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Forest Fire Detection using CNN

Minit Arora[1], Sanjay Sharma[2*]

[12]School of Engineering and Technology, Shri Guru Ram Rai University, Dehradun, Uttarakhand -248001, India

[1]minitarora@gmail.com, Orcid- 0009-0002-5310-4025

[2]sanjaypokhriyal@yahoo.com, Orcid -0000-0001-7625-5091

Corresponding author – [2]sanjaypokhriyal@yahoo.com*

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Abstract:

Forest fires contribute significantly to air pollution by emitting large quantities of carbon dioxide and carbon monoxide. These fires also release fine particulate matter into the air, worsening pollution levels and diminishing air quality. The impact on vegetation and wildlife is severe, resulting in substantial ecological damage and a reduction in biodiversity. Timely detection of forest fires is crucial for minimizing their destructive effects. While IoT sensors can be employed to identify smoke and fire, they are susceptible to damage during the blaze. A more effective approach to fire detection involves machine learning techniques. Various machine learning methods, such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Regression, and Support Vector Machines (SVM), can be utilized for this purpose .This paper analyses some machine learning techniques and proposes the use of a CNN based Model to detect fire

Keywords: Deep Learning, Convolution Neural Network, CNN, Air Quality index, ANN ,IOT.

1. INTRODUCTION

The interplay between climate change and wildfires has resulted in many regions worldwide experiencing more extensive, intense, and prolonged fires compared to previous years. If current trends persist, the long-term consequences for humans, wildlife, and the climate will be devastating. A wildfire is defined as an uncontrolled blaze that starts in a natural area such as a forest, grassland, or prairie. These fires can ignite anywhere and at any time, often stemming from human activities or natural phenomena like lightning strikes. The origin of 50% of reported wildfires remains undetermined. Extremely arid conditions, including droughts, and high winds contribute to an increased likelihood of wildfires. These blazes can disrupt the availability of water, electricity, and gas services, as well as communication and transportation networks. Additionally, wildfires deplete resources, destroy crops, cause fatalities among humans and animals, damage property, and deteriorate air quality.

Wildfires are known for their rapid expansion and resistance to extinguishment. Accurately pinpointing the affected area and evaluating the intensity of smoke poses a significant challenge, yet it is crucial for firefighters to implement appropriate measures and swiftly contain the blaze. Moreover, it is crucial to know critical information such as the location, extent, and intensity (i.e., risk level) of the smoke. Consequently, it is vital to develop a fire monitoring system capable of early detection of flames or smoke in specific areas and assessing their severity.

We have proposed a model that detects fire from a surveillance image which could be helpful to detect fire timely.

2. RELATED WORK

D. Q. Tran et al [1] introduced a model for forest fire response that focuses on implementing a bush fire defense system with two primary elements: detection and damage assessment. They utilized DetNAS, an object authentication method based on neural architecture search, to identify the most effective backbone. A fire dataset comprising approximately 400,000 images was employed for training and testing. A Bayesian neural network (BNN) was used to estimate the affected area. The system uses AI-enhanced CCTV cameras to transmit real-time data to a central server upon detecting smoke or flames in forested areas. Subsequently, the server dispatches a UAV to examine the fire site for damage. A regression model gathers data from the burning area to enable seamless monitoring and visualization of the fire. The total damaged area can be determined using a UAV and segmentation techniques. The main drawback of this response system is the difficulty in maintaining continuous real-time monitoring.

K Gayathri et al [2]introduce a Convolutional Neural Network (CNN) model for detecting forest fires. According to them, given the substantial environmental and economic impact of such fires, early detection is essential. The proposed system categorizes images into two groups: those containing fires and those without. It demonstrates superior accuracy compared to conventional methods like YOLO and SSD. The research utilizes a balanced dataset comprising 1,900 images, evenly split between fire and non-fire scenarios. The model is developed using deep learning techniques, implemented through Keras and TensorFlow frameworks. Its architecture incorporates convolutional layers, Global Average Pooling, dense layers, and dropout mechanisms to enhance performance. The CNN-based approach outperforms alternative methods, exhibiting high precision in fire detection. The researchers conclude that CNN models effectively identify fires in images and suggest potential future enhancements for smoke detection. This technology could be incorporated into existing surveillance systems for continuous monitoring.

M. Rahul et al [3]proposed a model utilizing deep learning techniques for early forest fire detection. The study proposed a convolutional neural network to swiftly identify forest fires through image recognition. To address this challenge, the researchers employed a transfer learning approach. The system processes image data and applies augmentation methods such as shearing to generate additional images. The study utilizes models like ResNet50 and VGC16 for image classification. Initially, the model divides the data into 80% training and 20% testing sets. The model is then trained to categorize data into fire and non-fire classes. The proposed model employs Resnet50 and transfer learning for training. A key limitation of this research is that not all images are successfully classified as either fire or non-fire.

Mohnish et al [4] in their paper introduce a Convolutional Neural Network (CNN) model based on Deep Learning for forest fire detection. The methodology employs three key techniques: Image

Collection, Pre-processing, and Image Classification. The process begins with pre-processing the dataset images before inputting them into the CNN for feature extraction and detection. Additionally, the research implements a hardware setup utilizing Raspberry Pi, which sends fire detection alerts via email, buzzer, and LCD display to relevant authorities. The model achieves detection accuracies of 93% and 92% on the training and testing datasets, respectively.

D. Georgiev et al.[5] proposed a system for early forest fire detection utilizing Convolution Neural Network and UAV imagery. This research presented a method for an autonomous, highly reliable early fire detection system that eliminates the need for maintenance or human intervention. Rather than relying on traditional methods, the system employs a real-time video feed from an unmanned aerial vehicle (UAV) that surveys the high-risk area, complementing lookout towers and satellite monitoring by providing enhanced visual coverage of the monitored region. Both optical and thermal cameras on the UAV are utilized to enhance predictions of potential fire occurrences. A web-based interface was developed using Node-RED technology to display the collected data in real-time and notify relevant parties. The primary drawback of this project is its reliance on two cameras for the final fire determination.

S. Wu et al. [6]in their paper explore a real-time forest fire detection system utilizing Object Detection Methods. The research addresses three primary issues: inaccurate identification, early warning systems, and forest fire detection. To identify forest fires, the study employs established object detection techniques, including faster R-CNN, YOLO (with variants tiny-yolo-voc, tiny-yolo-voc1, yolo-voc.2.0, and yolov3), and SSD. The SSD demonstrates superior real-time performance, detection accuracy, and advanced fire detection capabilities. The researchers modify the tiny-yolo-voc structure used in YOLO and propose a novel approach. Based on tinyyolo-voc1 experiments, this modification enhances the accuracy of fire detection. This study significantly contributes to ongoing forest surveillance and safety measures. However, the main limitation of this research lies in the challenges associated with real-time monitoring.

Qingjie Zhang et al.[7] introduce a novel forest fire detection technique utilizing deep learning, specifically a cascaded convolutional neural network (CNN). Our system incorporates two components: a global image classifier and a detailed patch classifier. The global classifier first assesses whether an image contains fire. If fire is detected, the patch classifier then pinpoints the exact fire locations. Our fire patch detector demonstrates 97% accuracy on the training set and 90% on the test set. To advance fire detection research, they present a new benchmark dataset featuring patch-level annotations, which we believe is the first of its kind. This benchmark is designed to enable researchers to evaluate and compare various fire detection models. Their method improves both the accuracy of fire detection and localization, making it suitable for practical applications such as early wildfire alert systems and automated surveillance.

B. Arteaga, et.al [8]examines the effectiveness of various Convolutional Neural Network (CNN) models in detecting forest fires using pre-trained images on cost-effective hardware like the Raspberry Pi. The research explores potential methods for predicting forest fires and presents two pre-trained CNN models to accomplish this task and evaluate their performance. The proposed models are derived from ResNet and two families of pre-trained CNNs, encompassing 8 models and 5 types. A key limitation of this study is that while the Resnet152 model can be utilized on a Raspberry Pi 3 Model

B, it cannot continuously process images. The research employed a small dataset consisting of 1800 images for analysis.

3. PROPOSED MODEL

The proposed model aims to accomplish two main goals:

1) Identify whether an image contains fire.

2) Display the result. The output will read "Fire" if flames are present, or "No Fire" if no fire is observed.

3.1 DATASET USED

Data sets has been extracted from Forest Fire Dataset available on Kaggle [9]This collection of images has been assembled to tackle the challenge of detecting forest fires. The dataset comprises 1900 images in total, evenly distributed between classes. Each image in the set is composed of three channels and has dimensions of 250 × 250 pixels. To create this dataset, various search terms were used across multiple search engines to gather images. Subsequently, the collected images underwent careful examination to remove any irrelevant elements such as individuals or firefighting equipment. This process ensured that each image focuses solely on the pertinent fire area. The resulting dataset is well-balanced, containing an equal number of images for each category.

The dataset consists of two sets of images

1. Training
2. Testing

In both categories of folders there are two sets of images labelled as FIRE and NO FIRE

Dataset contains 1520 images for training the model and 380 images for Testing For the proposed study training and testing purposes, the dataset is split 80:20.

3.2 MODEL DEVELOPMENT

The suggested framework will process images containing both fire and non-fire elements. These images are fed through various layers, including Convolution, Maxpooling, and Dense layers. Additionally, data augmentation techniques such as rescaling are employed to extract crucial features from the input image [10] The final classification is performed by the output layer, which displays "Fire" if fire is detected in the image, or "No Fire" if no fire is present.

The suggested framework incorporates three key components, as illustrated in:

• Gathering of Dataset

• Augmentation of Data and Extraction of Features

• Development and Training of Model

3.3 DETAILED MODEL

Model uses CNN (Convolusion Neural Network) as the base technique will take images as input followed by 4 sets of layers of Convolusion Layer with RELU (Rectified Linear Unit) and Sigmoid activation function for feature extraction and Maxpooling Layer for reducing the dimensionality of the features. This is followed by flatten function To minimize the loss following extraction, the model incorporates an optimizer and employs binary cross-entropy as the loss function, and result will be input to fully connected layers to classify the images into Fire and No fire .

Algorithm 1: Developing the Model

Step1: Input the dataset

Step2: Split the dataset into Training and Testing subsets and generate Training and Testing data Generators

Step3: Construct the preparation, analysis, and detection networks

Step4: Incorporate Pooling, Dense, and Conv2D(n,w,h) layers, where n represents the number of layers, w indicates the width of each layer, and h denotes the layer height. Include Pooling and implement ReLU() and sigmoid activation functions

Step5: Compile the final model

3.3 TRAINING AND TESTING OF MODEL

Algorithm:

Step 1: The model undergoes training using a prepared dataset.

Step 2: Model evaluation is conducted to determine how well it generalizes to similar data used in its training.

Step 3: The Matplotlib library is utilized to visualize the model's Training Accuracy.

Step 4: The trained model is then tested by inputting a random image.

Step 5: The final outcome is displayed as text on the given image, indicating whether a fire is detected or not.

Step 6: If a fire is identified, the output will read "Fire"; otherwise, it will display "No Fire".

3.4 STEPS IN THE MODEL

The model consists of the following steps

1. To begin, we'll utilize the training dataset.
2. The data has been divided into two segments: one for training and another for testing.
3. We'll construct and train the CNN model using the training portion.
4. During the training process, we'll extract the necessary features.
5. The output layer will serve as the classification layer, categorizing into two classes: Fire and No Fire.
6. We'll then apply our trained model to the test data.
7. The output will be "Fire" if a fire is detected; otherwise, it will be "No Fire."

Fig1. below shows a flowchart of the model.

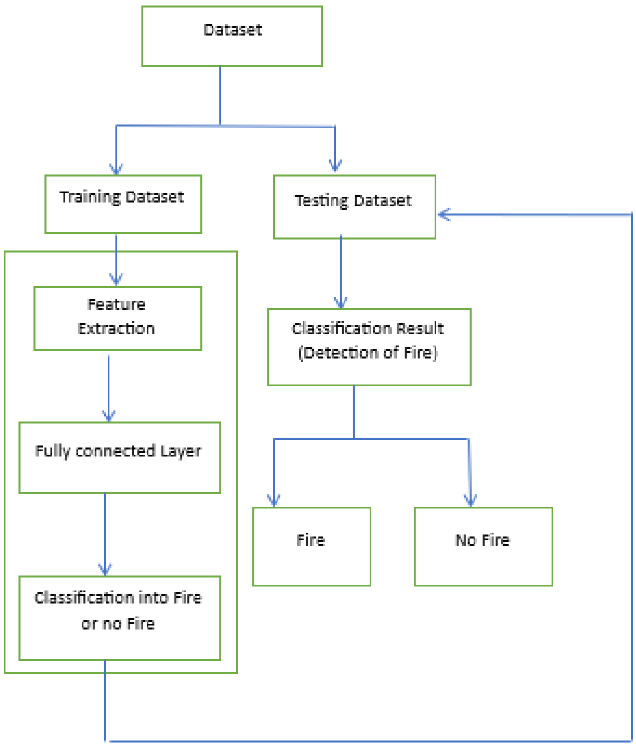

Fig1. Flowchart of the Model

4 . RESULTS AND DISCUSSIONS

The model predicts the correct result with an accuracy of 99% on the training dataset and 94% on the testing dataset . The graph below (Fig 2.) shows the performance of the model . Our model predicts the output correctly [11]

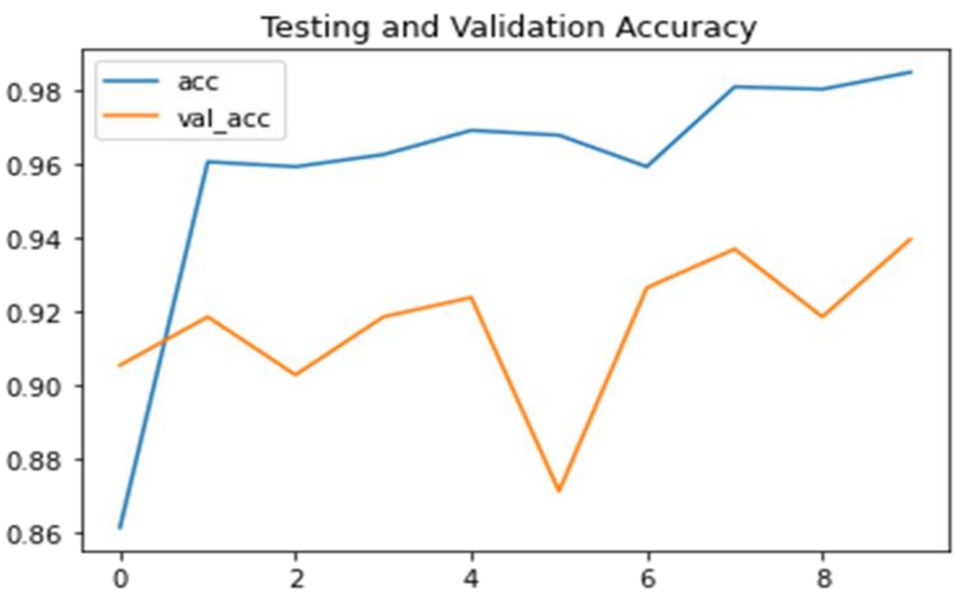

Fig2. Accuracy graph of the model

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The graph below (Fig 2) shows the loss in the graph

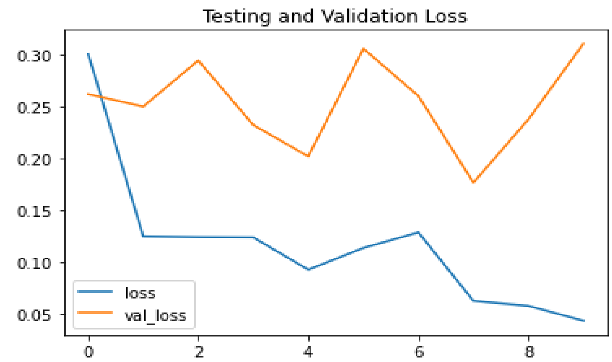

Fig 3. Loss values Graph

The system responds differently based on the type of image provided. When an image containing fire is submitted, the output indicates "fire."

Fig 4: Fire detection in the image

Conversely, if an image without fire is input, the system produces the result "No Fire."

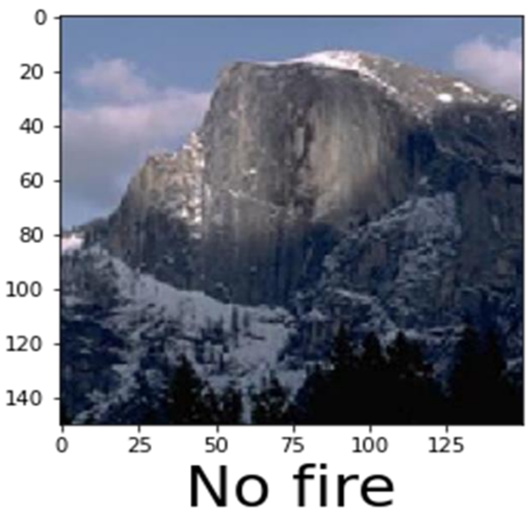

Fig 5. No Fire detected in the image

5. CONCLUSION

The research work is suggestive of the fact that the proposed model is based on CNN for any input image we are getting the results according to whether there is fire or not in the image. For fire we get the output "Fire" and we get the output "No fire" when fire is not detected in the image . The research also shows that model has a good accuracy of 99% on training data and 94% on the Test data which can be considered to be a good accuracy.

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