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Deep Learning-Based Fire and Smoke Detection System with MobileNet Architecture – A Review

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ABSTRACT

One of the most frequent yet undesirable phenomena brought on by climate change and rising temperatures is wildfires or any other areas. Therefore, there is a need for advanced yet user-friendly systems that at the very least enable the effective use of contemporary tools and solutions. Fire and Smoke detection are crucial tasks in ensuring the safety and security of various environments. In this project, we present a comprehensive solution for fire and smoke detection using deep learning techniques. The project is developed in Python, utilizing the powerful capabilities of the MobileNet architecture. The main objective of this project is to accurately identify fire and smoke instances in different scenarios, including images, videos, and real-time webcam feeds. The high accuracy indicates the model's ability to effectively classify fire, smoke, and normal instances, enabling reliable detection in various contexts. The proposed system allows for multi-purpose detection, providing real-time analysis of images, videos, and live webcam feeds. This versatility ensures the applicability of the solution in a wide range of scenarios, such as surveillance systems, fire alarm systems, and emergency response management. Overall, this project contributes to the field of fire and smoke detection by leveraging deep learning techniques and the MobileNet architecture. The developed system offers an efficient and accurate solution for identifying fire and smoke instances in different visual media, thus enhancing safety and security measures in various environments.

Keywords: Convolutional Neural network, Deep Learning, Image Classification, Fire Detection , MobileNet Architecture.

INTRODUCTION

At present, a large number of fire accidents occur every and cause serious economic losses. One critical application of deep learning is in the development of fire and smoke detection systems, which are essential for early warning and prevention of disasters in various environments, such as industrial facilities, commercial buildings, and even residential homes. This introduction will provide an overview of a cutting-edge fire and smoke detection system using the MobileNet architecture, highlighting the significance and benefits of this approach. Fire and smoke incidents can lead to catastrophic consequences, including loss of life, property damage, and environmental hazards. Traditional fire detection systems, often reliant on rule-based algorithms or human intervention, have limitations in terms of accuracy and responsiveness. Deep learning-based systems have emerged as a promising solution, leveraging the power of neural networks to detect fire and smoke with high precision and speed. Deep learning techniques have demonstrated remarkable capabilities in image recognition and classification tasks. Convolutional Neural Networks (CNNs) are particularly well-suited for visual data analysis, making them ideal for fire and smoke detection.

These systems can quickly analyzeimages or video streams and identify potential fire or smoke patterns, allowing for rapid response and mitigation. MobileNet is a deep learning architecture specifically designed for resource-constrained devices, such as smartphones and embedded systems. Its primary advantage lies in its efficiency and speed while maintaining competitive accuracy. MobileNet employs depthwise separable convolutions, which reduce the computational burden, making it suitable for real-time applications. These characteristics make MobileNet a natural choice for deploying fire and smoke detection systems on mobile devices and edge devices. To achieve this, a robust deep learning model is trained on a diverse dataset consisting of 3825 images of fire, smoke, and normal situations. The implemented deep learning model demonstrates impressive performance, achieving a training accuracy of 97.00% and a validation accuracy of 94.00%. The high accuracy indicates the model's ability to effectively classify fire, smoke, and normal instances, enabling reliable detection in various contexts.

LITERATURE REVIEW

Wangda Zhao (2020)[1] A unique picture fire detection technique was created using the faster-RCNN, R-FCN, SSD, and YOLO v3 advanced object identification CNN models. The suggested algorithms can automatically extract intricate picture fire attributes and find fire in a range of scenarios. The author also asserted that the CNN-based algorithms are more accurate than the conventional algorithms. The YOLO v3-based algorithm is the most accurate among all CNN models, detecting fire at a rate of 83.7 percent and 28 frames per second, respectively.

K. Muhammad, J. Ahmad, I. Mehmood, S. Rho & S. W. Baik (2018)[2] et al, suggested a Convolutional neural network (CNN) architecture for video surveillance that is cost-effective in detecting fires. The suggested model mainly concentrated on detection precision and computational complexity. The Google Net design, which has less computational complexity than other networks with high computational costs like AlexNet, served as the model's primary source of inspiration. According to the author, the suggested framework performs better on fire datasets and is appropriate for fire detection in CCTV security systems in practical applications.

Yuming Li, Wei Zhang, Yanyan Liu & Yao Jin(2022)[3] A quick and effective fire detection model is developed using the convolutional neural network MobileNetV3 and the anchor less structure. In two aspects, the suggested strategy performs better. The suggested technique is small enough to be readily deployed on visual mobile devices, which will first boost network speed. On two publicly available fire datasets as well as self-built datasets, the model's accuracy has been tested. The proposed framework's top speed of 29.5 f/s may meet real-time detection, making it appropriate for fire detection systems in practical applications.

Arpit Jadon, Akshay Varshney, Mohammad Samar Ansari (2020)[4] The author proposed a convolutional neural network model dubbed MobileNetV2 architecture to address the fire detection difficulties. In addition to a novel MobileNetV2 architecture that outperforms current options while being computationally realistic for implementation on less powerful hardware, the author also introduces a more transparent data handling technique. The metrics Accuracy, Precision, Recall, and F-Measure were used to assess this model's performance against current Convolutional neural network models on two datasets. The accuracy of the suggested model is 0.99, the highest of any model (99%).

Myeongho Jeon, Han-Soo Choi, Junho Lee, Myungjoo Kang (2021)[5] By emphasising the different sizes of flames in photographs, the author suggested a framework that improves the current Convolutional neural network-based fire image classification model. In order to include feature maps of different scales in the final prediction, the author suggested using a feature-squeeze block. The feature-squeeze block compresses the 13516maps' features both spatially and channel-wise, allowing for effective use of the data from the multi-scale prediction. A false positive rate of 0.0227% and an F1-score of 97. 89% were obtained from the experiment using the provided methodology.

Qingjie Zhang, Jiaolong Xu, Haifeng Guo(2016, January)[6]The researcher who conducted this study suggested a deep learning approach for identifying forest fires. In a combined deep convolutional neural network (CNN), the author trained a whole picture classifier as well as a fine-grained patch fire classifier. Here, the author used a system that operates in a cascading manner to detect the fire. On training and test datasets, the proposed fire patch detector achieves detection accuracy of 97% and 90%, respectively.

Mohit Dua, Mandeep Kumar, Gopal Singh Charan, Parre Sagar Ravi(2020, February)[7]The author of this study claims that a deep CNN technique is used in conjunction with transfer learning to detect fire. Here, unbalanced datasets that mimic real-world circumstances are used to evaluate and compare the various CNN models. He claimed that deep CNN models outperform more conventional CNN models in terms of performance. Finally, the author claimed that while MobileNet is quicker and smaller than VGGNet, its accuracy is about equivalent.

Problem Statement

Earlier fire and smoke were detected through already captured images, then that images detect the fire and smoke according their training dataset model. Here we are improving by using MobileNet Architecture and CNN model to detect the fire and smoke. For this we have taken a fire& smoke images dataset that contains a lot of images. Dataset is trained under MobileNet Architecture and CNN model. Before training the model, data augmentation is performed on the dataset for better performance. Then, the dataset is trained under the MobileNet Architecture and CNN model& detect the fire and smoke In a real-time scenario.

METHODOLOGY

A) Models

The proposed model takes the image as an input from the user and determines whether fire exists in the image or not. There have been two different sorts of models proposed.

1) Data Pre-processing
2) Image Classification

1) Data pre-processing
Data pre-processing is the process of preparing raw data for usage with machine learning models. It is the most important and first step in creating a machine learning model. We don't always come across clean and prepared data when working on a machine learning project. Furthermore, before any process, data must be cleansed and prepared. As a result, we use data pre-processing services.

STEPS IN DATA PRE-PROCESSING IN MACHINE LEARNING

i) Acquire the dataset:
The acquisition of the dataset is the initial stage in data pre-processing in machine learning. Before you can create and evolve Machine Learning models, you must first gather the required dataset. This dataset will be constructed from data collected from a variety of sources, which will then be integrated into a suitable format to make a dataset. The format of a dataset depends on the application.

ii) Import all the libraries:
Python is the most extensively used and recommended library among Data Scientists worldwide. The Python libraries can be used to conduct specialized data pre-processing tasks. The second stage in machine learning data pre-processing is to import all of the necessary libraries. The following Python libraries are often used in Machine Learning for data pre-processing:

a) NumPy - The most popular Python package for scientific calculations is NumPy. As a result, it's used to add any form of mathematical operation to the code. Large multidimensional arrays and matrices can also be used in NumPy programmers.

b) Pandas - Pandas are superb Python data manipulation and analysis tools that are open-source. It's frequently utilized for data collection, import, and upkeep. It includes Python data structures and data analysis tools that are fast and simple to use.

c) Matplotlib - Matplotlib is a Python 2D charting toolkit that may be used to create a variety of charts. It can produce publication-quality numbers in a variety of hard copies and interactive forms.

iii) Dividing the datasets into the test set and the training set:
During machine learning data preparation, we separate our datasets into a training set and a test set. This is a crucial stage in the pre-processing of the data since it enhances the functionality of our machine learning model. Let's say we used one datasets to train our machine learning model and a second datasets to test it. Our model will then struggle to comprehend the links between the models. If we correctly train the model and it has a high training accuracy, but then give it a new datasets, its performance will suffer. As a result, we make every effort to develop a machine learning model that works well with both training and test datasets. These datasets can be defined as follows:

iv) Data Augmentation:
To artificially enhance the size of an actual datasets, data augmentation techniques generate different versions of it. Computer vision and natural language processing (NLP) models use data augmentation methodologies to address data scarcity and insufficient data diversity.

Data augmentation tactics can help machine learning models. According to an experiment, a deep learning model with picture augmentation performs better in image classification task training and accuracy, as well as in validation loss and accuracy, than a deep learning model without image augmentation.

There are some Data augmentation techniques

- Adding noise: Adding noise to a blurry photograph might help it stand out. The image appears to be made up of white and black dots when it is called "salt and pepper noise."
- Cropping: An area of the photograph is chosen, cropped, and re-sized to its original size.
- Flipping: The image is horizontally and vertically flipped. Flipping the image protects the image's features while rearranging the pixels. For some photographs, vertical flipping is pointless.
- Rotation: The image is rotated by several degrees between 0 and 360. In the model, each rotated image will be unique.
- Scaling: The image has been re-sized in and outward. Scaling allows an object in a new image to be smaller or larger than it was in the original image.
- Translation: Because the image is displaced along the x-axis or y-axis, the neural network looks for it everywhere in the image.
- Brightness: The image's brightness is altered, and the new image will be darker or lighter. This method enables the model to detect images in various lighting conditions.
- Zooming: In the Zooming Augmentation technique, the image is randomly zoomed and new pixels are added.

2) Image Classification

The labeling of images into one of several predefined classifications is referred to as image classification. A single image can be categorized into an infinite number of categories. Manually reviewing and classifying images takes time, especially when there are a lot of them, as a result, using computer vision to automate the procedure would be quite beneficial.

Convolutional neural networks, or CNNs, are commonly used in deep learning image classification. The output of the nodes in the hidden layers of CNNs is not always shared with every node in the following layer. Machines can recognize and extract information from photographs using deep learning.

We employ MobileNet Architecture, a deep learning model based on Convolutional Neural Networks, for image classification. On the ImageNet datasets, MobileNet Architecture is an image recognition model that has been shown to achieve higher than 78.1 percent accuracy. The foundation of MobileNets is a set of depth-separable convolutional layers.

A depth wise convolution and a point wise convolution make up each depth wise separable convolution layer. If depthwise and point wise convolutions are counted individually, a MobileNet has 28 layers. By properly adjusting the width multiplier hyper-parameter, it is possible to further minimize the 4.2 million parameters that make up a normal MobileNet.

B) MobileNet Architecture

MobileNet is a convolutional neural network (CNN) architecture designed for efficient image classification and object detection on mobile devices with limited computational resources. It's specifically designed to be lightweight and fast while still maintaining good accuracy. A novel type of convolutional layer known as Depthwise Separable convolution is used in the considerably quicker and smaller CNN architecture known as MobileNet. These models are thought to be highly useful for implementation on mobile and embedded devices due to the small size of the model. Hence, MobileNet's name.

1) Convolution that is separable by depth:
1.1 Convolution by depth
1.2 Convolution by point
2) Dimensions of MobileNet
2.1 Multiplayer in Width
2.2 Multiplayer with Resolution-Aware

1) Convolution that is separable in depth

The depth-wise and point-wise convolutions are the two layers that make up the depth-wise separable convolution. In essence, the input channels are filtered in the first layer, and they are combined in the second layer to produce a new feature.

1.1) Depthwise Convolution: A 3x3 filter, for example, is used to convolve each input channel separately in this phase. Accordingly, if there are 'n' input channels, 'n' independent 3x3 convolutions—one for each channel—are applied to the input tensor. This procedure aids in extracting channel-specific properties.

1.2) Pointwise Convolution: A 1x1 convolution (pointwise convolution) is used after depthwise convolution. Convolution assists in combining data from various channels, resulting in interactions and connections between channels.

2) Parameters of MobileNet

Even though the basic MobileNet architecture is very simple and requires little computer power, it features two distinct global hyperparameters that significantly lower the computational cost.

One is the width multiplayer and another is the resolution wise multiplayer.

2.1) Width Multiplier: In order to construct these smaller and less computationally expensive models we introduce a very simple parameter α called width multiplier. The role of the width multiplier α is to thin a network uniformly at each layer.

$D_K . D_K . \alpha M . D_F . D_F + \alpha M . \alpha N . D_F . D_F$

2.2) Resolution Multiplier: Resolution Multiplier: A resolution multiplier is the second hyper-parameter to lower a neural network's computational expense. When we apply this to the input image, the internal representation of each layer is subsequently reduced by the same multiplier. In actuality, we set by adjusting the input resolution.

$D_K . D_K . \alpha M . \rho D_F . \rho D_F + \alpha M . \alpha N . \rho D_F . \rho D_F$

CONCLUSION

Fire is an abnormal event that can cause severe harm to people, animals, and property in a short period. Early fire detection systems are significant nowadays because they can provide an early warning system, potentially saving lives and decreasing property damage.

In this work, we looked at the MobileNet Architecture and Convolutional Neural Network model which automatically detects the fire in the images. Their performance is compared using the accuracy metric. Among the chosen models, the MobileNet Architecture is computationally efficient and is more accurate. MobileNet Architecture has given better performance (accuracy) in every scenario.

MobileNet Architecture has given an accuracy of 99%, and as CNN is a basic model, it has given an accuracy of 89%. The suggested model not only accepts inputs from the local system but can also catch images from the camera and accurately forecast whether or not a fire is present. Through this system, the fire can be identified through surveillance cameras and an alert will be sent to the forest officers so that fire can be controlled.

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