is increased, and the number of parameters is significantly reduced. DenseNet is based on the idea that shorter connections between layers near the input and layers near the output can be used to train convolutional networks to be much deeper, more precise, and more effective. Because of the capability of element reuse by various layers, which increments fluctuation in the succeeding layer info and improves execution, DenseNet201 utilizes the consolidated organization to give models that are easy to prepare and very parametrically effective. Figure 4.6 shows the working process of DenseNet201.

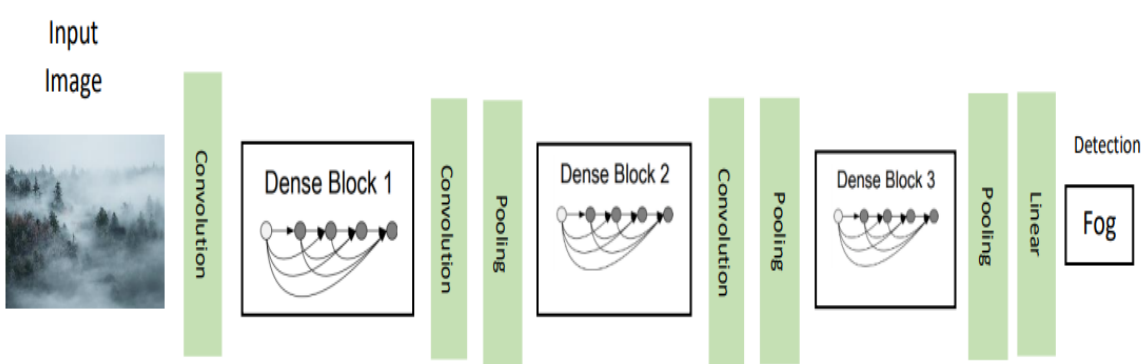
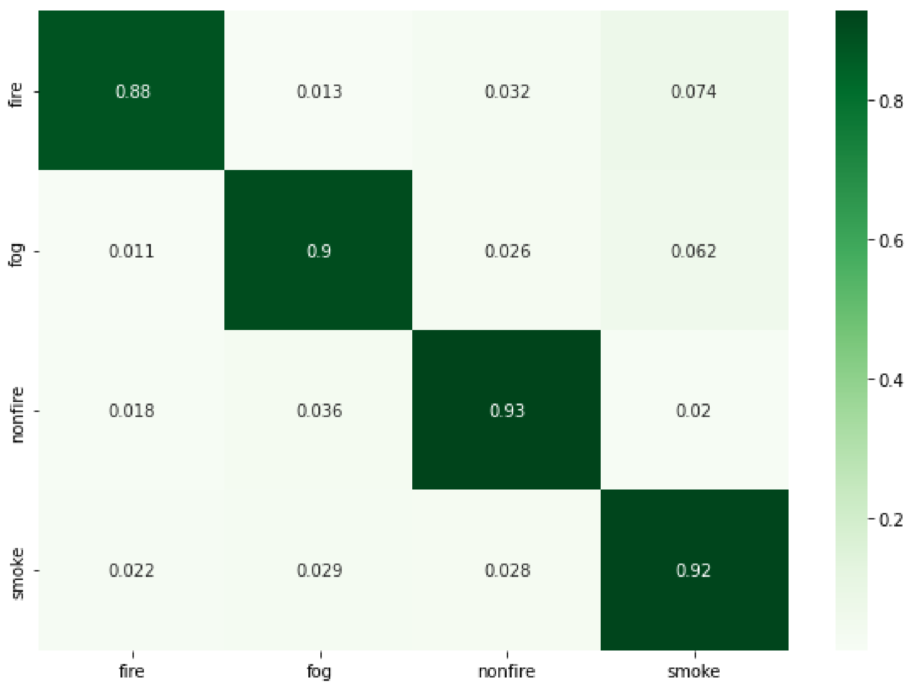


Figure 4.6: The process of DenseNet201

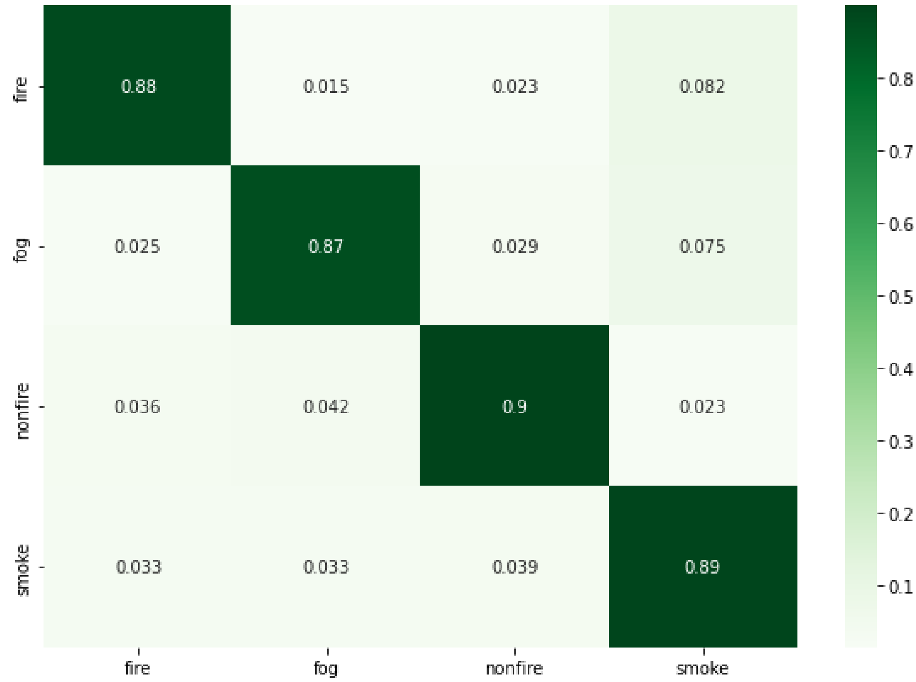
4.3 Discussion

In this study, a deep learning method for detecting smoke, fog, fire, and other types of smoke was presented. Here was applied VGG 16, DenseNet201, VGG19, Inception v3, MobileNetv2 models. The best accuracy is given by the DenseNet201 model which is 96.40%.

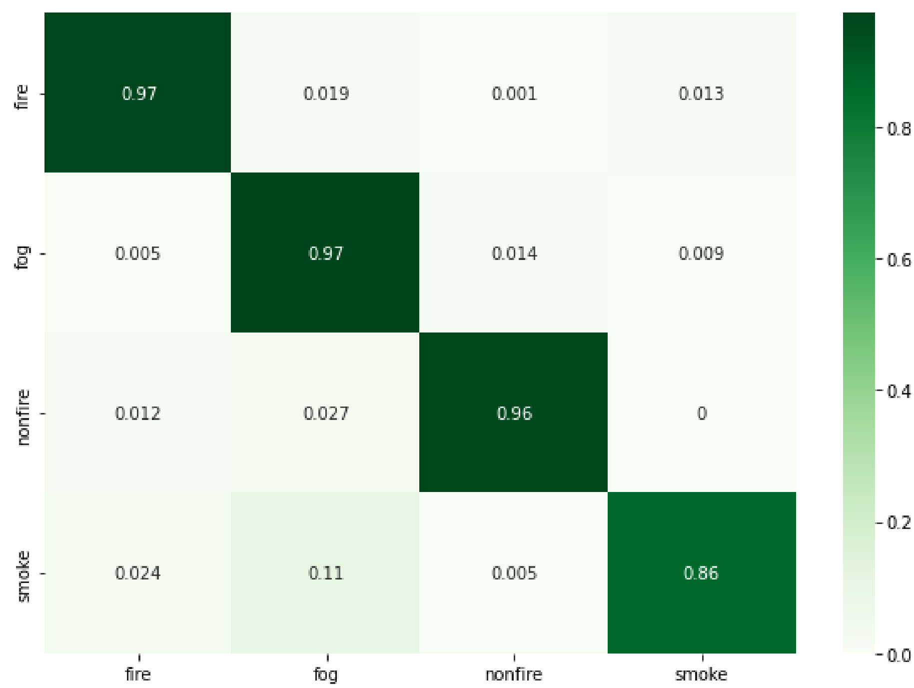
The confusion matrix shows that the detection stage's overall accuracy is very high. When the algorithm misclassifies anything or creates data conflicts, an error occurs. There were some errors even though the study employed the best model to diagnose cat illnesses. since the technology has some restrictions. When trying to categorize many classifications or detect illnesses, the system becomes confused. The confusion matrix is displayed in Figure 4.7



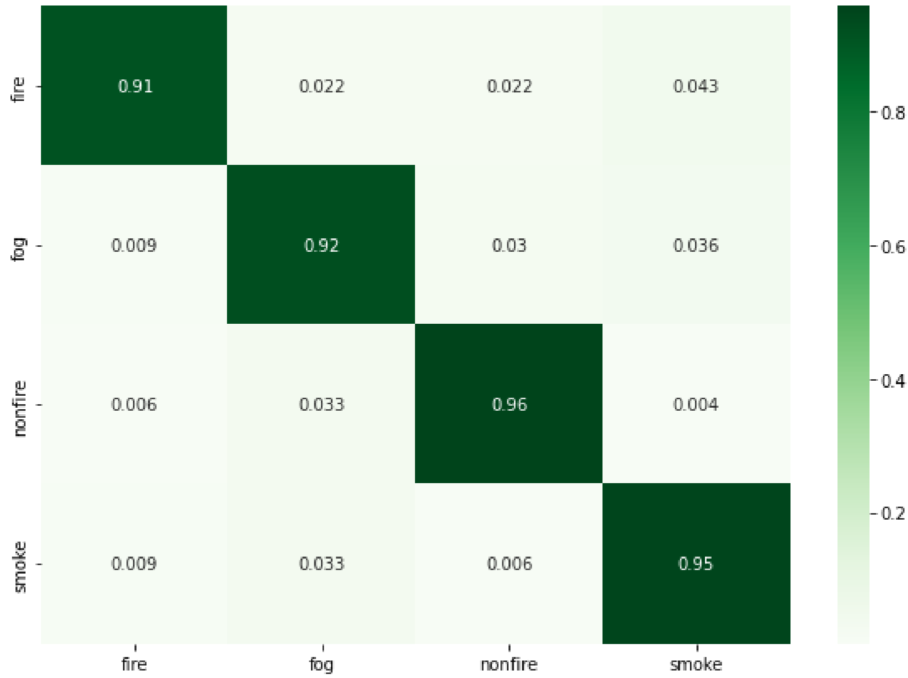
VGG16



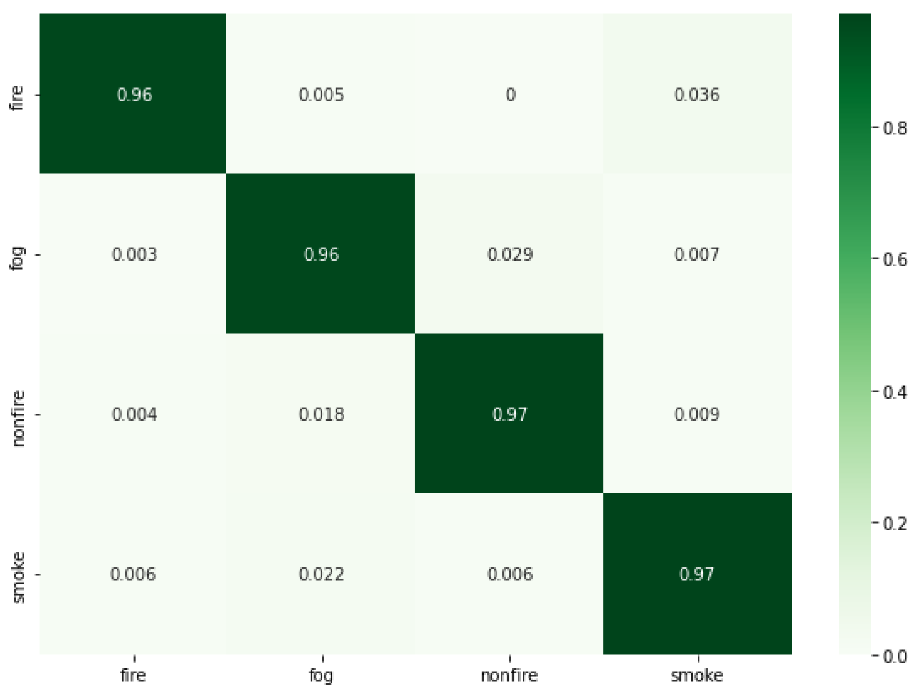
VGG19



Mobilenet V2



inception v3



DenseNet201

Figure 4.7: Confusion Matrix different models

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

It has a significant impact on the formation of ecosystems because it acts as a catalyst for transformation and regeneration. Fire, on the other hand, has the potential to kill because it destroys structures, forests, and wildlife habitats as well as pollutes the air with harmful fumes. Repeated fires destroy the organic material that keeps soil productive, reducing agricultural yields over time and necessitating more expensive fertilizers. Buildings, fields, and surrounding communities are all at risk from the smoke and flames that are spreading. Because of the extent of the damage, there could not be any work being done inside this medium term, which would reduce cash flow in the long run and increase the risk of a fire that would result in significant job losses. A natural disaster adversely affects our society and environment. Therefore, forest fire control is very important. That's why we need to take advance precautions to control forest fires. If the current condition of a forest can be detected through satellite, then timely warning and necessary action can be taken.

5.2 Impact on Environment

A look at how large-scale forest fires have affected the population as a whole in the past, now reveals that public concern for the issue is growing. Numerous media publications have focused on the remarkable social and environmental effects of forest fires. In addition to listing the harm done to the environment and the number of people involved in the suppression efforts, such as volunteer firefighters, army air and land resources, and so on, The media extensively report on emergency situations that result in evacuations, physical injuries, and, at worst, human deaths. A quantity and quality of articles, editorials, electricity outages, homes and businesses being destroyed, and communications are produced as a result of the annual news stories about blocked roads and railway lines, downed mobile and land telephone lines, and the way of life being destroyed in many communities. We provide these startling statistics, which we gathered from newspaper archives, to highlight the scope of a problem that is now unsustainable and to which the management and politicians who are accountable have grown accustomed. So, it is necessary to take timely action to control the fire. We have worked in this paper on forest fire detection using of deep learning models to control the forest fire.

5.3 Ethical Aspects

Around 85% of the time, people start wildland fires in the United States. Human-caused fires include unattended campfires, the burning of debris, equipment use, and malfunctions, carelessly tossed cigarettes, and intentional arsonist actions. Most of the time, a fire won't grow unless there is always fuel (dry vegetation) in its path. As a result, the most effective method for containing a forest fire is to prevent its spread, which can be accomplished by creating firebreaks in the form of small ditches or clearings in the forest. In this article, we'll discuss five morally significant wildfire-related topics.[23].

- Protection of people's lives and property comes first
- Supported by environmental protection
- Land management
- Climate change
- Accountability.

5.4 Sustainability Plan

For the protection of individuals, fire detection work is essential. To stop fire damage, a number of fires detecting systems were created. There are several technological options available. The majority of them are sensor-based and are only used inside. They use ionization, which necessitates being close to the fire, to detect the presence of smoke and fire-derived particles. They cannot be employed in huge covered areas as a result. Additionally, they are unable to offer details on the initial location of the fire, the direction in which the smoke spread, its magnitude, its pace of growth, etc. Emergency scenarios like fires, earthquakes, and floods pose a serious danger to the environment, property, and public health and safety. The most frequent kind of emergency is one involving fire, and a detailed examination of the situation is necessary for a prompt and accurate reaction. Finding fire as fast and precisely as possible in the surroundings is the first stage in this procedure. Forest fires in different countries cause economic and natural damage every year. In this paper, we have worked on forest fire detection through different algorithms with the help of deep learning. VGG 19, DenseNet201, VGG 16, MobileNetv2, and Inception v3 are used here throughout this work. To use this algorithm, we first have to collect data. Four types of images have been collected: fire, non-fire, smoke, and fog. The highest accuracy found in this paper from DenseNet201 is 96%.

CHAPTER 6

Summary, Conclusion, Recommendation and Implication for Future Research

6.1 Summary of the Study

In this study presents our proposal to the established contest for classifying images under many categories (fire, nonfire, fog, and smoke). The study's objective was to recognize forest fires using pictures. In our method, significant features are extracted from training photos using a variety of Convolutional Neural Network (CNN) models, and then these models are used to provide preliminary image label predictions. Here, four distinct models are used (VGG 16, DenseNet201, VGG 19, Inception v3, MobileNetv2). While the accuracy of our best model, DenseNet201, was 96% and its loss function was 0.16.

6.2 Conclusions

Traditional approaches are used to manually extract features from input images for methods of fire detection and classification, and a complicated classifier is then trained to categorize the images. Both method’s low productivity in terms of speed, particularly for the bigger image collection. A convolutional neural network (CNN) based on VGG 16, DenseNet201, MobileNetv2, and VGG 19, Inception-v3 are proposed for fire detection to enhance performance. DenseNet201 has the ability to automatically extract features; experimental and analytical findings show that this architecture produces high detection rates.

6.3 Implication for Further Study

We have discovered various areas for improvement in order to further improve our system. Our goal is to create a model that will help us understand global deforestation better. Fire detection in video sequences is also incorporated into deep learning frameworks that localize each frame of the input pictures using the deep belief network.

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