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Deep learning framework for forest fire detection using optical images

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ABSTRACT

Reducing environmental and wildlife losses is a burning challenge as the planet' s temperature is increasing. Natural calamities, such as forest fires, have a significant influence on both the acceleration of global warming and the sustenance of life on Earth. Research into the automatic diagnosis of forest fires is essential to investigate which can reduce the likelihood of catastrophic events. Early fire detection can also assist decision-makers in planning measures of mitigation and strategies for extinguishing the blaze. The issue with the existing fire detection methods is that there are many false alarms due to the lesser accuracy of the system. This study investigates the ability to spot fires in images using transfer learning models like ResNet50, InceptionV3, and EfficientNetV2L for four different algorithms in terms of accuracy, precision, and recall metrics. Experimental results are also evaluated based on training time, testing accuracy, and validation accuracy. The study addressed the deficiencies that are present in the existing infrastructure and developed a method that is both effective and reliable in its ability to detect forest fires in the beginning stages, with the end goal of preventing the annual waste of tones of resources that is caused by fires.

Keywords: forest fire; machine learning; deep learning; fire detection

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1. Introduction

Climate change has ushered in a multitude of profound effects, including an increase in the level of the sea, forest fires, intensified storms, and severe droughts, all of which pose significant risks to both human and animal lives worldwide[1]. Forest fires, a widespread consequence of these environmental shifts, pose a particularly grave danger to ecosystems, consistently ranking among the most devastating natural disasters[2]. Due to the significant differences between the characteristics of a forest fire and those of a building fire, the management of a forest fire must be carried out with extreme caution and efficiency. However, conventional solutions have proven cumbersome, costly, and only moderately effective in addressing the forest fire problem. Traditionally, smoke detection and temperature measures have been employed for fire detection[3,4], necessitating a large number of sensors to cover expansive areas. Developing error-proof systems is a difficult task, as it demands considerable time and resources during the establishment phase, highlighting the need for cost-effective solutions that leverage surveillance video streams to minimize infrastructure requirements[5].

The evolution of machine learning (ML) in the field of image processing has revolutionized the prediction and detection of forest fires, finding applications in various fields, including surveillance, advanced mechanics, video search, and more[6–9]. ML-based fire detection algorithms rely on the manual extraction of visual information from images as their foundation. Leveraging convolutional neural networks (CNNs), which have demonstrated remarkable success in image classification, coupled with the groundbreaking advancements in computer vision enabled by deep learning, holds promise for enhancing fire detection capabilities[10–13]. CNN-based algorithms process frames from surveillance systems as input, delivering predictive outcomes to alert systems[14].

The paper investigates the transfer learning models, including ResNet50, InceptionV3, and EfficientNetV2L, for fire detection applications using optical images. Four different algorithms are examined and evaluated based on accuracy, precision, and recall metrics, providing a comprehensive analysis of their effectiveness in detecting forest fires. The study includes a detailed evaluation of various aspects such as training time, testing accuracy, and validation accuracy to compare the performance of the proposed methods with existing approaches. We begin by discussing related work in section 2, followed by an overview of dataset availability and pre-processing in section 3. Section 4 presents the system architectures, while section 5 outlines the methodology adopted for the study. Results and analysis are detailed in section 6, concluding with a summary of findings and suggestions for future research directions.

2. Related work

Transfer learning, a machine learning approach leveraging computers, stands out as one of the most promising methods. In the study of Janku et al.[15], Levenberg' s method was applied to artificial neural networks (ANNs) to expedite solution development, yet encountered accuracy insufficiencies ranging from 61% to 92%, rendering it inadequate for fire detection due to high false alarm rates. Shen et al.[16], mentioned existing arrangements give low precision and a high rate of false alarms, both of which make it more difficult to detect the actual incidence of fire. In addition, the technology was not able to identify fires that occurred in extremely large areas (for example—forest areas, urban areas, warehouses, or oil reservoirs, etc.). Numerous studies have explored the application of CNN in smoke and fire detection, presenting various methodologies and innovations. The study of Chen et al.[17] utilized ResNet and InceptionNet with SVM for fire detection, showcasing ResNet' s superior performance. Li and Zhao[14] proposed techniques for detecting fires using CNN models for enhanced object identification, like YOLO v3, R-FCN, and Faster-RCNN. The accuracy of proposed and current fire detection algorithms was compared, and it was shown that CNNs based on object detection performed better than other techniques. Mahmoud et al.[18] developed a time-efficient fire detection system utilizing CNN and transfer learning, emphasizing its real-time applicability and reduced training time. Tan and Le[19] proved the value of transfer learning by using a well-selected v3-base dataset of recorded and online videos to improve the InceptionV3 and MobileNetV2 models. Cheng[20] introduced Fast R-CNN for smoke detection, achieving higher detection rates with fewer false alarms.

Sousa et al.[21] outlined the common difficulties and restrictions of these methods, along with concerns regarding the quality of the dataset, and suggested a framework that combines data augmentation with transfer learning that has been verified on a variety of datasets. Guede-Fernández et al.[22] developed a real-time smoke detection system using RetinaNet and Faster R-CNN, aiding in wildfire containment. Luo et al.[23] employed motion characteristics and CNNs for smoke detection, while Sharma[24] and Muhammad et al.[25] utilized VGG16, ResNet50, AlexNet, and GoogleNet architectures for fire detection, demonstrating improved performance and were able to discriminate between images that showed the fire and ones that did not. Qin et al.[26] and Jeon et al.[27] introduced novel frameworks utilizing depth-wise separable CNNs and multi-scale prediction techniques, respectively, for accurate fire detection.

It is evident from the aforementioned research studies that CNNs hold great promise for fire detection and can help build a strong system that can considerably lower the loss of life and property caused by fires. This paper investigates the utilization of transfer learning models, including EfficientNetV2L, InceptionV3, and ResNet50, for the detection of fires in the optical images. The traditional approach to machine learning involves manual feature extraction, a process that demands extensive prior domain knowledge and meticulous feature engineering[28,29]. This method is labor-intensive, time-consuming, and prone to errors, especially when applied to new datasets. In contrast, transfer learning proves advantageous by requiring less extensive data collection, computational complexity, and processing power[2,22,30,31]. It offers a compelling alternative by leveraging pre-trained models that have been fine-tuned, reducing the risk of errors and eliminating the need for extensive manual feature engineering.

3. Dataset

A dataset is an essential component for making any kind of CNN architecture comparisons. The models are helpful in finding solutions to issues that occur in the actual world. The dataset was obtained through IEEE Dataport[28], and it consists of 43,965 images that need to be separated into the fire and non-fire categories as illustrated in **Figures 1** and **2** shows some images of the area of interest. The classification of these images is carried out using a deep learning model that incorporates a number of distinct CNN architectural configurations. To assess the model' s accuracy, the images are divided into training, testing, and validation datasets. The datasets utilised to establish the most effective CNN method that may be employed for the goal of fire detection[29] and this is done by analysing the data.

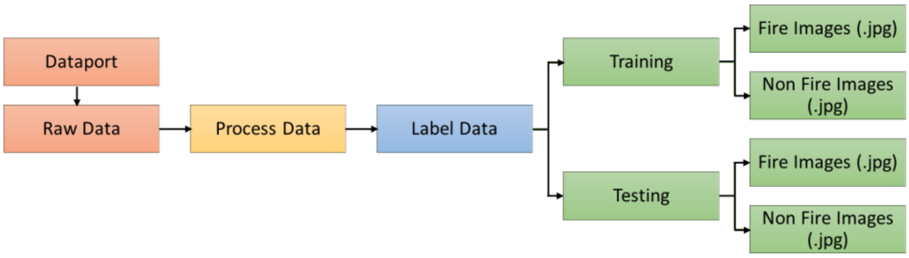

Figure 1. Illustration of the dataset preparation process.

Figure 2. Dataset preview comprising 43,965 images.

4. System architecture

The training of the model consisted of many parts, the first of which was the preprocessing of the data. The other two steps were the extraction of features and the selection of the model. The original data, whether it be an image or a video, is cut up into individual frames and then preprocessed into a format that is appropriate for input into the pre-built model. Deep learning bottleneck features are utilised to construct a feature vector that is then applied to transfer learning[30,32]. In the following stage of the system' s architectural development, the features which are causing bottlenecks will be given to the specific classification model. The building of a classification model was accomplished through the utilisation of the training dataset.

After receiving the results of the classification, subsequent steps are carried out in accordance with the results that were acquired. If the system detects a fire, the appropriate parties will be contacted with the images that include a date and time stamp if it was captured on camera. This will serve as a warning, and the logs will be updated in accordance with the event. **Figure 3** shows the steps involved in system design.

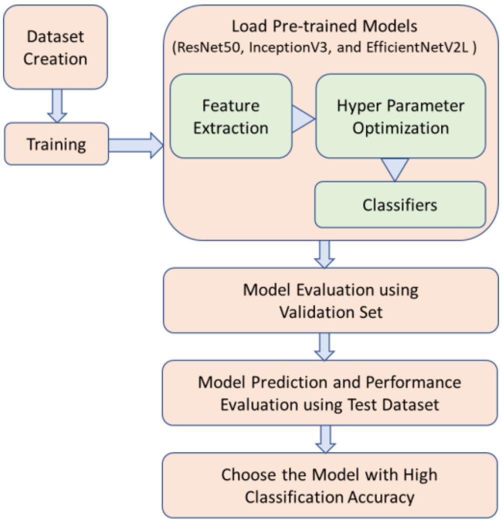

Figure 3. The architecture of the fire detection system.

4.1. ResNet50

ResNet50 is a deep CNN architecture introduced by Microsoft Research scientists in 2015. It was developed to tackle the issue of disappearing gradients in extremely deep neural networks[33]. The name "ResNet50" refers to the 50 layers that make up the ResNet50 architecture, containing a total of 48 convolutional layers. The other layers are referred to as the Max Pooling and Average Pooling respectively. The "residual block" serves as the fundamental building block of the ResNet50 architecture and enables the model to learn residual functions in relation to the input rather than learning the full function from the start.

When compared to models with fewer layers that stack numerous images, multiple-layer neural networks generate a higher amount of mistakes throughout the training process. This enables the model to be more accurate while yet being deeper. Two convolutional layers plus a shortcut link make up each residual block. In order to enable the model to learn the residual function, the shortcut connection skips one or more layers and adds the output of the layers that were skipped to the output of the block.

The ResNet50 design also has a fully connected layer at the end and a global average pooling layer that is used to categorize the input picture into several groups. It is possible to use shortcut connections in the ResNet50 architecture, which enables shortcut connections to reduce the number of training errors. Bypassing some levels of model 0 is made possible by the use of direct linkages.

4.2. InceptionV3

InceptionV3 is another type of CNN model developed by researchers in Google in 2015. It was developed to enhance the accuracy of the classification tasks while maintaining a relatively low computational cost[34]. The InceptionV3 architecture has a number of "Inception modules" that are similar to InceptionNet but have been altered for increased effectiveness and precision. The use of "factorised" convolutions, which divide the convolution process into smaller operations, and the use of these layers, which lessen the dimensionality of the input before performing convolutions, are two examples of these improvements[34]. This model also has a depth of 48 layers, and it is possible to import it directly from Keras.

At the end of the network, InceptionV3 uses a global average pooling layer and a fully connected layer to classify the input image into different categories. These architectures of convolutional neural networks are trained using the ImageNet database, which contains more than a million images. The model is put together using a variety of components, including convolutions, maximum pooling, average pooling, and other building blocks.

4.3. EfficientNetV2L

EfficientNetV2L is another type of CNN introduced by GoogleAI in 2021, developed to improve image classification task accuracy while using the least amount of memory and processing power during training and inference. The design of the model is similar to the EfficientNetV2 model, but with an additional "Lite" dimension that further reduces the model's size and computation[35]. A feature fusion module in EfficientNetV2L integrates the features that were learned by the network' s various layers, enabling the model to capture both low-level and high-level properties of the input picture. To categorize the input picture into several groups, EfficientNetV2L utilizes a fully connected layer after a global average pooling layer at the end of the network. EfficientNetV2L has achieved state-of-the-art performance on a variety of image classification tasks while requiring less computational and memory resources when compared with earlier models.

This model performs noticeably better than the one that was used in the previous generation of CNNs. With increased learning, the model achieves very good results when it is applied to the ImageNet dataset[19]. The training for the model took place in fewer than 24 h. **Tables 1–3** describe in detail the layers and the architecture with the stride and depth of the ResNet50, InceptionV3, and EfficientNetV2L, respectively.

Table 1. ResNet50 architecture.

Stage	Operator	Stride	No. of channels	#Layers
0	Conv 7 × 7	2	64	1
	Max-Pooling	2	1	
1	Conv 1 × 1	2	64	9
2	Conv 3 × 3	1	64	
3	Conv 1 × 1	2	256	
4	Conv 1 × 1	2	118	12
5	Conv 3 × 3	1	128	
6	Conv 1 × 1	2	512	
7	Conv 1 × 1	2	256	18
8	Conv 3 × 3	1	256	
9	Conv 1 × 1	2	1024	
10	Conv 1 × 1	2	512	9
11	Conv 3 × 3	1	512	
12	Conv 1 × 1	2	2048	
13	Max Pooling & FC	-	1000	1

Table 2. InceptionV3 architecture.

Stage	Operator	Stride	No. of channels	#Layers
0	Conv 3 × 3	2	3	1
1	Conv 3 × 3	1	32	2
2	Conv padded	1	32	2
3	Pool 3 × 3	2	64	0
4	Conv 3 × 3	1	64	2
5	Conv 3 × 3	2	80	2
6	Conv 3 × 3	1	192	2
7	3 × Inception (Concat filter, 1 × 1, 3 × 3)	1 & 2	288	12
8	5 × Inception (Concat filter, 1 × 3, 3 × 1)	1 & 2	768	18
9	2 × Inception (Concat filter, 1 × 3, 3 × 1, 1 × 1)	1 & 2	1280	6
10	Pool 3 × 3	-	2048	0
11	FC & Softmax	-	1000	1

Table 3. EfficientNetV2L architecture.

Stage	Operator	Stride	No. of channels	#Layers
0	Conv 3 × 3	2	24	1
1	Fused-MB Conv 1, k 3 × 3	1	24	2
2	Fused-MB Conv 4, k 3 × 3	2	48	4
3	Fused-MB Conv 4, k 3 × 3	2	64	4
4	MB Conv 4, k 3 × 3, SE 0.25	2	128	6
5	MB Conv 6, k 3 × 3, SE 0.25	1	160	9
6	MB Conv 6, k 3 × 3, SE 0.25	2	272	15
7	Conv 1 × 1 & Pooling & FC & SoftMax	-	1792	1

5. Methodology

The first stage is to collect pictures for the problem statement. The dataset consists of the fire images and non-fire images. The images featuring actual fire can be found among the favorable examples. An image could have elements that look like fire but aren’t actually hot. These are examples of what are known as “false positives” in the field. The collecting of false-positive images is a breeze in comparison to the acquisition of fire samples. It is necessary to collect a wide variety of images if we want to improve our ability to identify fires. The images are divided into datasets for training and testing, respectively. There are currently 27,117 fire images in the database from IEEE Dataport and 16,848 images unrelated to fires. For testing, 8600 fire and non-fire images were considered. The model is trained on a computer that has an Nvidia GTX 1650 and a total of 32 gigabytes of RAM and video memory combined.

In the next stage, the image features are retrieved with the help of Keras and a variety of pre-trained models. Because they are trained on such a large variety of datasets, these transfer learning models do exceptionally well when it comes to locating the discriminatory segments. The model is trained using large-scale picture classification issues taken from the ImageNet database. The task of classification is handled by fully connected layers, whereas the task of recognising features is handled by convolutional layers. In the very last stage, we will get rid of the layer that is entirely connected so that we can extract the image feature.

In the end, we will have a feature vector. On the other hand, the dimensions of this feature vector can vary according to the model. Relying on the model, the feature vector’ s length may alter. Transfer learning enables a CNN model which has previously been trained on a difficult set of issues to tackle an easier, more basic problem. The study does not require advanced computational resources because transfer learning entails applying the weights produced from previously taught structures, as shown in **Figure 4**.

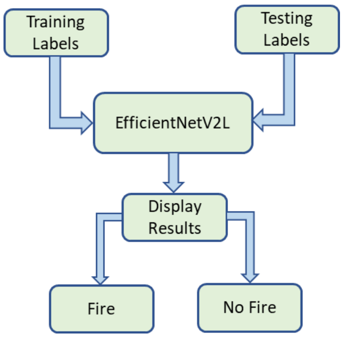

Figure 4. Feeding data and getting the results.

The fact that we do not need to start from scratch when developing the system is by far the most significant benefit offered by the system[36]. There was work done with InceptionV3, InceptionResNetV2, and ResNet50. The process of extracting features from images and executing various machine learning algorithms is the foundation of fire detection in images. **Table 4** analyses how well different transfer learning models function and presents its findings on the basis of accuracy, precision and recall for four different classification techniques. The EfficientNetV2L CNN model was shown to produce the greatest results, followed by the InceptionV3 model and then the ResNet50 model. The combination of EfficientNetV2L and decision trees achieved the best level of accuracy that could be measured.

Table 4. Performance analysis of various transfer learning models.

Network	Algorithm	Accuracy	Precision	Recall
ResNet 50	Decision Tree	98.22%	95.99%	96.25%
	Naïve Bayes	90.21%	93.84%	61.81%
	Logistic Regression	91.68%	91.26%	70.34%
	SVM	95.01%	92.79%	84.78%
Inception V3	Decision Tree	97.50%	96.63%	96.87%
	Naïve Bayes	91.19%	97.43%	79.09%
	Logistic Regression	92.92%	97.21%	83.94%
	SVM	96.83%	97.67%	93.98%
EfficientNet V2L	Decision Tree	98.23%	96.18%	96.34%
	Naïve Bayes	90.21%	74.99%	87.81%
	Logistic Regression	91.47%	98.51%	64.85%
	SVM	96.19%	97.63%	86.39%

6. Results and discussions

The objective of this research was to devise a technique that is able to determine whether or not the images include any fires. In contrast to the conventional procedures, this method is both economical and quick to carry out. In this study, we have evaluated a number of different models that are presently available for transfer learning. The EfficientNetV2L model was selected, along with the decision tree classifier, because it was shown to have superior performance metrics in contrast to the other two networks. The model proved to be the deciding factor. The application was able to achieve a validation accuracy of 99.5% and operated pretty smoothly overall.

Figure 5 demonstrates the testing and validation accuracy of the transfer learning models ResNet50, InceptionV3, and EfficientNetV2L architectures. Also, it is clearly evident that EfficientNetV2L is performing well in terms of testing and validation accuracy. After conducting various experiments with different epochs, it was observed that at an epoch of 50, the models were converging and giving the optimum training time. It can be observed from the figure, that the gap between validation and test accuracy is significant, indicating the better generalization of the model and no overfitting. **Table 5** gives the performance analysis of all three models considering the metrics of training time, testing accuracy, and validation accuracy. With the utilization of transfer learning (TL), video and images can be classified into fire occurrences which can be used for prior detection of wildfires. The proposed model uses optical images to identify instances of fires. The cost of creating the system is extremely low, and expertise in either hardware or a particular field is not necessary for its implementation in any way, shape, or form.

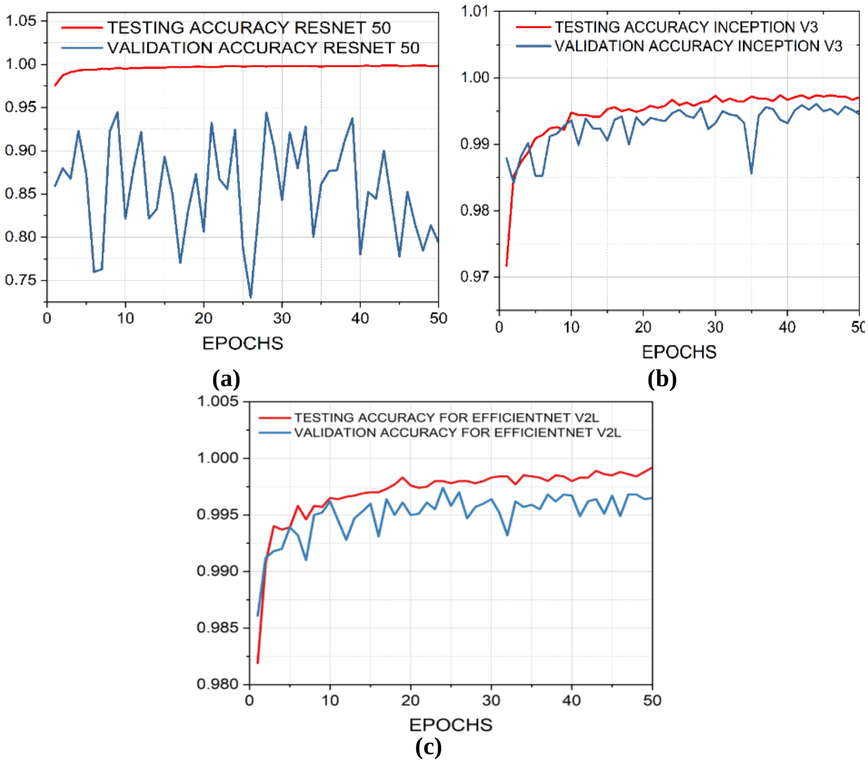

Figure 5. Testing and Validation accuracy for **(a)** ResNet50; **(b)** InceptionV3; **(c)** EfficientNetV2L architecture.

Table 5. Performance analysis of the model.

Model	**Training time**	**Prediction time**	**Testing accuracy**	**Validation accuracy**
ResNet50	12,419 s	1.44 s	99.65%	85.51%
InceptionV3	18,293 s	2.12 s	99.47%	99.28%
EfficientNetV2L	11,797 s	1.37 s	99.70%	99.50%

7. Conclusion and future scope

In the past ten years, computing, calculations, and algorithmic development have all shown exponential growth. Because of these advancements, we have achieved tremendous success in a number of different areas, one of which is the detection of unusual occurrences and activities in surveillance recordings. Every year, forest fire mishaps kill and destroy numerous individuals all over the world, producing huge damage and taking countless lives in the process. To prevent additional harm to the environment, it was necessary to come up with a solution that is accurate and efficient in terms of cost. This could only be accomplished through the utilization of a transfer learning model that is quick enough to identify fires in their incipient stages. The model was trained on the images from the IEEE Dataport and is able to identify fires accurately and quickly enough to be trained in a shorter amount of time. The study compared and analyzed various CNN architectures such as ResNet50, Inception V3, and EfficientNetV2L, for four different ML algorithms: Decision tree, SVM, logistic regression, and Naive Bayes. Based on accuracy, precision, and recall, the EfficientNetV2L model performs best in comparison to the others. In comparison to the previous systems, this form of fire detection is not only more affordable but also more accurate.

Recent studies have shown that it is essential to recognize fire incidents as fast and accurately as possible in the early phases of their development in order to stop them from spreading. As a direct result of this, we intend to carry on with our research in this area and make our findings even more comprehensive. We intend to implement the most recent CNN models in the near future so that we can promptly discover fire occurrences while maintaining a low percentage of false positives.

Author contributions

Conceptualization, DG and PK; methodology, DG; software, PK; validation, DG, PK and RS; formal analysis, DG; investigation, PG; resources, DG; data curation, RS; writing—original draft preparation, DG; writing—review and editing, DG; visualization, DG; supervision, RS; project administration, RS. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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