Image Analysis for Detecting Wildfire Using Deep Learning

BY

Sifat Bin Solaiman

ID: 201-15-3463

FINAL YEAR DESIGN PROJECT REPORT

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

Supervised By

Partha Dip Sarker

Lecturer

Department of CSE

Daffodil International University

Co-Supervised By

Amir Sohel
Lecturer (Senior Scale)

Department of CSE

Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

June, 2024

APPROVAL

My Project titled "**Image Analysis for Detecting Wildfire Using Deep Learning**", was submitted by **Sifat Bin Solaiman**, **ID: 201-15-3463** to the Department of Computer Science and Engineering. This assignment, given and approved by the faculty of Daffodil International University as a requirement for the Bachelor of Science in Computer Science and Engineering, meets the standards for both structure and substance. The presentation is scheduled for 15, July, 2024.

BOARD OF EXAMINERS

Chairman

Dr. Sheak Rashed Haider Noori (SRH)
Professor & Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner 1

Amit Chakraborty Chhoton (ACC)
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner 2

Mr. Mohammad Jahangir Alam (MJA)
Sr. Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

External Examiner

Dr. Md. Arshad Ali (DAA)
Professor
Department of Computer Science & Engineering
Hajee Mohammad Danesh Science and Technology University

DECLARATION

I affirm that I have completed this assignment under the guidance of Partha Dip Sarker, an Assistant Professor in the Department of CSE at Daffodil International University. I hereby affirm that this project, in its whole or any portion thereof, has not been previously presented elsewhere for the purpose of obtaining any degree or certificate.

Supervised By:

পার্থ দীপ
9/7/24

Partha Dip Sarker

Lecturer

Department of CSE

Daffodil International University

Co-Supervised by:

Amir Sohel

Lecturer (Senior Scale)

Department of CSE

Daffodil International University

Submitted by:

Sifat

Sifat Bin Solaiman

ID: 201-15-3463

Department of CSE

Daffodil International University

ACKNOWLEDGEMENT

First and foremost, I would want to express my utmost thankfulness and appreciation to the All-Mighty Allah, whose divine mercy has enabled me to successfully complete my research project during the last year of my studies.

I am very thankful and express my deep gratitude to **Partha Dip Sarker, Assistant Professor, Department of CSE Daffodil International University, Dhaka, and Co-supervisor Amir Sohel, Lecturer (Senior Scale), Department of CSE, Daffodil International University, Dhaka.** I am deeply grateful to my supervisor for their profound expertise and unwavering passion in the field of Machine Learning, which significantly contributed to the successful completion of this project. Without their unyielding patience, professional guidance, continuous motivation, diligent oversight, constructive feedback, valuable insights, thorough review of multiple flawed drafts, and meticulous corrections at every stage, this project would not have been possible.

I would like to extend my heartfelt appreciation to Dr. Sheak Rashed Haider Noori, Professor and Head of the Department of CSE, and Dr. S. M. Aminul Haque, Associate Professor and Associate Head of the Department of CSE, for their invaluable assistance in completing my project. My gratitude also goes to all the faculty members and staff of the CSE department at Daffodil International University for their generous support and guidance in both the technical and administrative aspects of my study.

Additionally, I would like to thank all my peers from Daffodil International University who actively participated in this discourse while managing their academic commitments.

Ultimately, I would want to convey my appreciation to my parents for the enduring affection and forbearance they have shown towards me throughout my existence. They have consistently provided support and encouragement to me throughout my whole life.

ABSTRACT

Approximately 80% of the total organisms on Earth rely on trees for sustenance and shelter. Homo sapiens mostly inhabited forested environments throughout their existence. Wildfires have the potential to do harm to forests. Wildfires are an inevitable consequence of the presence of trees. Uncontrolled Wildfires occur in trees above a height of 1.8 meters (6 feet). In recent years, there has been a significant surge in the number of academics who are interested in using computer vision and image processing techniques to detect flames in images. This study examines several deep learning algorithms used in the detection of Wildfires and does a comparative analysis among them. I collect the dataset from online which is analyzed using four different deep learning models: DenseNet201, MobileNetV2, InceptionV3, VGG16. It contains 18,415 images divided into four categories: fire, non-fire, smoke, and fog. The experimental results showed that wildfire predictions have a high level of accuracy, with VGG16 achieving the highest accuracy rate of 97%.

TABLE OF CONTENTS

LIST OF FIGURES

FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 Introduction

Forests are immensely valuable natural assets that play critical roles in both ecological and economic domains. They provide several functions, including the provision of products and employment opportunities, preservation of biodiversity, regulation of water flow, prevention of soil erosion and degradation, and maintenance of climatic stability via carbon sequestration. In the year 2000, trees were discovered to occupy a total of 3.9 billion hectares, accounting for almost 30% of the Earth's land surface [1]. Approximately 95% of the woods were in their natural state, while the other 5% were intentionally cultivated. In 2015, over 93% of the Earth's surface area, equivalent to almost 3.7 billion hectares, remained covered by natural forests [2]. Activities such as farming, urbanization, and resource extraction are rapidly and extensively destroying natural forests worldwide [3]. As a result, there is a growing need for the establishment of formally designated protected zones for indigenous woods. The user's text is [4]. The most significant danger in the forest that is uncontrollable is a wildfire. Deforestation results in the eradication of many species of flora and fauna in forests, disrupting the equilibrium of environment, biodiversity, and the ecology. These massive flames have the ability to rapidly propagate and alter their course from their initial point of origin. Ensuring Wildfire protection is crucial for the advancement of land utilization and the improvement of living conditions in all nations. Wildfires result in the mortality of trees, shrubs, and unprocessed wood. Fires impair the forest's capacity to safeguard the environment and regulate water runoff. In addition, they cause the destruction of structures and, in some instances, whole communities, as well as the decimation of animal species. A Wildfire poses significant risks to both human residents and agricultural animals [5]. By using dynamic image datasets and evaluating many variables, deep learning algorithms can accurately determine the intensity of a Wildfire based on its temperature. Data science encompasses several disciplines such as deep learning, statistics, and predictive modelling. This is particularly advantageous for data scientists who are required to collect, examine, and comprehend a substantial amount of data. Deep learning accelerates and streamlines this procedure. Due to advancements in scientific technology, Wildfires may now be rapidly detected using several methods. The primary objective of the study is to identify the optimal model for distinguishing between a photograph of a Wildfire and an actual Wildfire. Recently, there has been a growing interest among academics in using computer vision and image processing techniques to detect flames in photographs. This research compares several deep learning-based techniques for the classification of Wildfires. From the dataset I classified about five distinct deep learning methods: InceptionV3, DenseNet201, VGG16, and MobileNetV2. The collection has a total of 18,375 images, which are categorized into four distinct groups: fire, non-fire, smoke, and fog. According to the trial research, Wildfire forecasts were shown to be more precise, with VGG16 achieving the highest accuracy rate of 97%. This research has collected images depicting fire, non-fire, fog, and smoke resulting from a fire. The information has undergone several preparatory measures, including rectifying any inconsistencies in the data, augmenting it, magnifying it, inverting it, resizing it, and so on. Wildfire prediction was accomplished using deep learning algorithms. This study also examined and contrasted many established methods for addressing the same problem, including, DenseNet201, inceptionv3, VGG16 and MobileNetv2. Here are the remaining details for this investigation. Section 2 provides an in-depth analysis of prior research and presents my informed perspectives on it. Section 3 provides a detailed description of the recommended procedure and the necessary information for conducting the experiment. On the section four presents the results and remarks of the experiment. After that on the section five I discusses the impacts on society and the global community. Finally, on the section six I discuss about the conclusion of the section as well as some suggestions for future developments.

1.2 Motivation

Individuals, fauna, and flora globally face the peril of perishing in wildfires. Rapid reaction time and a large identification area do not serve their typical purposes in the context of fire detection [6]. Typically, the forest has an intricate ecology. The habitat supports a diverse array of organisms, provides abundant resources, and regulates the emission of carbon dioxide. Wildfires may occur unpredictably in forested areas, resulting in significant destruction [7, 8]. Annually, wildfires claim over 85% of the Earth's tree population, resulting in detrimental climatic alterations and contributing to global warming. A wildfire distinguishes itself from other forms of fires due to its distinct patterns of movement, sensory perception, and visual appearance. After deforestation, wildfires are the second most prevalent cause of deteriorating forest conditions worldwide. Annually, fires inflict harm and devastation upon several sections of forested land, despite ongoing efforts to ensure the safety of woodlands. From 1998 to 2017, a total of 2400 individuals lost their lives due to asphyxiation, injuries, and burns caused by wildfires and volcanic eruptions. These events also impacted 6.2 million individuals globally. However, as a consequence of climate change, wildfires are increasing in size and frequency. Consequently, air pollution has the potential to induce health complications such as cardiovascular and respiratory disorders. Considering the impact of fires on mental health and emotional well-being is crucial [9]. Upon perusing several scholarly articles, it becomes evident that wildfires annually inflict damage upon both the economy and the natural environment. To assess the precision of several deep learning models, I choose to focus on Wildfires and collect diverse arrays of images. This instills in me a desire to take further action.

1.3 Research Questions

Here are some potential research questions for my paper on "Image Analysis for Detecting Wildfire Using Deep Learning":

1. What are the primary characteristics of this database?
2. What is the operational mechanism of the algorithm used in this research?
3. What methods may be used to forecast Wildfires?
4. What will be the accuracy success rate of picture detection?

1.4 Main Objective

Here are five research objectives for my research paper on "Image Analysis for Detecting Wildfire Using Deep Learning":

1. To explore the efficacy of deep learning algorithms in detecting and categorizing wildfire-related patterns and features within satellite or aerial imagery.
2. To evaluate the effect of different image resolutions on the accuracy and efficiency of wildfire detection using deep learning techniques.
3. To explore the potential of transfer learning in enhancing the performance of deep neural networks for wildfire detection by leveraging pre-trained models on related tasks.
4. To develop and evaluate a robust and real-time deep learning-based wildfire detection system capable of handling diverse environmental conditions and input data sources.

5. To investigate the influence of hyperparameter tuning on the precision, recall, and overall performance metrics of deep learning models for wildfire detection.

Those research objectives provide clear directions for my study, focusing on assessing model performance, identifying strengths and weaknesses, exploring dataset augmentation, investigating optimization techniques, and determining practical model choices for real-time Wildfire Detection systems.

1.5 Rationale of the Study

I have thoroughly reviewed numerous scholarly articles on methodologies for forecasting wildfires. These research papers cover a broad spectrum of topics, including digital processing for wildfire accounting and mapping, remote sensing processing, mapping surface fuel models, analyzing long-term satellite images, and utilizing deep learning techniques. Although several articles have been published on the use of deep learning for fire prediction, many of them have shown that employing multiple classes and models can be ineffective. Consequently, I was driven to achieve optimal outcomes and use various approaches. Ultimately, I have discovered the most precise method for utilizing these techniques.

1.6 Report Layout

I follow this structure for my research paper:

1. Chapter 1 of "Image Analysis for Detecting Wildfire Using Deep Learning" covered the fundamental concepts. The goal, objective, and motivation of my work is inconsequential.
2. The second chapter's portion provides a concise overview of the topic and consequences mentioned in earlier research studies.
3. On the research methodology section, The Proposed Methodology’s, abou Datasets, implementation, data Preprocessing, and upgraded model are all detailed in Chapter 3.
4. The specific results from the experiment are outlined in Chapter 4.
5. The environmental and societal implications of my actions, etc., are discussed in Chapter 5.
6. In Chapter 6, I describes a summary, conclusion and outline the project's potential future directions.

1.7 Project Management and Finance

Project management is the use of appropriate tools, methods, and individuals to accomplish defined project objectives. Project management involves the strategic planning and diligent oversight of a project's advancement to assure its successful attainment of predetermined objectives. It is essential to assess and control risks, efficiently distribute resources, create a feasible budget, and maintain open communication with teams and stakeholders. Project management include the tasks of arranging and facilitating meetings, performing tests, and inputting data into databases. The meeting agenda and minutes, which outlined the status of the investigation and next steps, were issued punctually. Over time, many materials have accumulated and are now accessible via the Madcaps chat app. Conducting research, evaluating sources, analyzing information, using critical thinking, developing a strategy, and composing the paper are all essential components of a comprehensive research paper on financial subjects. The correlation between research administrations.

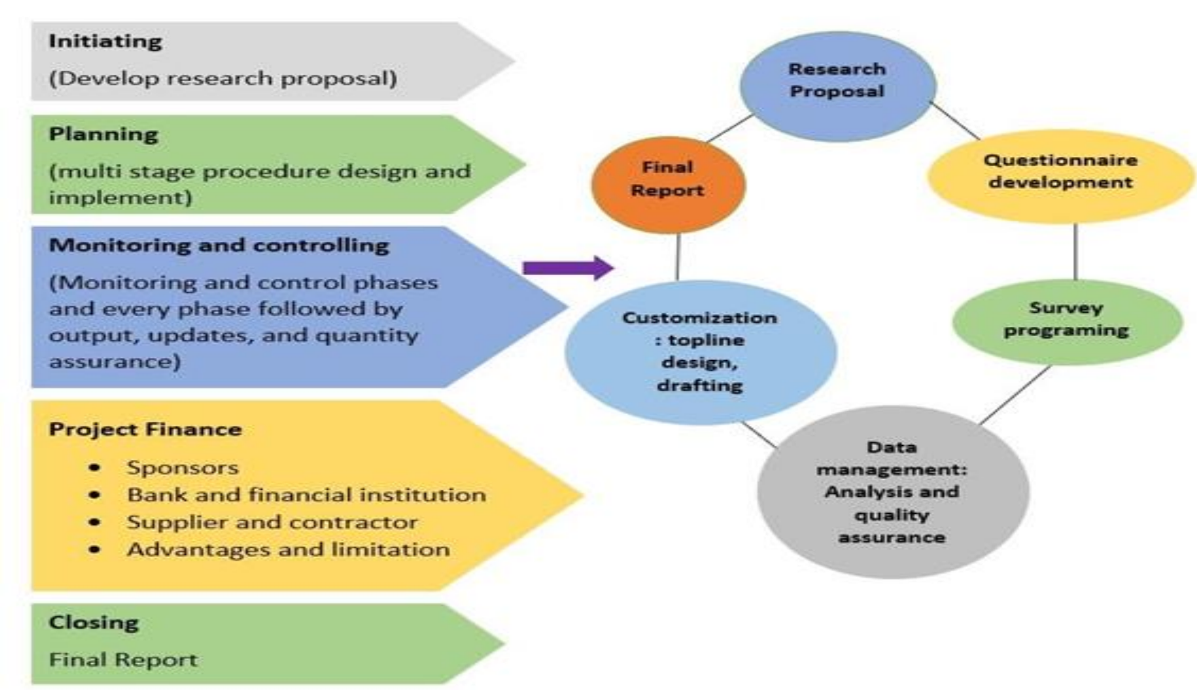

Figure 1.1: Research management & Finance

CHAPTER 2

BACKGROUND Study

2.1 Introduction

Wildfire, sometimes referred to as a wild-land fire, Wildfire, or rural fire, is an unforeseen and unmanageable fire that originates in an area of vegetation combustion, regardless of whether it occurs in an urban or rural setting. Wildfires are essential for the survival of several forest ecosystems in their original condition. The smoke emitted by wildfires may have detrimental effects on my health, ranging from irritation of the eyes and lungs to more severe consequences such as coughing, asthma exacerbation, cardiac failure, and premature mortality. A number of different specialists have worked on various topics that have to do with employing machine learning methods or the Internet of Things to locate Wildfires. Artificial intelligence and deep learning are extensively used technologies for addressing a diverse array of challenges. Various of pre-trained models have been used by others researchers, however, the Deep-learning approach seems to be the most effective at detecting Wildfires.

2.2 Related Works

Various strategies and procedures have been used by individuals to detect Wildfires. Various methodologies include distinct advantages and disadvantages. Below is a comprehensive examination of the primary methodologies used in the detection of Wildfires.

Ruchkin et al. [10] proposed the practical & professional strive made in the field of fire controlling. Satellite imagery may be used to detect fires, locate hotspots, model fire behavior, determine how spread flames, and track their development, according to the authors. Neuro processing systems NM640X, which possess the ability to adapt to changing circumstances, are used to implement intelligent communication systems. Gomes, P. et al. [11] proposed the use of stationary intelligent surveillance cameras using a vision-based approach to distinguish between fire and other objects. The individuals estimated the dimensions of the anticipated entity in the two-dimensional representation, triggered alarms with geographical references, and deliberated about the nature of the entity and its motion while determining strategies to reduce the occurrence of erroneous warnings generated by mobile objects exhibiting a fiery coloration. Finally, a calibration approach based on GPS was used to provide a comprehensive understanding of the camera-world mapping process. Based on empirical evidence, the suggested methodology achieves a 93.1% success rate in accurately detecting fires, with a handling frequency of 10 Hz, which is often sufficient for practical applications. The authors of the paper are W. B. Horng et al. [12]. The fire region of the image is generated by extracting fire characteristics from the HSI color model and inputting them into a neural network. Subsequently, the fire area segmentation process is executed to eliminate spurious fire regions such as fire shadows and objects that resemble fire. The fire zones are thereafter divided into approximate sections. The white pixel ratio and the disparity among the outline images are next used to determine the intensity of the fire, which may be categorized as minor, moderate, or significant. Experiments demonstrate that the approach may effectively discern various categories of flames with a high degree of accuracy. Bragilevsky et al. [13] participated in the challenge and presented their results on the programmer, along with their suggestions for improvement. An issue arose in the process of labelling satellite photos. The ResNet50 model got a score of 92.8% by the use of a sophisticated Convolutional Neural Network (CNN) model, in addition to many additional CNN designs. The well recognized VGG network architecture served as the inspiration for the deep convolutional neural network model. Vanni et al. [14] used a CNN with Transfer-learning techniques to enhance the exact value of fire detection by using Inception-v3. The framework utilizes satellite imagery to train and divides information into two categories: fire and non-fire photographs. This division allows for the creation of a confusion matrix, which accurately assesses the performance of the framework. Additionally, it employs a local binary code to extract the specific region in the satellite image where the fire occurred, hence reducing the occurrence of false alarms. When evaluated on a benchmark dataset with a more realistic distribution, Jivitesh et al. [15] discovered that conventional Convolutional Neural Network performed incorrectly. They suggested using more profound convolutional neural networks to detect flames in photographs. Subsequently, these networks may be enhanced via the process of fine-tuning, which involves optimizing the performance of a completely interconnected layer. I used two state-of-the-art Resnet50 models that had undergone prior training, in addition to Deep-Learning Convolutional Neural Network and Vgg19, to develop their forest-fire detect mechanism. In addition, I generated a deliberately biased dataset to accurately reflect real-world conditions, which I then used to evaluate the performance of the Deep Convolutional Neural Networks (CNNs). It was discovered that my more complex Convolutional Neural Networks (CNNs) performed well on a more challenging dataset. Specifically, the Resnet50 model narrowly outperformed the VGG16 model. Therefore, these findings may have an impact on the development of more advanced instruments for detecting fires. Abhay et al. [16] Provide a model for detecting wild-fires and a comprehensive tracking mechanism referred to as RCNN. This technology uses video frames captured by unmanned aerial vehicles (UAVs) to detect and locate forest fires. The authors propose the implementation of an extensive monitoring system and a framework for distinguishing forest fires. This is based on the significant discovery that UAV drone video profiles have the capability to differentiate between flares. The proposed CNN model accurately and consistently detects forest fires with a success rate of 95.29%. Jiao, Z. et al. [17] conducted a research in which they took the YOLOv5 with the model based learning technique to achieve real-time fire detection using UAVs. They aimed to enhance the efficiency and accuracy of fire detection using UAVs, achieving a remarkable success rate of 94%. In their study, Jamil et al. [18] provide a convolutional neural network model specifically designed for detecting fires in surveillance videos. The CNN model has the advantages of both speed and cost-effectiveness. The model is implemented using the GoogleNet architecture because to its computational efficiency and superior performance for the given challenge, in contrast to more computationally demanding networks such as AlexNet. This research is accurate 94.43% inspection of the time. Pasquale et al. [19] provide a methodology for detecting fires by examining surveillance films captured by police cameras. Two significant additions were made. Initially, a multi-expert system integrated many types of information that were relevant for analyzing color, shape alteration, and motion. The primary advantage of this approach is that it significantly enhances the overall system performance with less effort required from the inventor. Furthermore, a novel approach to characterize movement using a bag-of-words technique has been proposed. The new approach was tested using an extensive collection of fire photographs sourced from both online and real-life platforms. The findings indicate a constant decrease in the occurrence of false positives, while maintaining the system's accuracy and its compatibility with embedded systems. Osman et al. [20] provide a fire monitoring mechanism that utilizes video and analyses color, space, and time data. The mechanism utilized covariance-based characteristics pulled from video blocks, including both spatial and temporal aspects, in order to detect fire. Their investigation showed an accuracy rate of 90.32%. Rafiee et al. [21] proposed a method to use the dynamic and persistent characteristics of fire and smoke. The static characteristic of the analysis is the two-dimensional wavelet. They used it to analyze the color and motion characteristics by observation variations in the energy of two-dimensional wavelets. Furthermore, the recommended strategy utilizes the dynamic characteristics of smoke and fire, which are inherently chaotic. Chen, T. H. et al. [22] demonstrated the first method of activating fire sirens via the use of visual processing. They were accurate 87.10% of the time when using the RCB and HSI color models.

2.3 Comparative Analysis and Summary

Table 2.1: Comparative analysis of Related Works

SL No	Name	Model	Accuracy
1	Bragilevsk et al. [13]	ResNet, VGG16 Network Model	Height accuracy about 92.8% on (ResNet)
2	Vanii et al. [14]	InceptionV3 Model	94% (InceptionV3)
3	Jivitesh et al. [15]	ResNet, VGG Model	Height Score 92% on ResNet
4	Abhay et al. [16]	RCN	Get about 95.29% on (RCN)
5	Jiao et al. [17]	YOLOv5	94% (YOLOv5 Model)
6	Jamil et al. [18]	Convolutional Neural Network architecture	Get about 94.43%
7	Pasquale et al. [19]	(ME+SV+ CE) MES model	93.45%

8	Osman et al. [20]	SVM model & Covariance matrix-based-finding model	Get about 90%
9	Rafiee et al. [21]	RGB color model & YUV	Get about 87% on (YUV)
10	Chen et al. [22]	HSI color model & RCB	Get about 87%
11	On my research	Inceptionv3, VGG16, MobileNetv2, DenseNet201	97% (VGG16)

2.4 Scope of the Problem

The research article focuses on the methodology for detecting and classifying forest fires. The feasibility of this endeavor is enabled by deep learning. Initially, it is important to collect visual representations in order to assist me in detecting and locating forest fires. Thus far, I have collected a total of 18415 images depicting flames, non-fires, smoke emanating from fires, and fog. Many of the researchers I have studied have focused on the RGB color model or have conducted various studies. I acquired extensive knowledge for my project via the use of deep learning techniques. I discovered research publications that only examined the effects of fire and the absence of fire. However, I discovered that images depicting smoke without actual flames provide a challenge in distinguishing between fog and non-fire photographs. Some of the photographs were obtained via Online, while others were gathered through independent study, resulting in a challenging selection process.

2.5 Challenges

When I tried to make my research paper that time I faced many challenges:

- Data Availability and Quality: Limited access to diverse and high-quality wildfire imagery. Inconsistencies in labeled data, such as mislabeled images or incomplete annotations.
- Computational Resources: Requirement for significant computational power and memory, especially if working with big datasets and complicated deep learning algorithms. Potential challenges related to the time and resources needed for model training and optimization.
- Generalization and Transferability: Difficulty in ensuring that the developed models generalize well across different geographical locations, climates, and environmental conditions. Challenges in achieving transferability of models trained on one dataset to another dataset with distinct characteristics.
- Interpretability and Exploitability: Inherent complexity of deep learning models may hinder the interpretability of results, making it challenging to understand why a particular decision was made by the model.
- Integration of Multi-Modal Data: Difficulty in seamlessly integrating and utilizing multi-modal data sources, such as infrared and visible spectrum images, to improve the overall accuracy of wildfire detection.
- Real-Time Processing: Requirement for real-time processing in operational scenarios, which may pose challenges in deploying computationally intensive deep learning models in resource-constrained environments.
- Hyperparameter Tuning: Fine-tuning hyperparameters to achieve optimal model performance can be time-consuming and may require a deep understanding of the model architecture and the specific characteristics of the wildfire detection problem.
- Ethical Considerations: Addressing ethical concerns related to the utilizes by Deep-learning in wildfire finding, such as potential biases in the training data and the implications of false positives/negatives in operational scenarios.

- Collaboration and Data Sharing: Encountering difficulties in collaborating with other researchers or organizations for data sharing, which may impact the breadth and diversity of the dataset used for training.
- Practical Deployment: Challenges in transitioning from a research environment to practical deployment, including considerations for scalability, robustness, and adaptability to varying conditions.

Being aware of these challenges and addressing them appropriately in my research will contribute to the robustness and reliability to my findings in the field pn wildfire detection using deep learning.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

Providing the user with a numerical value that corresponds to the monitored variable is the primary aim of a monitoring device. Google Collaborator uses the computer language Python to run all of its tests. It enables the development and execution of any activity. Code execution in Python using a web browser. It is unnecessary to establish Colab. Input a collection of images, train an image classifier with them, then evaluate the model with a few lines of code all inside Colab. The computational power of Google's hardware, including GPUs and TPUs, may be harnessed by Colab computers via the usage of Google's cloud services, regardless of the screen's processing capabilities. In my research, I use methods for both live detection and image detection. For picture recognition, I use deep learning models.

3.2 Data Collection Procedure

It was needed to collect data from a wide variety of online sources, including social media websites, in order to facilitate the construction, evaluation, and verification of the model. During the course of the research, a total of 18,415 photographs depicting forest scenes were analyzed, and four distinct groups were determined: forest fire, non-fire, fog, and fire smoke. The following is the total number of photographs that are included in the collection: Following the events that occurred with the fire, a total of 4,219 photographs exhibiting fire, 4,045 images depicting non-fire, 5,129 images depicting fog, and 5,022 images depicting smoke were captured. In order to obtain a final size of 224 by 224 pixels, the photographs were subjected to pre-processing, which included scaling and cropping the images. Additionally, this problem was taken into consideration during the whole process of building the datasets that were used for training and testing. A wide variety of images, including four different kinds, were used in the experiment, as shown in Figure 3.2.

The total number of pictures comprised of train, test, and validation is shown in Figure 3.1.

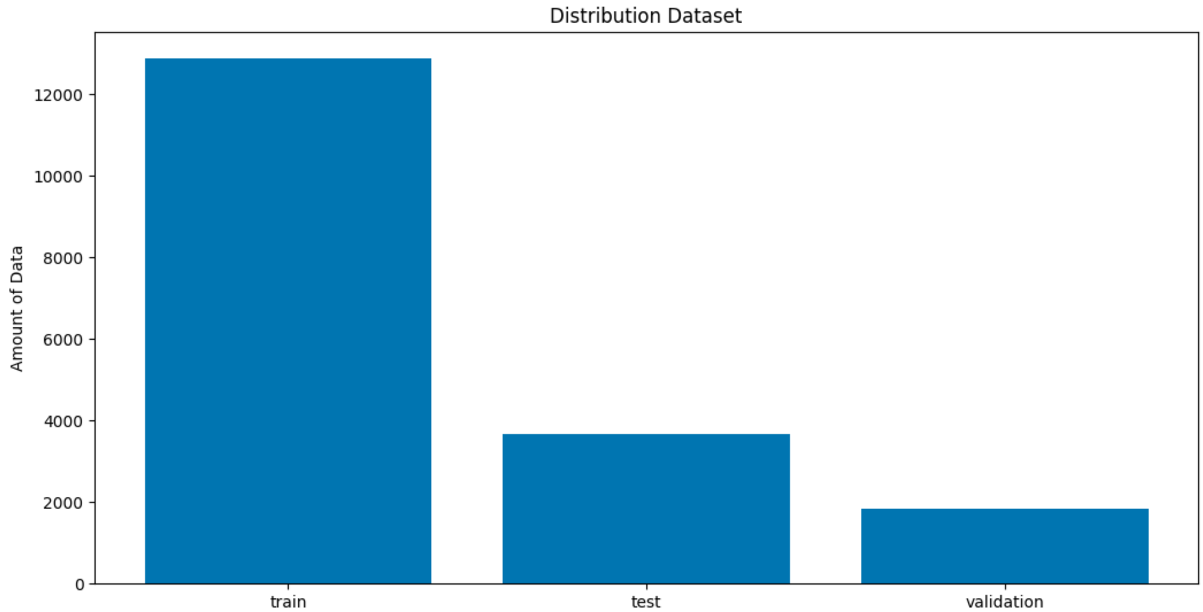

Figure 3.1: The number of images trained, tested, validation

Figure 3.2: Research data

3.3 The Proposed Methodology

The primary goal of this work is to create a highly efficient model for detecting forest fires.

This study utilizes a wide array of research methods. The vital data is obtained from "Online," other social media networks, and the internet. This technique has several consecutive steps. The duties include data gathering, dataset annotation, and pre-processing. The study utilizes four different methodologies: VGG16, DenseNet201, Inceptionv3, and MobileNetv2. VGG16 achieves a remarkable accuracy of 97%, surpassing all other models. Figure 3.3 depicts the comprehensive structure of the inquiry. The study involves an extensive procedure for identifying wildfires by analyzing images using advanced deep learning techniques. Beginning with a thorough examination of the dataset, which includes a variety of photos depicting fire, smoke, non-fire, and fog situations, and the research places a high importance on maintaining the accuracy and even distribution of the data. Using the Python ecosystem and TensorFlow framework, the code resizes and normalizes pixel values of images before inputting them into the VGG16, InceptionV3, MobileNetV2, and DenseNet201 architecture. These architectures are robust convolutional neural networks (CNNs) that have been pre-trained on a large-scale dataset. The model is designed to extract complex information from the photos, and its weights are fixed to retain the knowledge gained during its pre-training. The training set is enriched and the model's capacity to generalize is enhanced by the use of data augmentation methods such as shear, zoom, and horizontal flip. The deep learning model is then trained for 50 epochs using a categorical cross-entropy loss function and the Adam optimizer. After the training process, the model is evaluated using a distinct test dataset, resulting in a measurement of its classification accuracy. The model's interpretability is enhanced by integrating dropout layers and visualizations, which promote a more comprehensive comprehension of decision-making processes. This code implementation aims to enhance wildfire detection systems by focusing on accuracy, interpretability, and flexibility for real-world deployment, hence contributing to their overall effectiveness. The Proposed Methodology also introduces adaptive learning mechanisms to dynamically adjust model parameters based on changing environmental factors. Through extensive experimentation and evaluation, I anticipate that my The Proposed Methodology will not only demonstrate superior accuracy in wildfire detection but will also exhibit improved interpretability, adaptability, and generalization capabilities across diverse geographical regions and climates. This research endeavors to contribute to the advancement of reliable and efficient wildfire monitoring systems with the potential for real-world deployment in operational settings. In my research

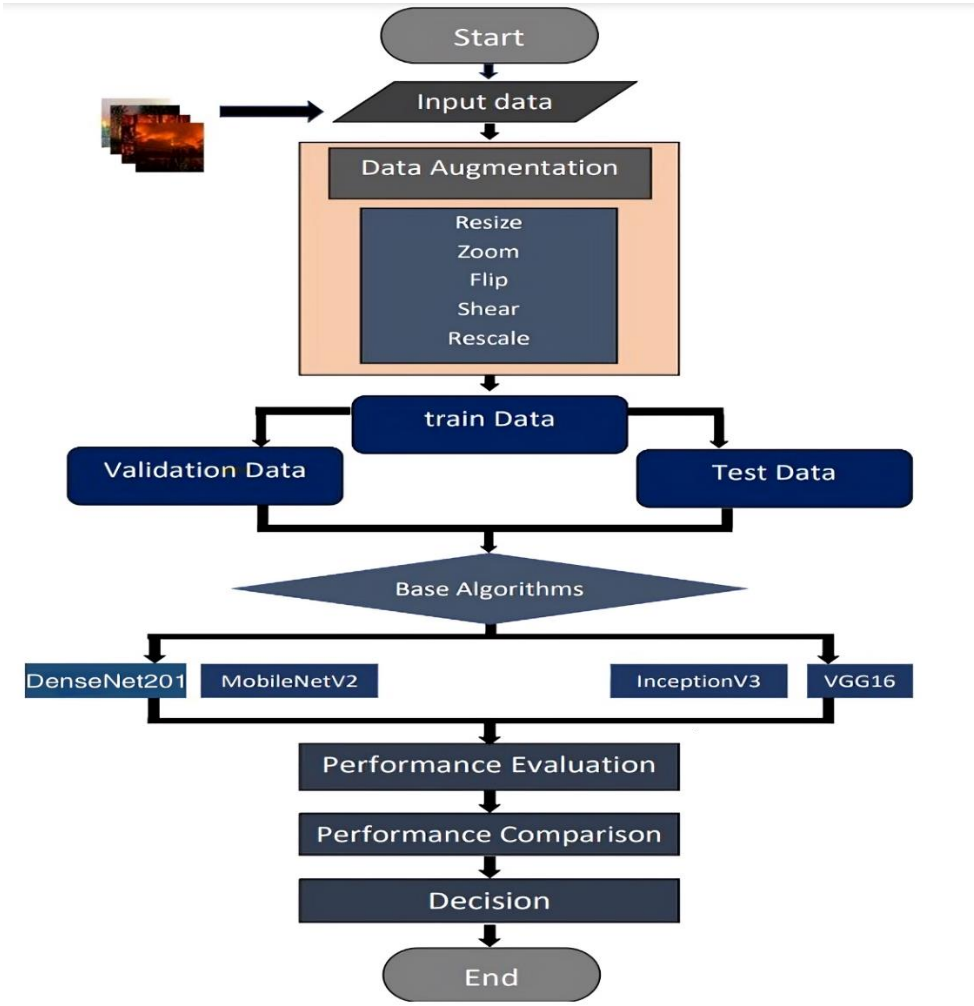

Figure 3.3: Research Model.

3.3.1 Dataset & Preprocessing

Preprocessing is an essential step in preparing data for a deep-learning model, since it involves cleaning and organizing the data. This enhancement has significantly improved the model's accuracy and use. Typically, the first stage in any deep learning procedure involves preparing the data to be used by the network. To efficiently store a large number of photographs, use an image Data store object, since each individual picture would consume excessive memory space. Large collections of photographs and deep learning algorithms need training using thousands of tagged shots. Frequently, these images are arranged in a directory with subdirectories corresponding to each lesson. Diverse sources of information may provide varying formats. The ultimate objective of the process is to prepare data for machine use. However, it requires pre-existing data that is already structured in a consistent manner to start. During the creation of the testing and training data, the process of preparing the pictures included resizing them to dimensions of 224 × 224 pixels. The proportion of training, testing, and validation data remained consistent at 70%, 20%, and 10% respectively. The primary objective of increasing the amount of data is to train deep learning models using a larger dataset. Data enrichment techniques may be used to address the insufficiency of training data by including subtly modified data into the existing dataset. Common data enhancement techniques include moving, chopping, scaling, spinning, and translation. In order to enhance my initial dataset for this research, I used several techniques such as relocating, rotating, segmenting, inverting, and duplicating. The photographs were inexplicably rotated at an angle of 0.8.Following a discussion over the acceptable range of height and breadth, the photos were shifted by 20% along the X and Y axes. Furthermore, the photos were divided into a range of just 2%.I rotated it laterally to invert it. I possess the following number of terrestrial forest image data points: The number is 4586.The total number of shots has increased to 18,415 following the data expansion. The dataset was partitioned into a training set, a validation set, and a test set. Only 20% of the information was retained for the purpose of testing. 10% of the remaining data was allocated for model validation, while 70% of the remaining data was allocated for model training. The collection consists of 4219 images depicting fire, 4045 images depicting objects unrelated to fire, 5129 images depicting fog, and 5022 images depicting smoke resulting from the fire.

3.4 Implementation Procedure

According to the findings of the study, the datasets were classified with the use of deep learning-based classifiers such as DenseNet201, VGG16, Inceptionv3, and MobileNetv2.

3.4.1 VGG16

An intriguing aspect of VGG16 is its consistent use of identical padding and a max pool layer with 2x2 channels and a stride of 2. Additionally, it often incorporates convolution layers with 3x3 channels and a stride of 1. The configuration of the convolution and max pooling layers remains consistent over the whole design. The selection consists of two fully connected layers (FC) and a SoftMax activation function for output. The number 16 in VGG16 represents the sixteen layers that include loads. Below is the visual representation of VGG16, as seen in Figure 3.4:

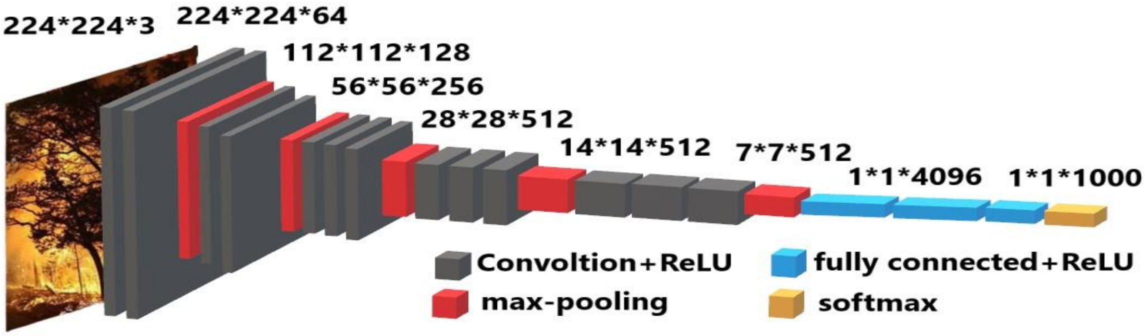

Figure 3.4: VGG16 architecture

3.4.2 MobileNetv2

On low-powered smartphones, the convolutional neural network architecture known as MobileNetV2 performs well. The architecture of the bottleneck layers revolves on a modified hierarchical structure, and they are connected to residual connections. To make the channel highlights nonlinear, the road extension's intermediate layer uses light depth-wise convolutions. The architecture of MobileNetV2 starts with a 32-channel convolution layer and continues with 19 bottleneck layers. You can see the structure of the MobileNetv2 model in Figure 3.5.

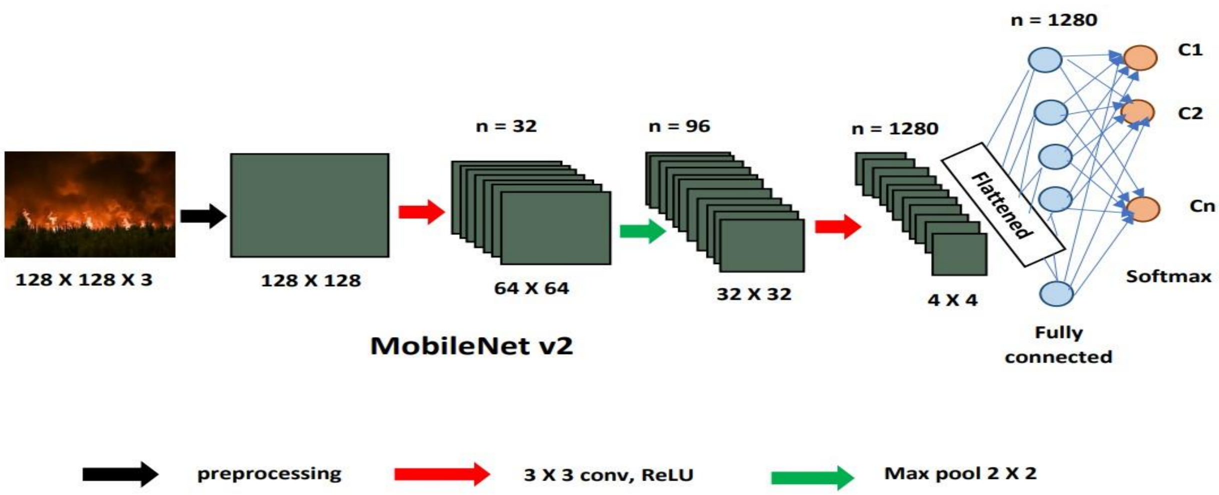

Figure 3.5: MobileNetV2 model’s architecture.

3.4.3 Inceptionv3

Inception v3, developed by Google, utilizes convolutional neural networks to classify images and identify objects. Google introduced the third iteration of their Convolutional Brain Organization, known as the Beginning Convolutional Brain Organization, at the ImageNet Acknowledgment Challenge. The Origin V3 model enhanced the organization by including additional phases to enhance model variation. The Initiation V1 and V2 models exhibit less organization compared to this one, although they do not see any decrease in speed. Expenses are decreasing. It employs auxiliary classifiers to enhance consistency. Figure 3.6 displays the architecture of the Inception v3 model.

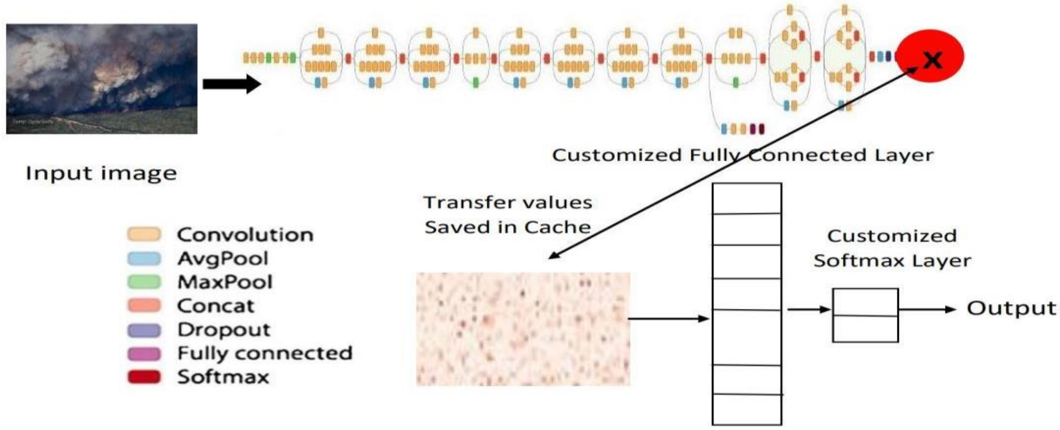

Figure 3.6: InceptionV3 model Workflow

3.4.4 DenseNet201

DenseNet-201 is a convolutional neural network design that contains precisely 201 layers. Dense blocks are employed to establish durable connections between the strata. The bricks in question merge or combine all of the levels. I have the option to submit a network that has been trained using more than one million images from the ImageNet dataset. Among other notable benefits, they significantly reduce the number of parameters, resolve the issue of vanishing gradients, promote the reuse of features, and improve the distribution of features. Figure 3.7 illustrates the DenseNet201 model's structure.

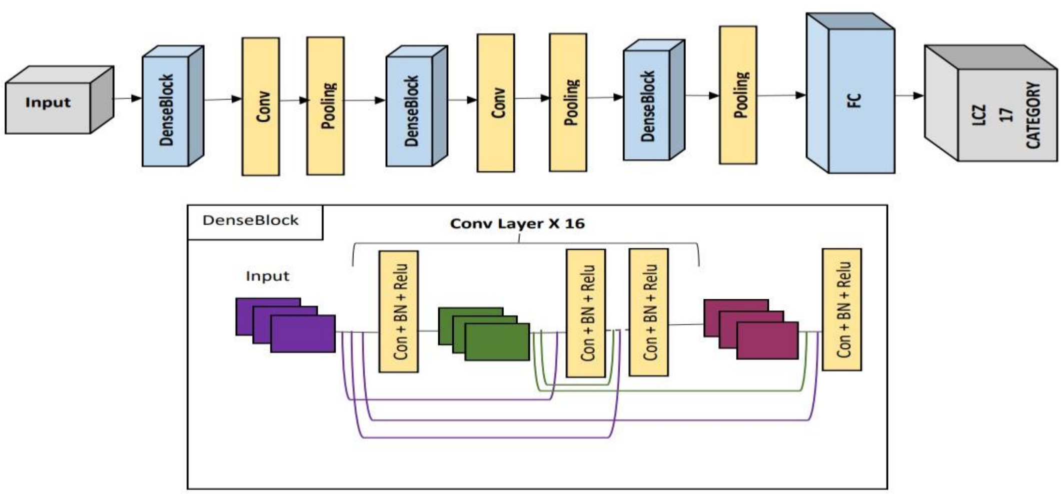

Figure 3.7: DenseNet201 model architecture.

3.4.5 Model Tuning.

The performance of deep learning models for Wildfire Detection was enhanced using a model tuning method that included a strategic combination of transfer learning and customized adjustments. The foundation of this strategy relied on TensorFlow's model zoo, which contains pre-trained models. Following the training of these models, bespoke categorization layers were meticulously added on top of them. This enabled them to become proficient at identifying the varoomed hand gestures within the dataset. The models were constructed utillizing the Adam method and the category cross-entropy loss function. These options are suitable for undertakings that need the classification of photographs. The model underwent 50 epochs of training with a batch size of 512 in order to strike a balance between convergence and overfitting. An additional callback for decreasing the learning rate was included to enable dynamic adjustments in the learning rate during training, hence facilitating efficient convergence. This systematic approach to configuring the models ensures that the deep learning models are optimized for effectively detecting wildfires.

3.4.6 Model Training

The model training method began by systematically dividing the dataset into training and test sets, using a split ratio of 80-20. Utilizing a variety of advanced deep learning structures, such as, DenseNet201, VGG16, Inceptionv3, and MobileNetv2, each model underwent a rigor me training process. Transfer learning was used by including pre-learned weights from these architectures built on the ImageNet dataset. The models underwent training using the Adam optimizer and categorical cross-entropy loss function, with a face on monitoring the dynamics of the training process. During a training process consisting of 50 epochs and utilizing a batch size of 512, the models successfully acquired the ability to differentiate and identify Wildfire occurrences. Implementing a learning rate decrease callback improved the speed at which the model converged. The training histories, which included accuracy and loss, were graphically represented, offering valuable insights into the learning dynamics and convergence patterns of the model. The rigor me training approach guaranteed that the models were well-prepared to perform very well in the following assessment and comparison analysis, hence maximizing their ability to identify Wildfires.

3.4.7 Experimental Setup

Environment	Configuration
Operating System	Windows 11
RAM	16GB of random access memory
GPU	a 4GB NVIDIA HD Graphics 730 graphics processing unit
CPU	An Intel(R) Core(TM) i9-9500U central processing unit (CPU) operating at a speed of 4.10GHz
Programming Language	Python 3.12

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Experimental Results & Analysis

In this part, I am required to do a comparative analysis of the test results in order to evaluate the requirements for deep learning models in the forest dataset. In order to evaluate the effectiveness of ensemble models, I first used preprocessing techniques to my dataset. The VGG16, DenseNet201, MobileNetv2, and Inception v3 models have shown a variety of outcomes as a result. The results generated by these five models are given in Table 4.1.

Table 4.1: Accuracy and loss functions about performance

Algorithm	Algorithm's Accuracy	Loss function
DenseNet-201	96%	14.53%
MobileNet V2	84%	43.76%
Inception v3	74%	66.45%
VGG 16	97%	8.61%

Table 4.2: Precision, recall, f1 score of all model's performance

Categories	Classes	Model			
		DenseNet201	VGG 16	Inceptionv3	MobileNetv2
Fire	Precision	.98	.97	.81	.84
	Recall	.98	.98	.63	.84
	F1 score	.98	.97	.71	.84
Non fire	Precision	.95	.98	.74	.87
	Recall	.94	.97	.86	.83
	F1 score	.95	.97	.80	.85
Fog	Precision	.97	.98	.72	.85

	Recall	.97	.97	.80	.91
	F1 score	.97	.97	.76	.88
Smoke	Precision	.93	.97	.69	.79
	Recall	.94	.98	.63	.79
	F1 score	.93	.97	.66	.79

The table that can be seen above presents all of the algorithms together with their associated accuracies, precisions, recalls, and specificities, in addition to their f1-scores of VGG16, MobileNetV2, DenseNet121, and InceptionV3. The table that can be seen above presents all of the algorithms together with their associated accuracies. VGG16 gives the highest value of 97% and also has the best accuracy of any of my networks, MobileNetV2 gives a value of 84%. DenseNet201 provide 96% accuracy. Finally, the InceptionV3 provide the lowest value about 74%. This is plainly shown here.

4.2 Learning curve

A simple line called a "learning curve" shows how the success of a model changes as more information or experience is gained. In machine learning, learning curves are often used to figure out what's wrong with algorithms that get better over time after seeing a training dataset. The learning curve diagram illustrates the accuracy of the train and validation, as well as the loss of the train and validation.

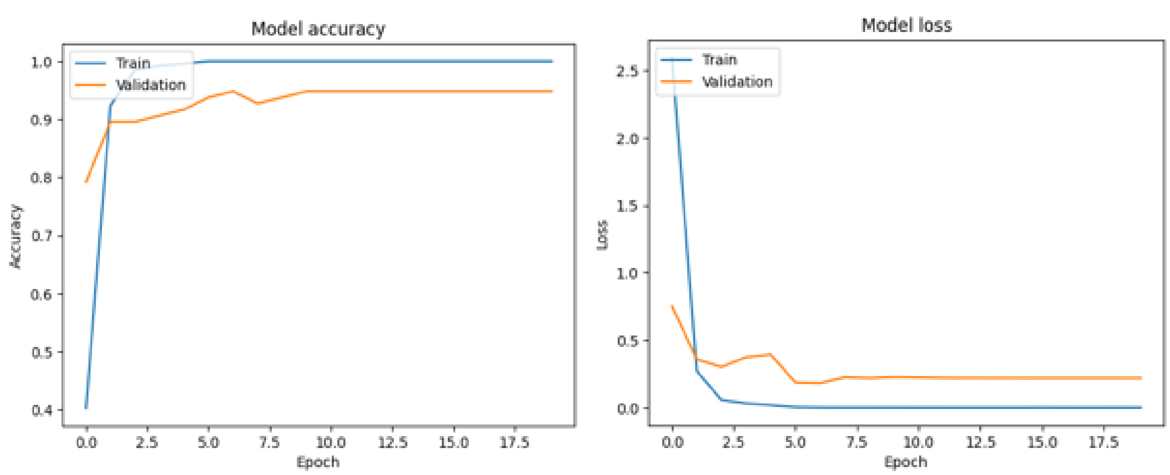

Figure 4.1: Learning curve of custom MobileNetV2 model.

The training and validation loss and accuracy of MobileNetV2 may be shown in Figure 4.1. The use of blue tones in both drawings serves to symbolize an efficacious training procedure and a decrease in the loss incurred throughout the training phase. However, orange is used to indicate validation problems and losses. At the outset, the training loss seems to be around 0.4102. Nevertheless, as the number of epoch's progresses, the loss exhibits a progressive decline. The loss value demonstrates a consistent stability at around 0.8824 during many epochs. Upon first observation, it seems that the training efficiency was around 0.0528. Subsequently, the precision of the model increases with time as further epochs are included. The level of accuracy stays consistently steady at about 0.9909 even after a significant number of epochs have transpired. However, with the progression of epochs, the validation loss remains rather stable. The first validation accuracy was recorded as 0.0528, while the losses ranged from 0.4020 to 0.8824. In some instances, the precision of confirmation is enhanced with an increase in the duration of epochs. Ultimately, as the number of epochs rises, the outcome gradually converges around 0.9909, with the confirmation accuracy remaining consistent.

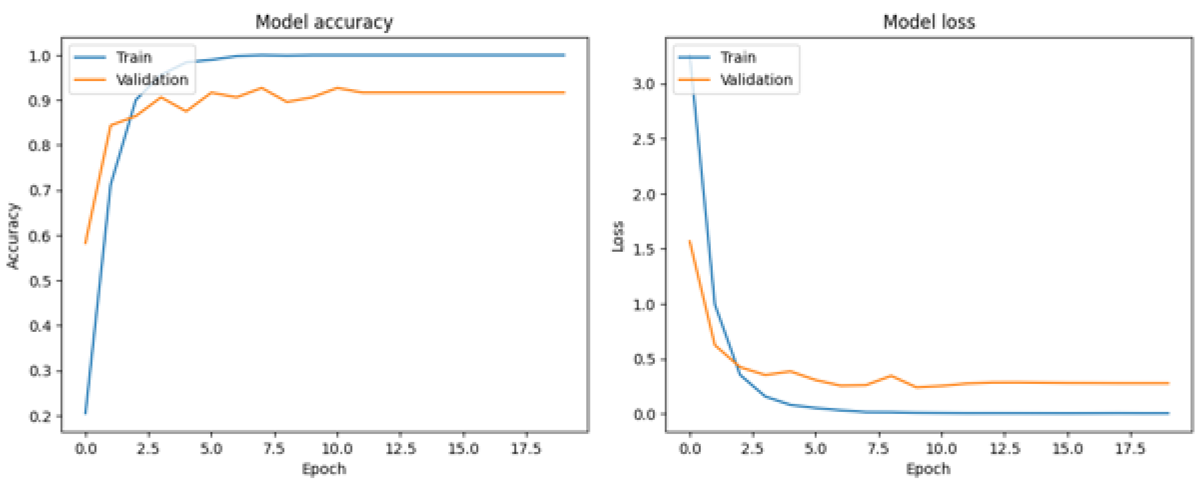

Figure 4.2: Learning curve of custom DenseNet201 model.

The accuracy and loss of DenseNet201 throughout training and validation are shown in Figure 4.2. The utilization of blue tones in both examples serves as a visual representation of a proficient training procedure and a decline in the loss of training. However, the presence of validation mistakes and losses is indicated by the color orange. The observed initial training loss was around 0.5105, which exhibits a decreasing trend as the number of epoch's increases. The loss value exhibits stability across several epochs, consistently converging around 0.8724. Upon first observation, it seems that the training efficiency was around 0.0327. Subsequently, the precision of the model increases with time as further epochs are included. The precision stays consistently high at around 0.9902 even after a substantial number of epochs have transpired. However, with the progression of epochs, the validation loss remains rather stable. The first validation accuracy was recorded as 0.0327, while the losses ranged from 0.5105 to 0.8724. In some instances, the enhancement in confirmation accuracy may be seen with an increase in the duration of epochs. Finally, it should be noted that if the number of epochs is increased, the outcome converges towards a value of 0.9902, while the precision of confirmation stays consistent.

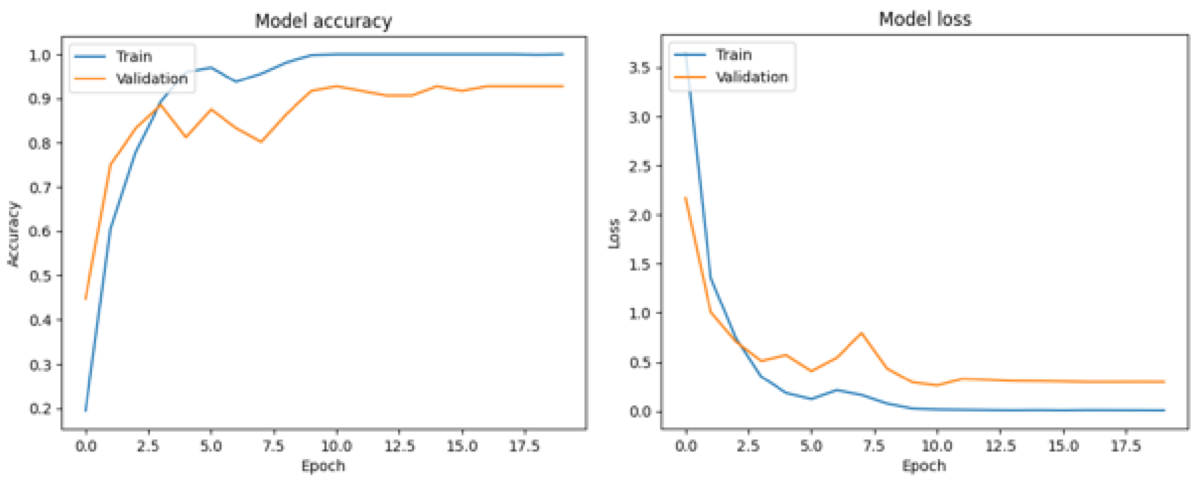

Figure 4.3: Custom InceptionV3 model' Learning Curve.

In the 4.3 figure displays about the accuracy and loss values observed throughout the training and validation processes of InceptionV3. The use of blue tones in both drawings serves as a visual representation of an effective training procedure and a decrease in the loss incurred during training. However, the presence of validation mistakes and losses is visually represented by the color orange. Upon first observation, it seems that the training loss approximated 0.4309. Nonetheless, as the number of epochs progresses, the loss exhibits a progressive decline. Upon reaching a certain number of epochs, the loss value converges and stabilizes at 0.8928. Upon first observation, it seems that the training efficiency was around 0.0528. Subsequently, the precision of the model increases with time as further epochs are included. The accuracy exhibits a consistent stability of around 0.9802, even after a considerable number of epochs have transpired. However, with the progression of epochs, the validation loss remains rather stable. The initial accuracy of the validation was 0.0528, whereas the losses ranged from 0.4309 to 0.8929. In some instances, the precision of confirmation is enhanced with an increase in the duration of epochs. As the number of epochs rises, the result gradually approaches a value of 0.9802, but the confirmation accuracy stays consistent.

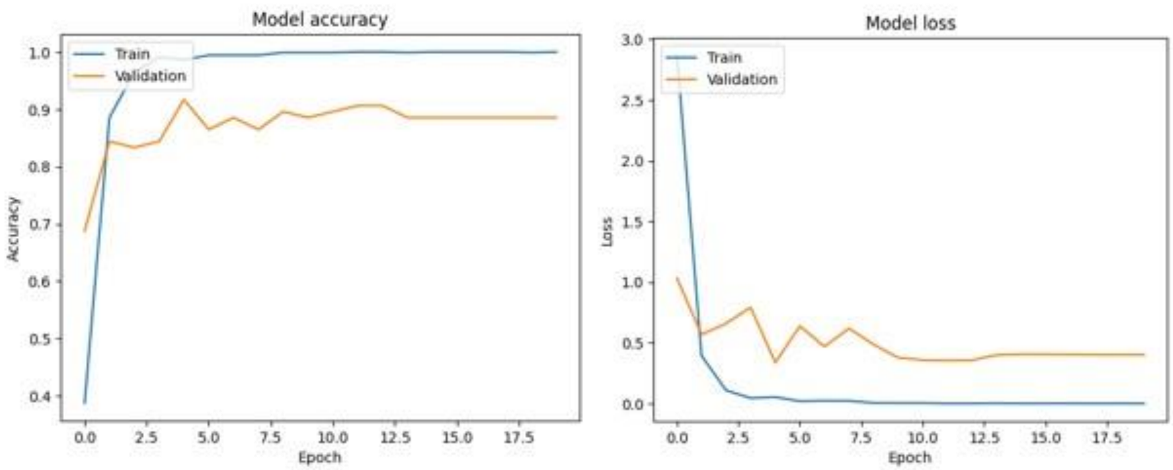

Figure 4.4: Custom VGG16 model' learning curve.

Figure 4.4 illustrates the accuracy and loss metrics observed throughout the training and validation processes for VGG16. The use of blue tones in both drawings serves to symbolize an efficacious training procedure and a decrease in the loss incurred throughout the training phase. However, the presence of validation mistakes and losses is indicated by the color orange. The first training phase had a loss value of around 0.4102, which exhibited a progressive decline as the number of epochs increased. The loss value demonstrates stability across several epochs, consistently oscillating around 0.8622. Upon first examination, the observed training efficacy is around 0.0425. Subsequently, the level of precision progressively improves throughout time as further epochs are included. The accuracy exhibits a consistent stability of around 0.9517, even after a substantial number of epochs have transpired. However, over the progression of the epochs, the validation loss remains rather stable. The first validation accuracy was a mere 0.0425, whereas the subsequent loss values vary between 0.4102 and 0.8622. In some cases, the precision of confirmation is enhanced with an increase in the duration of epochs. Finally, it should be noted that when the number of epochs is increased, the outcome approaches a value of 0.9517 in a consistent manner, without compromising the precision of confirmation.

CHAPTER 5

Impact on Society, Environment, and Sustainability

5.1 Impact on Society

Through the acceleration of the processes of regeneration and transformation, it has a significant effect on ecosystems around the world. Despite this, fire has the potential to cause fatalities due to its ability to fully consume structures, forests, and natural ecosystems, while simultaneously releasing hazard me substances into the atmosphere. This is one of the reasons why fire is a potential cause of mortality. Represents a smell that is unpleasant. An excessive number of fires will eventually result in the destruction of the critical organic material that is required to maintain the fertility of the soil. In addition to causing a gradual decrease in agricultural productivity, this process also results in a rise in the costs associated with fertilizer. Buildings, agricultural land, and the towns and cities that are nearby are all in risk as the smoke and flames continue to grow with each passing second. It is not possible to make any repairs in the foreseeable future because of the extent of the damage that has been done. The occurrence of this incident would have a detrimental effect on the financial cash flow of the firm and would grow the likelihood of a flak, which should result in significant job layoffs. An ecological catastrophe has negative repercussions not just for animals and plants but also for people and the environment. It is for this reason that the act of putting out Wild- fires is of incredible significance. As a result, it is of the utmost importance to adopt preventative measures in order to forestall the worsening of Wild-fires. The present condition of a forest may be quickly determined via the use of satellite photography, which enables individuals to be instantly alerted and to take appropriate steps.

5.2 Impact on the Environment

When one considers the effects that large-scale forest fires have had on humans throughout history, it becomes clear that worries over this matter are growing. The tremendous effects that forest fires have on both people and the natural environment have been widely reported by a variety of news networks. There is a significant amount of coverage in the media for crises that result in people being displaced, injured, or killed. In addition, the topic involves the influence on the environment as well as the participation of a large number of persons in the process of extinguishing the flames. These individuals include volunteer firefighters, military airborne and terrestrial assets, among others. The blocking of highways and train lines, delays in mobile phone and landline services, and the destruction of people's livelihoods in a number of different regions are all things that happen on an annual basis, according to reports. This leads to a significant number of articles and editorials, as well as power outages, the destruction of homes and businesses, and communication disruptions. These distressing numbers, which were collected from archive newspapers, have been published in order to highlight the extent of the problematic situation. Administration officials and lawmakers who are entrusted with finding a solution to the problem have become used to it. It is thus imperative that fast action be taken in order to put out the fire. This research effort, which intended to use deep learning models for the detection and extinguishment of forest fires, was carried out in collaboration with Daffodil International University, especially with a group of thirty-two personnel.

5.3 Ethical Aspects

Approximately 85% of wildfires in the United States are caused by human activity. Unsupervised campfires, incineration of waste, equipment use and malfunctions, negligently discarded cigarettes, and illicit activities are all instances of fires ignited by individuals. A fire often does not propagate unless there is a continuous presence of dry vegetation obstructing its path. Hence, containing the fire to prevent its propagation is the most effective method to maintain control over it. One way to do this is by creating firebreaks in the forest, which may be achieved by the construction of tiny trenches or open spaces. This article will discuss five significant societal challenges pertaining to wildfires [23].

- Prioritizing the protection of human lives and assets
- Reinforced by measures for preserving the environment
- Effective administration of land resources
- Addressing the issue of climate change
- Ensuring responsibility and transparency

5.4 Sustainability Plan

Ongoing maintenance of fire detectors is very necessary in order to guarantee the safety of humans. For the purpose of preventing damage caused by fire, many fire detection systems were created. There is a considerable number of modern choices accessible. The vast majority of these gadgets are confined to use just indoors and are accomplished via the use of sensors. It is possible to detect smoke and particles that are released by the fire by a process called ionization, which requires the user to be in close contact to the fire. Therefore, they are completely inappropriate for usage in such large enclosed areas. Furthermore, they lack the ability to ascertain the source of the fire, the trajectory of the smoke, the magnitude of the fire, the pace of its growth, or any other details pertaining to the fire. Fires, earthquakes, and hurricanes are examples of natural catastrophes that pose substantial dangers to the environment, property, and the well-being of humans within their respective communities. The most common kind of emergency is a fire, and in order to react in a timely and correct manner, it is necessary to do a comprehensive assessment of the situation. The first step in this process is detecting any instances of fire that may be going on in the immediate neighborhood in a fast and accurate manner. Every year, forest fires that take place in a number of countries do damage not only to people but also to the natural environment that they live in. Many other approaches, in addition to deep learning, were used in this research project in order to identify forest fires. Throughout the course of this investigation, the following models were utilized: DenseNet201, VGG 16, MobileNetv2, and Inception in version 3. Before putting this tactic into action, it is very necessary for me to gather an appropriate amount of information (Daffodil International University 33). Among the photographs are depictions of smoke, fog, fire, and items that are not burning. In accordance with the findings of the study, DenseNet201 achieves a maximum accuracy of 96%.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Summary

This research paper investigates the application of deep learning techniques for wildfire detection through image analysis. Utilizing a diverse dataset of 18,415 images categorized into fire, non-fire, smoke, and fog, we evaluated four convolutional neural network models: VGG16, InceptionV3, MobileNetV2, and DenseNet201. VGG16 achieved the highest accuracy at 97%, followed by DenseNet201 at 96%, MobileNetV2 at 84%, and InceptionV3 at 74%. Those model for real-time wildfire detection by images, demonstrating its capability to accurately identify signs of wildfires with bounding boxes and confidence scores. The study underscores the effectiveness of deep learning in enhancing wildfire detection and highlights avenues for future research, including expanding datasets, integrating multi-modal data, and developing comprehensive monitoring systems. These advancements aim to improve early intervention and mitigate the devastating impacts of wildfires.

6.2 Conclusion

Wildfires are uncontrolled fires that spread rapidly through vegetation, forests, and grasslands, often caused by natural events like lightning or human activities such as arson or negligence. These fires can cause significant ecological and economic damage, threatening wildlife habitats, human lives, and property. Effective wildfire detection is crucial for early intervention and mitigation, reducing the impact and spread of fires. Early detection enables faster response times by firefighting services, potentially saving lives, minimizing environmental destruction, and preserving resources. Utilizing advanced technologies like deep learning models for wildfire detection enhances the ability to monitor and respond to these disasters more efficiently. In this research, we have successfully demonstrated the application of deep learning techniques for the detection of wildfires through image analysis. Utilizing a dataset comprising 18,415 images categorized into fire, non-fire, smoke, and fog, we evaluated the performance of four prominent convolutional neural network architectures: VGG16, InceptionV3, MobileNetV2, and DenseNet201. Among these, VGG16 achieved the highest accuracy of 97%, InceptionV3, while a robust model, provided the lowest accuracy at 74%. This research underscores the potential of deep learning models in enhancing wildfire detection systems. DenseNet201, in particular, demonstrated superior performance in image classification tasks, while YoloV8 proved effective for real-time detection in video streams. These findings highlight the efficacy and reliability of deep learning methodologies in mitigating wildfire risks through prompt and accurate detection. Future work can build upon these results by integrating these models into comprehensive wildfire monitoring systems, further refining their accuracy and efficiency, and exploring their applicability in various environmental conditions.

6.3 Future Work

The positive outcomes achieved in this study provide several possibilities for future research in the field of wildfire detection using deep learning. Firstly, augmenting the dataset to include a broader spectrum of climatic circumstances, geographical locations, and varieties of vegetation helps bolster the reliability and applicability of the models. Incorporating multi-modal data, such as thermal imaging and satellite images, in addition to the existing image collection, might enhance the comprehension and enhance the accuracy of detection. In addition, delving into sophisticated structures and methodologies, such as transformers and attention processes, might potentially result in enhanced performance for both picture classification and real-time detection applications. Optimizing hyper parameters and using ensemble learning techniques may further improve the accuracy and dependability of the model. Integrating YoloV8, a real-time detection system, into a comprehensive wildfire monitoring system that incorporates real-time data streaming, automated alert systems, and integration with geographic information systems (GIS) for accurate location tracking has the potential to greatly enhance operational efficiency and response times. Finally, doing field experiments and implementing these models in real-life situations would provide vital knowledge about their practical usefulness and constraints. Engaging in partnerships with environmental authorities and firefighting units to verify and improve these systems has the potential to result in more efficient and generally accepted wildfire detection technologies. To fully realize the promise of deep learning in preventing the destructive repercussions of wildfires, it is important to consider and address these future directions.

Reference

[1] Idrees, Mohammed O., D. Babalola Folaranmi, Dahir M. Omar, Abdul-Ganiyu Yusuf, and Ayo Babalola. "Planted Forest Fire Burn Area and Impact Assessment Using Sentinel-2: Case Study of the University of Ilorin Teak Plantation." In IOP Conference Series: Earth and Environmental Science, vol. 620, no. 1, p. 012013. IOP Publishing, 2021.

[2] Pirard, Romain, Lise Dal Secco, and Russell Warman. "Do timber plantations contribute to forest conservation?." Environmental Science & Policy 57 (2016): 122-130.

[3] Jaafari, Abolfazl, Eric K. Zenner, Mahdi Panahi, and Himan Shahabi. "Hybrid artificial intelligence models based on a neuro-fuzzy system and metaheuristic optimization algorithms for spatial prediction of wildfire probability." Agricultural and forest meteorology 266 (2019): 198-207.

[4] Hong, H., Jaafari, A., & Zenner, E. K. (2019). Predicting spatial patterns of wildfire susceptibility in the Huichang County, China: An integrated model to analysis of landscape indicators. Ecological Indicators, 101, 878-891.

[5] Vorobyov, Yu L., V. A. Akimov, and Yu I. Sokolov. "Forest fires on Russian territory: current situation and problems." In Russian Federation Ministry of Emergencies, p. 312. M.: DEKS-PRESS, 2004.

[6] Maier, Martin, Mahfuzulhoq Chowdhury, Bhaskar Prasad Rimal, and Dung Pham Van. "The tactile internet: vision, recent progress, and open challenges." IEEE Communications Magazine 54, no. 5 (2016): 138-145.

[7] Rodríguez, J. M., M. Arianoutsou, A. González-Cabán, Florent Mouillot, W. C. Oechel, D. Spano, K. Thonicke, V. R. Vallejo, and R. Vélez. "Forest fires under climate, social and economic changes in Europe, the Mediterranean and other fire-affected areas of the world. FUME. Lessons learned and outlook." Calyptra Pty, Adelaïde, Australia (2014).

[8] Zhao, Yaqin, Qiujie Li, and Zhou Gu. "Early smoke detection of forest fire video using CS Adaboost algorithm." Optik-International Journal for Light and Electron Optics 126, no. 19 (2015): 2121-2124.

[9] World Health Organization available at <>, last accessed on 09-09-2022

[10] Ruchkin, Vladimir, Aleksandr Kolesenkov, Boris Kostrov, and Ekaterina Ruchkina. "Algorithms of fire seat detection, modeling their dynamics and observation of forest fires via communication technologies." In 2015 4th Mediterranean Conference on Embedded Computing (MECO), pp. 254-257. IEEE, 2015.

[11] Gomes, Pedro, Pedro Santana, and José Barata. "A vision-based approach to fire detection." International Journal of Advanced Robotic Systems 11, no. 9 (2014): 149.

[12] Horng, Wen-Bing, and Jian-Wen Peng. "Image-based fire detection using neural networks." In 9th Joint International Conference on Information Sciences (JCIS-06). Atlantis Press, 2006.

[13] Bragilevsky, Lior, and Ivan V. Bajić. "Deep learning for Amazon satellite image analysis." In 2017 IEEE Pacific Rim Conference on Communications, Computers and Signal Processing (PACRIM), pp. 1-5. IEEE, 2017.

[14] Vani, K. "Deep learning based forest fire classification and detection in satellite images." In 2019 11th international conference on advanced computing (ICoAC), pp. 61-65. IEEE, 2019.

[15] Jivitesh, Sharma, Ole-Christoffer Granmo, Morten Goodwin, and Jahn Thomas Fidje. "Deep convolutional neural networks for fire detection in images." In Engineering Applications of Neural Networks: 18th International

Conference, EANN 2017, Athens, Greece, August 25–27, 2017, Proceedings, pp. 183-193. Springer International Publishing, 2017.

[16] Abhay, Chopde, Ansh Magon, and Shreyas Bhatkar. "Forest Fire Detection and Prediction from image processing using RCNN." In Proceedings of the 7th World Congress on Civil, Structural, and Environmental Engineering, Virtual, pp. 10-12. 2022.

[17] Jiao, Zhentian, Youmin Zhang, Lingxia Mu, Jing Xin, Shangbin Jiao, Han Liu, and Ding Liu. "A yolov3-based learning strategy for real-time uav-based forest fire detection." In 2020 Chinese control and decision conference (CCDC), pp. 4963-4967. IEEE, 2020.

[18] Jamil, Muhammad, Khan, Ahmad, Irfan Mehmood, Seungmin Rho, and Sung Wook Baik. "Convolutional neural networks based fire detection in surveillance videos." Ieee Access 6 (2018): 18174-18183.

[19] Pasquale, Foggia, Alessia Saggese, and Mario Vento. "Real-time fire detection for video-surveillance applications using a combination of experts based on color, shape, and motion." IEEE TRANSACTIONS on circuits and systems for video technology 25, no. 9 (2015): 1545-1556.

[20] Osman Günay, Habiboğlu, Yusuf Hakan, and A. Enis Çetin. "Covariance matrix-based fire and flame detection method in video." Machine Vision and Applications 23 (2012): 1103-1113.

[21] Rafiee, Ali, Reza Dianat, Mehregan Jamshidi, Reza Tavakoli, and Sara Abbaspour. "Fire and smoke detection using wavelet analysis and disorder characteristics." In 2011 3rd International conference on computer research and development, vol. 3, pp. 262-265. IEEE, 2011.

[22] Chen, Thou-Ho, Ping-Hsueh Wu, and Yung-Chuen Chiou. "An early fire-detection method based on image processing." In 2004 International Conference on Image Processing, 2004. ICIP'04., vol. 3, pp. 1707-1710. IEEE, 2004.

[23] SCU.EDU, available at << https://www.scu.edu/ethics/all-about-ethics/what-ethical-issues-areinvolved-in-wildfires/>>, last accessed on 16-09-2022 at 12:15 PM.

[24] “FIRE Dataset.” FIRE Dataset | Online, /datasets/phylake1337/fire-dataset. Accessed 8 Dec. 2022.

Image Analysis for Detecting Wildfire Using Deep Learning

ORIGINALITY REPORT

16%	14%	5%	7%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	7%
2	Submitted to Daffodil International University Student Paper	2%
3	Submitted to CSU Northridge Student Paper	1%
4	Submitted to Grambling State University Student Paper	<1%
5	Abdul Haque, Nadeem Akhtar. "Ensemble model for ECG Classification", 2022 5th International Conference on Multimedia, Signal Processing and Communication Technologies (IMPACT), 2022 Publication	<1%
6	Submitted to Southern New Hampshire University - Continuing Education Student Paper	<1%
7	aaltodoc.aalto.fi Internet Source	<1%

8	ebin.pub Internet Source	<1%
9	Submitted to The University of the West of Scotland Student Paper	<1%
10	www.researchgate.net Internet Source	<1%
11	deepai.org Internet Source	<1%
12	m.moam.info Internet Source	<1%
13	Submitted to Geomatika University College Student Paper	<1%
14	arxiv.org Internet Source	<1%
15	Mimoun YANDOUZI, Mounir GRARI, Mohammed BERRAHAL, Idriss IDRISSI et al. "Investigation of Combining Deep Learning Object Recognition with Drones for Forest Fire Detection and Monitoring", International Journal of Advanced Computer Science and Applications, 2023 Publication	<1%
16	core.ac.uk Internet Source	<1%

17	"Computational Vision and Bio-Inspired Computing", Springer Science and Business Media LLC, 2021 Publication	<1 %
18	Submitted to University of Northampton Student Paper	<1 %
19	Submitted to Indian Institute of Technology, Bombay Student Paper	<1 %
20	brage.bibsys.no Internet Source	<1 %
21	ceur-ws.org Internet Source	<1 %
22	www.geeksforgeeks.org Internet Source	<1 %
23	Submitted to Liverpool John Moores University Student Paper	<1 %
24	Taimoor Khan, Zulfiqar Ahmad Khan, Chang Choi. "Enhancing real-time fire detection: an effective multi-attention network and a fire benchmark", Neural Computing and Applications, 2023 Publication	<1 %
25	icente.selcuk.edu.tr Internet Source	<1 %

26	openaccess.altinbas.edu.tr Internet Source	<1 %
27	Hikmat Yar, Zulfiqar Ahmad Khan, Imad Rida, Waseem Ullah, Min Je Kim, Sung Wook Baik. "An efficient deep learning architecture for effective fire detection in smart surveillance", Image and Vision Computing, 2024 Publication	<1 %
28	Submitted to University of Wales, Bangor Student Paper	<1 %
29	essay.utwente.nl Internet Source	<1 %
30	iris.unica.it Internet Source	<1 %
31	khazna.ku.ac.ae Internet Source	<1 %
32	umpir.ump.edu.my Internet Source	<1 %
33	web.archive.org Internet Source	<1 %
34	"Advances in Computational Intelligence Systems", Springer Science and Business Media LLC, 2024 Publication	<1 %

35	ElHofy, Ahmed Ismail. "Federated/Deep Learning in UAV Networks for Wildfire Surveillance", California State University, Long Beach, 2023 Publication	<1 %
36	Koustav Kumar Mondal, Debasis Das. "FlameNet: A Real-Time, Lightweight Fire & Smoke Detection Solution for Internet of Vehicles", 2023 International Wireless Communications and Mobile Computing (IWCMC), 2023 Publication	<1 %
37	Ruchkin, Vladimir, Aleksandr Kolesenkov, Boris Kostrov, and Ekaterina Ruchkina. "Algorithms of fire seat detection, modeling their dynamics and observation of forest fires via communication technologies", 2015 4th Mediterranean Conference on Embedded Computing (MECO), 2015. Publication	<1 %
38	Sohaib K. M. Abujayyab, Ismail R. Karas, Javad Hashempour, E. Emircan, K. Orçun, G. Ahmet. "Chapter 31 Wildfire Detection from Sentinel Imagery Using Convolutional Neural Network (CNN)", Springer Science and Business Media LLC, 2024 Publication	<1 %

coek.info

39	Internet Source	<1 %
40	ethesisarchive.library.tu.ac.th Internet Source	<1 %
41	repository.library.carleton.ca Internet Source	<1 %
42	sel.ist.osaka-u.ac.jp Internet Source	<1 %
43	www.coursehero.com Internet Source	<1 %
44	www.frontiersin.org Internet Source	<1 %
45	www.mdpi.com Internet Source	<1 %
46	www.researchsquare.com Internet Source	<1 %
47	"Engineering Applications of Neural Networks", Springer Science and Business Media LLC, 2017 Publication	<1 %
48	Eram Mahamud, Nafiz Fahad, Md Assaduzzaman, S.M. Zain, Kah Ong Michael Goh, Md. Kishor Morol. "An explainable artificial intelligence model for multiple lung diseases classification from chest X-rav	<1 %

images using fine-tuned transfer learning", Decision Analytics Journal, 2024
Publication

49	Sayed Pedram Haeri Boroujeni, Abolfazl Razi, Sahand Khoshdel, Fatemeh Afghah et al. "A comprehensive survey of research towards AI-enabled unmanned aerial systems in pre-, active-, and post-wildfire management", Information Fusion, 2024 Publication	<1 %

Exclude quotes	Off	Exclude matches	Off
Exclude bibliography	On		