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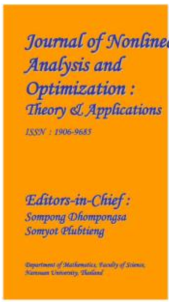

DETECTION OF FOREST FIRES UTILISING CONVOLUTIONAL NEURAL NETWORKS (CNN)

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ABSTRACT:
Humanity relies on forests as a vital resource because of the many direct and indirect advantages they provide. Natural disasters, like forest fires, have a major influence on both the rate of global warming and the viability of life on Earth. Research into methods for automatic forest fire detection is, hence, crucial for the mitigation of such catastrophes. Noticing fires early might also help decision-makers plan ways to put out the blazes. Fire and smoke detection in images is the focus of this research, which employs computer vision methods grounded on artificial intelligence. While Convolutional Neural Networks (CNNs) have shown to outperform state-of-the-art approaches in image classification and other computer vision applications, their training period may be somewhat lengthy. Additionally, inadequate data could cause a pretrained CNN to function poorly. Transfer learning is used to pre-trained models to solve this issue. The use of transfer learning, however, may damage the equations' classification skills on the original datasets. To solve this problem, we use learning without forgetting (LwF), which trains the network to do a new job while keeping all of its previous training data.
Key words: Convolutional Neural Networks (CNN), Artificial Intelligence (AI), Forest, Fire.

1. INTRODUCTION

As a result of climate change, forest fires are becoming more common throughout the world, wreaking havoc on ecosystems and draining economies [1]. Summer forest fires may be caused by both natural and man-made sources, including debris and other biomes, as well as human negligence. Wildfires may be both a blessing and a curse for communities; they can clear away vegetation, kill off animals, and improve ecosystems, but they can also destroy homes and kill people. There has been a consistent increase in the number of forest fire events in recent years. To prevent the felling of trees, there is a growing movement to install systems that can detect and report forest fires automatically.
In order to lessen the effect of fire catastrophes, several techniques, both old and new, for detecting smoke and fire have been proposed. Researchers in these fields have taken a keen interest in smoke detection systems that use either vision or sensors. The five main kinds of smoke detectors are light detectors, gas detectors, temperature detectors and composite detectors, which are based on the types of sensors used and their intended uses [2]. For this purpose, temperature and smoke detectors are often used. Both the detection range and the detection speed are severely limited by the sensor-based approach [3]. It is crucial to limit the amount of time that elapses since fire spreads quickly. Afterwards, scientists began collecting images of fires and used their colour features to identify flames once video surveillance technology became widely available. The most common visual representations of fire in movies and photos usually include horizontally oscillating flames that display various degrees of orange or yellow. Plumes of smoke, made of soot or burned particles, may be any shade of white, grey, or black. Finding smoke in images and videos has its own set of problems.
A system's efficiency depends on its capacity to differentiate between real fire pictures and those that just provide the appearance of flames. The use of primary colour features for fire detection leads to more false positives [4]. We developed techniques based on image processing to capture the

characteristics of fires, including their colour, shape, flickering, frequency, and dynamic textures. To detect fire, these algorithms use the CIELab, YCbCr, RGB, and YUV colour spaces.

We have provided motion data along with the colour information. A greater dependence on fire detection systems has resulted from the methods discussed in [5]. Nevertheless, a new obstacle has emerged in the realm of image processing with the use of security camera photos. Video cameras produce an endless stream of pictures, which drives up the cost of storage and processing. The need to improve the system's accuracy and autonomy led to the introduction of several fire detection techniques and technologies. Recent advances in video surveillance have coincided with advances in machine vision image processing, which has enabled quicker transmission and sensing [6]. Consequently, a plethora of new fire detection approaches have been made possible by advancements in computer vision-based smoke and fire detection systems. An artificial vision-based smoke and fireplace detection system may build a detection model that depends on pictures captured by video surveillance and characteristics extracted from them. Afterwards, this model may be used for smoke and fire detection. Hence, traditional machine learning and computer vision algorithms based on deep learning have been suggested for use in attempting to detect smoke and fire in pictures.

Figure 1. Fire Classification

Machine learning has been applied for a variety of applications, including forest fire prediction and detection. Offer a comprehensive survey of the application of machine learning methods in forest fire detection. Algorithms for detecting fires using machine learning depend on manually collecting visible information from photos. These features only highlight the flame's surface features, which could cause data loss during manual extraction. In contrast to machine learning methods, deep learning [7] can extract and learn complex feature representations automatically. The achievements of CNN in image classification and the rapid advancement of deep learning in computer vision have made fire detection a very promising field of study. CNN-based approaches utilise frames captured by surveillance systems as input, with the prediction outcome being transmitted to an alarm system. Several CNN variations have been used for fire detection tasks, including Inception.

Classifying images of fire and smoke has previously proven problematic due to the wide parameter space employed by off-the-shelf deep architectures such as VGG16, DenseNet, Inception, and

Xception, among others. When confronted with huge parameter spaces, transfer learning may be a feasible alternative. Then, information acquired in one area can be applied to another with less data. Deep architectures utilising pre-trained models can be constructed with as little as two or three photos [8]. According to [9], deep learning models perform better when trained on a large number of samples. Overfitting and sliding into a local optimum can happen when training samples are insufficient [10]. Transfer learning can assist us in handling such issues. Many computer vision tasks, such as object detection and face recognition, have recently experienced success with deep learning, but their utility in fire detection has been limited. The study on fire detection may be limited due to a scarcity of data available for training deep learning models. As a result, we are now driven to prioritise the acquisition of a substantial number of fire/smoke photos from various sources. Furthermore, even if a pre-trained CNN classifier is trained to categorise specific types of tasks using transfer learning, the model can perform well on tasks for which it has been prepared, but underperforms when a new, but similar task is presented. In the field of machine learning, this is referred to as "the catastrophic forgetting phenomenon." This behaviour encouraged us even more to investigate the idea of LwF for identifying smoke and forest fire photographs from a fresh dataset.

2. LITERATURE SURVEY

2.1 Computer Vision (CV)

Understanding and interpreting digital images is known as computer vision [11]. Digital picture interpretation and comprehension have several practical uses, particularly in the domains of automated inspection and machine vision. In the subject of automatic inspection, computer vision can be used to inspect product quality as it is manufactured. Machine vision uses computer vision to "see" the world and direct robots or other machines. Computer vision has a number of applications, such as medical diagnosis, video surveillance, and 3D reconstruction. In each of these applications, computer vision can be used to interpret and comprehend digital images in order to accomplish a desired outcome. Recently, the utilisation of

Computer vision has made significant advancements through the use of deep learning. Compared to typical machine learning approaches, deep learning has the benefit of learning several layers of data representations, which can better capture the complex structure of data and increase pattern recognition performance. Computer vision encompasses various areas of research, such as classification, segmentation, and object identification.

2.1.1 Categorization (CLA)

Traditionally, image categorization was performed by human experts who inspected photos and identified which category they fell into. Machines currently conduct picture categorization, and they can learn to recognise patterns in photos better than people [12]. Deep learning networks can be trained to identify and classify different objects in photos through image classification. A deep learning network may be trained to identify the characteristics of a dog, such as its fur, eyes, and ears. After undergoing training, a deep learning network can be utilised to categorise photos into several classifications. An image classification task, such as distinguishing between images of dogs and cats, can be accomplished using a deep learning network [13]. Deep learning for image classification has the benefit of acquiring the ability to identify intricate patterns that surpass human detection capabilities. Deep learning networks sometimes surpass classic picture categorization methods in performance [14].

2.1.2 Segmentation (SEG) refers to the process of dividing a larger entity into smaller, distinct parts or segments

Deep learning has been used to segment images into regions that represent different objects or classes of objects. A deep neural network for image segmentation would often contain multiple layers, each of which is in charge of incrementally refining the picture segmentation [15]. The initial layer of a deep neural network (particularly CNN) for image segmentation is often a convolutional layer that learns to detect picture features.

These qualities can range from basic features like edges or corners to more intricate ones like the forms of objects [16]. The convolutional layer generates a collection of feature maps, which are subsequently transmitted to the subsequent layer. The following layer is usually a pooling layer, which decreases the dimensionality of the input by averaging the values in a small region of the input feature maps. Subsequently, there are completely connected layers (one or more) that acquire object recognition

skills. The network's ultimate layer will produce a collection of labels indicating the specific category or categories of object(s) that are present in the image. While there are many other picture segmentation techniques, the majority fall into one of three categories: instance, panoptic, or semantic.
a) Semantic segmentation: this method separates objects in an image from their background. Typically, this task is achieved by identifying and classifying every object in the image based on a predefined set of labels. A segmentation algorithm can be trained to identify several types of vehicles, including autos, trucks, and buses.
b) Instance segmentation: is a method used to accurately identify and separate individual items inside a picture. This is commonly achieved by identifying the individual pixels that form an object and subsequently grouping them again.
A segmentation algorithm may be trained to identify distinct regions of the human body, including the head, chest, and legs [17] as in Figure 2. Panoptic segmentation is a method used to create a three-dimensional depiction of an item using only one photograph. This is achieved by projecting the surface of the object into a three-dimensional grid and subsequently reconstructing the object by extrapolating the information from the grid cells. Often, this technique is employed to find items that are too small or challenging to find with other techniques.

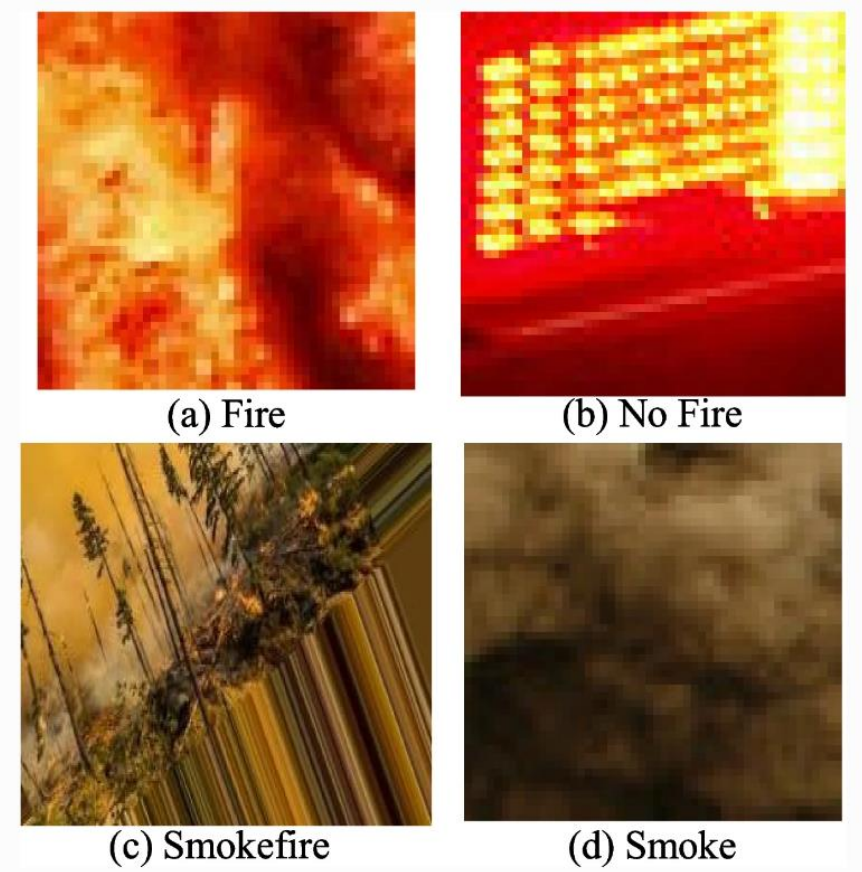


Figure 2. Forest fire datasets

2.1.3 Object Detection (OD)

Object detection in computer vision refers to the process of precisely identifying and 4ptimize4o a particular object inside an image or video sequence. Object detection can be used to find a single object or a collection of objects [18]. Many object identification methods, particularly deep learning-based object detectors, have emerged in recent years. Deep learning-based object detectors have demonstrated cutting-edge performance on a range of object detection benchmarks. Among the most widely used deep learning-based object detectors are the YOLO, SSD, and Faster R-CNN algorithms. The YOLO method is a rapid and effective object detector that identifies objects across various sizes. The SSD method is a high-speed and precise object detector that can detect things in immediate time.

3. PROPSOED METHODOLOGY

The dataset for the proposed study was created using geostationary weather satellites MODIS, VIIRS, Copernicus Sentinel-2, and Landsat-8. These satellites are utilised for fire detection all over the world because of their high temporal precision and capacity to identify flames in remote regions. A compilation of the forest fire's satellite imagery has also been made. The imagery were manually labelled by hand with symbols that mean "Fire," "No Fire," "Smoke," and "Smoke Fire." It has 4800 pictures in the dataset that was collected. To increase the number of images, image augmentation techniques such shifting, flipping, rotating, scaling, blurring, padding, cropping, translation, and affine modification were used. After augmentation, 6,911 photos make up the collection. After that, the datasets were split into three categories: testing, validation, and training. Ten half of the dataset was used for testing, and the rest, or eighty percent, was used to train the classifier. The image distribution within the training, testing, and validation datasets in Figure 3.

	File	Label
0	../input/fire-dataset/fire_dataset/non_fire_im...	nofire
1	../input/fire-dataset/fire_dataset/fire_images...	fire
2	../input/fire-dataset/fire_dataset/fire_images...	fire
3	../input/fire-dataset/fire_dataset/non_fire_im...	nofire
4	../input/fire-dataset/fire_dataset/fire_images...	fire

Figure 3. Fire Datasets

Furthermore, we evaluated the efficacy of the proposed models in applying the insights acquired from the classification of forest fire and smoke images to the BoWFire dataset, which was contributed to the compilation. The BoWFire dataset, available at http://bitbucket.org/gbdi/ bowfire-dataset/downloads/, comprises 240 photographs that are categorized into four groups: fire images, no-fire images, smoky fire images, and light photographs. Although small in size, this dataset poses substantial difficulties because of the inclusion of fire-like sunset and sunrise scenarios, fire-colored objects, and architectural lighting.

CNN:

Complex vision problems have been efficiently solved making use of various types of CNN basic designs. Convolution and pooling are the two primary operations in a Convolutional Neural Network (CNN). The capacity to extract features from images via convolution with various filters allows for the retention of the corresponding spatial information. CNNs are employed as feature extractors and classifiers in image processing applications, notwithstanding their usefulness in image processing and classification. Instead of exclusively using stacked convolutional layers like LeNet, AlexNet, and VGG, modern network architectures such as ResNet, Inception, and Xception are investigating novel methods to construct convolutional layers in an effort to improve learning efficiency. VGG is a commonly utilised convolutional neural network (CNN) architecture due to its simplicity. This project involves training the VGG16, InceptionV3, and Xception models to accurately classify photos of fire. The VGG16 (Visual Geometry Group) CNN architecture is widely employed and is specifically implemented in ImageNet, a massive visual database initiative. VGG16 is commonly used in several types of deep learning image categorization algorithms due to its ease of implementation. Despite being introduced in 2014, it still stands as one of the most exceptional vision architectures up to now. VGG employs 1×1 convolutional layers to modify the decision function without changing the receptive fields, resulting in a reduction in linearity. Due to the small size of the convolution filters, VGG can have a lot of the load layers. Having more layers makes the algorithm work better, of course. InceptionV3 is a convolutional neural network (CNN) architecture that is a variant of the Inception family. It incorporates various modifications, like smoothed-label and batch normalisation, to enhance its performance. InceptionV3 primarily emphasises optimising computational resources by modifying the previous Inception architectures to enhance their efficiency. It has been discovered that Inception networks are more computationally efficient than VGGNet. As a result of this efficiency, Inception networks generate fewer parameters and use less resources than previous generations. We employed dimension reduction, factorised convolutions, regularisation, and parallel calculations to enhance the efficiency of InceptionV3 for the project.

Excessive Inception is a variant of the Inception module. InceptionV3 is surpassed by Xception on the ImageNet dataset and by a wide margin on a larger dataset with 17,000 classes. Depthwise Separable convolutions necessitate less computing than separable convolutions. Therefore, Xception necessitates a smaller parameter count in comparison to other convolutional neural network variations. However, it is worth noting that depth-wise 2D convolutions can be slower than regular 2D convolutions in terms of computational speed, despite their advantage of requiring less memory. Crucially, it possesses an equivalent amount of model parameters as Inception, leading to enhanced computational efficiency. Xception and Inception differ in yet another manner. Following the initial procedure, the presence or lack of non-linearity is determined. The Inception model incorporates non-linearity by applying filtering and compression techniques to the input space, but the Xception model does not.

The VGG16 model, originally designed as a deep convolutional neural network (CNN), outperforms ImageNet in several tasks and datasets. The purpose is to decrease the degree of parameters in convolution layers and expedite the training duration. VGG16 is widely regarded as one of the most popular models for image recognition. InceptionV3 significantly reduces processing expenses while maintaining high speed and accuracy. InceptionV3 employs directed acyclic graphs for powerful processing.

On the ImageNet dataset and in most conventional classification challenges, the Xception architecture fared better than VGG16, ResNet, and InceptionV3. Conventional network architectures, such VGG16, consist solely of stacked convolutional layers. However, more recent network architectures, such as InceptionV3 and Xception, aim to develop new and inventive methods for constructing convolutional layers as a way to enhance learning efficiency. Thus, our work has employed the VGG16, InceptionV3, and Xception CNN architectures.

1. Variables

Shared parameters → P_S (Network parameters updated for original forest fire dataset)

Task-specific parameters for original forest fire dataset → P_O

Task-specific parameters for Bow Fire dataset → P_n

(X_n, Y_n) ◊ Training data and class label for the Bow Fire dataset

2. Procedure

Y_o = Pre-trained CNN (X_n, P_S, P_O) → find Y_o for each image in the Bow Fire dataset.

Add nodes in the output layer for each class in the Bow Fire dataset.

Initialize P_n with random weights.

Train the network with Bow Fire dataset images.

Compute Yo^ =Pre-trained CNN (X_n, Ps^, Po^)

Compute Yn^ =Pre-trained CNN (X_n, Ps^, Pn^)

Compute loss functions for images in the original and Bow Fire dataset and update P_S, P_O, and P_n.

Repeat from step 4 till convergence

Transfer learning

The process of applying data from a source domain (such as ImageNet) to a target domain with a significantly smaller sample size is known as transfer learning. Usually, this entails starting a model with weights that have already been trained from VGGNet, Inception, or another source, and then utilising it to extract features or fine-tuning the last few layers on a fresh dataset. Transfer learning enables us to repurpose these models for other applications, such object recognition for self-driving cars or caption creation for videos. This study involves the extraction of features and the fine-tuning of a pre-trained model. A concise comment on customisation is provided thereafter.

Extractor of attributes:

This method extracts important features from new samples by using previously learned representations. We have developed a novel classifier that utilises the feature mappings obtained from the previous dataset (ImageNet) and applies them to the pre-trained model. Retraining the entire model using this method is nonessential. The fundamental convolutional network possesses inherent characteristics that can be employed to identify images in a broad sense. The pre-trained model's final classification layer is unique to ImageNet, but our layers are proprietary to the classes the model is customised for.

Appraiser:

Using this strategy, we train the newly added classifications and the unfrozen levels of the models after unfreezing a couple of their top layers. The model's feature representations can be modified, if needed, to enhance their relevance to the unique dataset under analysis. Furthermore, the weights of multiple upper levels of the convolution base will undergo retraining during the fine-tuning phase, in addition to the classification layers. This will be accomplished as a method to attain maximum efficiency. Because the early convolution layers have relatively generic traits, as we go through the network, the layers learn increasingly task-specific characteristics. Therefore, early layers are retained frozen while upper layers are retrained during fine-tuning. By using fine-tuning, we may leverage pre-trained networks to classify distinct categories in datasets that have not been previously trained on. Retraining the weights of the top layers on a new dataset results in fine-tuning, which produces higher accuracy than feature extraction-based transfer learning.

4. RESULT ANALYSIS

To fully utilise deep learning models, it is essential to select the right hyperparameters. A more objective approach would be to search for different hyperparameter values and select the subset that performs the best on a given dataset. This process is commonly known as hyperparameter optimisation or tuning. Any optimisation process begins with the definition of the search space. When looking for something, Bayesian optimisation, random search, and query grid are the easiest and most common ways to do it. In this study, Bayesian optimisation is employed to select optimal values for hyperparameters. The models are executed several times using various sets of hyperparameter values. However, earlier model knowledge is taken into account when determining the subsequent model. The most accurate models can supposedly be reached faster using the Bayesian Optimisation approach. As a result, we employed this search strategy to identify the hyperparameters' ideal values. According to the literature survey, the learning rate, optimizer, activation function, batch size, number of epochs, and number of neurons have all been tweaked in various research endeavours. Therefore, in the suggested study, the aforementioned hyperparameters have been fine-tuned using Bayesian Optimisation.

Table 1: Search space.

Parameter	Search space
Optimizer	Adam, RMSProp, SGD, Adagrad, Adadelta
Number of neurons in customized layers	64, 128, 256, 512, 1024
Activation function	Relu, Elu, LeakyRelu and Tanh
Learning rate	1e−3, 1e−4, 1e−5, 1e−6
Number of epochs	100, 125, 150, 200
Batch size	32, 64, 128

Table 2: Parameters and their values.

Hyperparameters	VGG16	InceptionV3	Xception
Optimizer	Adam	Adam	Adam
Learning rate	1e−01	1e−05	1e−03
Activation function	Elu	Relu	Relu
Number of neurons in customized layers	512	256	256
Number of epochs	100	70	75
Batch size	128	64	64

We conducted tests to assess the efficacy of pre-trained models using feature extraction, fine-tuning, and learning without forgetting. Our more thoroughly models were trained with GPU-enabled Kaggle kernels. Tensorflow and Keras frameworks are utilised to train the models. The models have undergone training using the hyperparameters given in Table 2. Table 3 displays the optimised values of hyperparameters that produced the most favourable outcomes during the training process. The models were executed for 100 epochs, however, we terminated them prematurely. Early stopping is a technique in which the model is trained for an arbitrary number of epochs and then terminated when there is no progress in validation accuracy or reduction in validation loss. As previously stated, we conducted two distinct sets of tests. We removed the classifier from these models and replaced it with a customised classifier to allow us to conduct these tests. We incorporated two fully linked layers and a softmax layer into the VGG16 model. An additional completely connected and softmax layer was successfully used in both InceptionV3 and Xception. We have retrained the fifth, eighth, and seventh top layers of VGG16, InceptionV3, and Xception, respectively, while fine-tuning the models.

Table 3: Accuracy and validation of models.

Models		Validation accuracy (%)	Testing accuracy (%)
VGG16	Feature extractor	95.18	94.38
	Fine tuner	96.32	95.46
InceptionV3	Feature extractor	93.93	92.04
	Fine tuner	97.87	97.01
Xception	Feature extractor	98.27	97.77
	Fine tuner	99.12	98.72

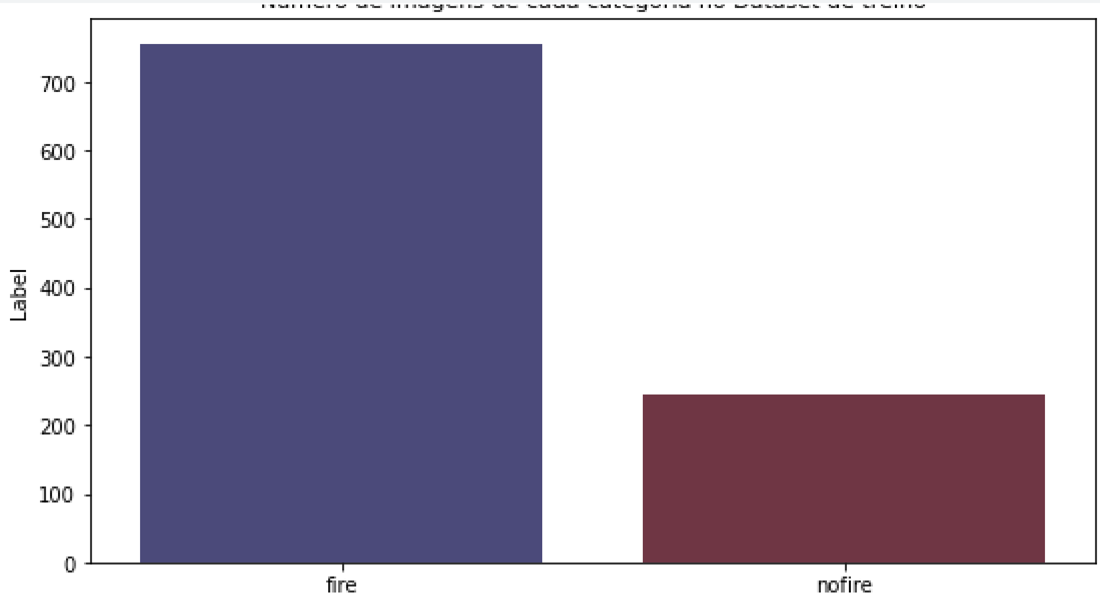
```
import pandas as pd
import numpy as np
import datetime as dt
import os
import os.path
from pathlib import Path
import glob
import cv2
```

The above are the various packages being used for performing the detecting the forest fire along with CNN.

```
filepaths = pd.Series(png_filepaths, name = 'File').astype(str)
labels = pd.Series(labels, name = 'Label')

# Concatenando...
df = pd.concat([filepaths, labels], axis=1)

# Mudando os nomes...
df['Label'].replace({"non_fire_images":"nofire","fire_images":"fire"}, inplace=True)
```



The above figure makes the label of fire and nofire classification based on the various images being used in the datasets.

Training dataset:

Number of images: 899

Number of images with fire: 684

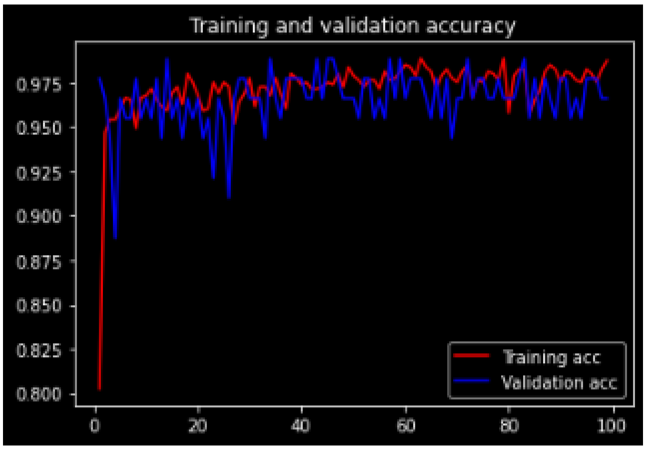
Number of images without fire: 215

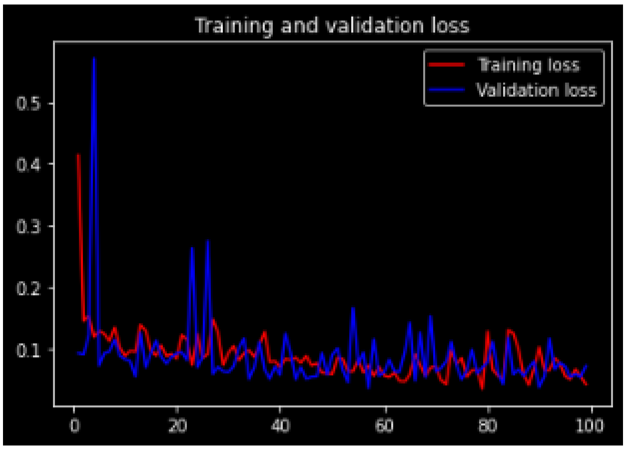
Test dataset:

Number of images in the test dataset: 100

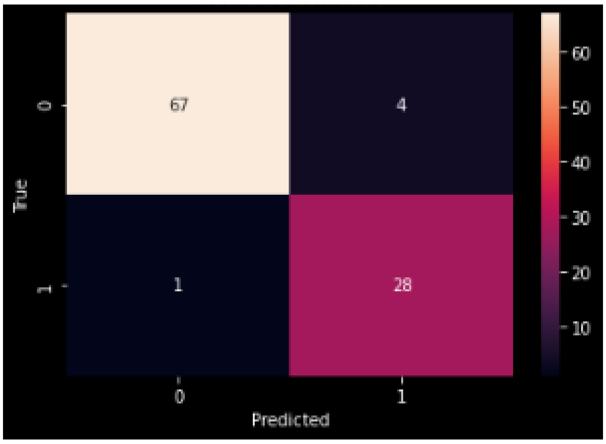
Number of images with fire: 71

Number of images without fire: 29





	precision	recall	f1-score	support
0	0.99	0.94	0.96	71
1	0.88	0.97	0.92	29
accuracy			0.95	100
macro avg	0.93	0.95	0.94	100
weighted avg	0.95	0.95	0.95	100



CONCLUSION

Lessening the disastrous impacts of wildfires requires precise and rapid detection of active flames in their early phases. Few research have focused on actively monitoring flames using deep learning approaches in real-time. Through this research, we aimed to understand if and how smoke and forest fire detection algorithms may mutually benefit from past training. We used the models to glean unique traits and then fine-tuned them by hand-adjusting them. The results show that the Xception-based model outperformed the others, with a 98.72% accuracy rate. We found that the Learning without

Forgetting (LwF) method outperformed feature extraction while preserving the unique characteristics of the original dataset. Surprisingly, the new job fared better than the original dataset when using the parameters that were fine-tuned using LwF. According to new studies, the key to preventing the spread of flames is rapid and accurate early detection. So, we want to keep digging into this field and see what more we can uncover. We want to use state-of-the-art CNN algorithms to swiftly identify fire occurrences while minimising false positives. Learning without Forgetting (LwF) and multitask learning are other topics that pique our attention.

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