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Deep Learning-Based Forest Fire Detection Using MobileNetV2: A Comprehensive Study and Performance Evaluation

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Abstract: Early detection and correct recognition of flames are essential to protect property and human life. This working paper seeks to study several publicly approaches, including deep learning-based approaches, for identifying and differentiating fires. To achieve exact fire detection and classification, the research has proposed a unique method that combines the MobileNet backbone with the Convolutional Neural Network (CNN) configuration. This model performs the best according to the results, boasting an impressive 98% accuracy rate on a challenging and lucrative dataset. The use of cutting-edge technology is a significant weapon in the fight against fire catastrophe, as it immediately highlights the significance of highly effective fire detection in minimizing potential damage and/or the size of the calamity. The current work uses a noteworthy method for detecting fire occurrences in the environment under various conditions: extensive testing and analysis of the suggested CNN+MobileNet algorithm, demonstrating excellent accuracy levels. The findings of this study provide essential building blocks for the automated fire detection system, which will raise public awareness of safety by encouraging the adoption of preventative measures in areas prone to fires.

Keywords: Deep learning; Classification; sustainability; forest fires.

1 Introduction

Because of the strength of natural disasters, fires can endanger individuals, their cherished possessions, and the surrounding area.[1] Natural disasters occur randomly across a wide range of environments, including grasslands, forests, shrublands, and deserts.[2] They can travel quite quickly, especially in strong winds. If the fires are not promptly found and put out, woods, wildlife, and human settlements might all be destroyed. Deaths, financial losses, and ecological disturbances could follow from this.

Accurately and quickly identifying fires is essential to averting severe catastrophes and minimizing damage and human casualties. Conventional fire detection systems depend on specific sensor support, such as temperature, gas, smoke, and flame detectors.[4] Although this strategy was incredibly successful, it had several shortcomings, including restricted coverage areas, sluggish reaction times, and complex public access. Thankfully, advances in computer vision and image processing techniques have created new avenues for automated fire detection.

The visual fire detection system is better than conventional sensor-based methods. These systems' mechanism uses color, form, and movement as visual cues to detect fires using cameras and image processing algorithms. Because these vision-based technologies can identify fires in real-time, analyzing current and recorded video feeds makes it easier to respond to an incident and apply chemical intervention. Conversely, as this study demonstrates, sensor-based technologies are typically more affordable, scalable, and adaptable to various environmental circumstances [6].

Manufacturing advancements in image processing, computer vision, and machine learning have sped the dynamic of fire detection strategies, allowing the academic community to examine and thoroughly exhaust many fire detection systems. The color analysis technique is well-liked because it takes advantage of these varied aspects of fire and sets itself apart from other firefighting tools. This method divides an image into many color spaces using thresholding algorithms and then uses algorithms to classify the pixels into fire and non-fire areas. In addition to optical flow, feature-based techniques like dynamic texture analysis have been used to develop high-level fire detection features [7].

Using machine learning, vision technology, and image processing, researchers have conducted several methodical studies on fire detection. Because fires have distinct hues, professionals who investigate fires employ color analysis techniques. Each pixel's emissivity is determined to determine whether or not it has burned, as this eliminates specific color spaces. One of the human eye's other talents is locating fire sources in excellent resolution. Dynamic texture analysis and optic flow are feature-based techniques frequently used to do this task. It is a powerful tool if deep learning

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can be specifically trained to determine when a fire emergency has occurred. The application of CNNs—a kind of deep learning model—in image processing technologies is among the most notable instances of their use. CNN models may recognize and categorize photographs and videos taken during fire exercises, as they have proven. The CNN model easily separates fire entities from non-fire sorts of data by using machine learning and a hierarchy feature definition method that depends on raw pixel data. In this approach, CNNs can recognize patterns in fire and incorporate them into their design. Thus, this research aims to demonstrate CNNS as a kind of deep learning and determine whether or not fire detection and classification can be accomplished with it. Using CNNs and developing novel image recognition techniques, the suggested method for implementing the system seeks to improve fire detection systems' efficiency, accuracy, and dependability. This project aims to create effective fire detection techniques through extensive testing and performance analysis; as a result, we will safeguard people, the environment, and property.

2 Related works

To identify and track the flames, the research assessed and investigated vision transformers and deep learning networks [9]. When wildfires start to occur more frequently due to the effects of climate change, it will be necessary to implement automatic fire detection systems based on cutting-edge technology. The study looks at the primary research that suggests using deep learning approaches to solve this issue. It emphasizes the advantages of using traditional machine learning algorithms over their drawbacks. This work aims to understand the reasons behind the widespread use of those datasets and the difficulties they encounter. This data indicates that deep learning algorithms will be the most advantageous in future efforts to identify, segment, and classify wildfires.

In this article, we [10] explore how convolutional neural networks (CNNs) and transfer learning can be applied to computer vision applications that use AI to detect fire and smoke in photos. This research aims to address the deep neural network transfer learning problem, which results in poorer classification performance and longer training times when pre-trained models are used. Following InceptionV3, Xception, and other pre-trained models—which are necessary for fire detection applications to improve the accuracy and efficacy of their results—transfer learning can be used. The findings show that Xception produces a maximum correctness of 98.72%, indicating that further development is probably possible when using the LwF technique. In summary, the suggested approach Xception beats LwF on a fresh validation dataset with an accuracy of 91.41% and spends 96.89% of the time on the previous data, demonstrating that the suggested method adapts to new workloads with minimal accuracy loss on the current data. The analysis in this work shows that the proposed models perform better and emphasizes how LwF provides new data tasks without sacrificing performance compared to the original ones.

This study will separate fire pixels [11] from image and video datasets [12] using computer vision. To keep abreast of the rampant forest and wildfires of recent times, the need for functional fire warning systems has become paramount. Although deep learning algorithms are increasingly used in fire analysis, they usually perform poorly in simulating fire in cases where there is a lack of data and are highly sensitive to changes in data complexity. To circumvent these challenges, a machine learning procedure is used to identify relevant features from public and private datasets. This is accomplished through feature selection techniques. To add more, it turns out that discriminative features for categorization with little computational expense are found using information-theoretic feature selection strategies.

Consequently, RBF can be merged with the traditional SVM machine classifier to classify pixels as fire or no fire. The model attains impressive performance metrics that indicate an overall accuracy of 96.21%, sensitivity of 94.42%, specificity of 97.99%, precision of 97.91%, recall of 94.42%, and F-measure and G-mean values of 96.13% and 96.19%, respectively. It follows from the results gained to differentiate the pixels on fire from those that are not, proving the possibility of improving the fire detection system.

This article [12] attaches great importance to forest fire detection, reminding us that immediacy and accuracy are crucial in quick and effective emergency response. The research aims to attempt to apply pre-trained networks for forest fire detection. Through human-based machine learning evaluation on the Fire Luminosity Airborne-based dataset acquired by Unmanned Aerial Vehicle, many deep learning algorithms are evaluated, such as InceptionV3, DenseNet121, ResNet50V2, NASNetMobile, and VGG-19. Algorithm performances are enhanced using transfer learning techniques. Hybrid methods use algorithms like Support Vector Machine, Random Forest, Bi-directional Long Short-Term Memory, and Gated Recurrent Unit. The model was a significant accomplishment, with DenseNet121 getting 97.95% accuracy when initialized with random weights and 99.32% with the ImageNet weights in the transfer learning methodology. The study presents future studies and operations for this critical area, with transfer learning suggested as a powerful tool in forest fire detection and management.

The primary goal of this work is to explain a problem that is becoming increasingly globalized: forest fires are caused by human activity and climate change [13]. The work highlights the importance of early and precise detection to lessen the destructive impact of forest fires. It also presents a novel approach to identification that uses the Detectron2 platform and a deep learning method. The algorithm, which can achieve substantially higher precision than current methods, is trained using a dataset of 5200 annotated trainable pictures. The experimental conditions are given where the suggested approach is broadly applicable and has a high capacity for long-range, daytime, and nighttime small flame detection. With the help of the Detectron2 algorithm, the effectiveness of the fire detection method has increased, and its accuracy has improved to a much higher 99.3% precision rate. These results show that the suggested approach may help minimize the effects of forest fires in the actual world while aiding in their detection.

This research work [14] will implement deep learning algorithms on photographs of fire scenes to fulfill the aim of real-time prediction of fire heat release rate (HRR) in sudden fire situations that traditional fire calorimetry techniques cannot efficiently capture. The main objective is to use 69,662 pictures taken at custom fire scenarios, using the kinetic heat release rates and collecting a huge sample of 112 fire tests from the NIST Fire Calorimetry sample necessary for the training deep learning model. The next step is to determine how many real fire examples and fire lab tests the algorithm will be able to deploy to a wide range of fire sources, backdrops, lighting conditions, and camera settings. The results demonstrate the potential of deep learning algorithms to provide an alternative method of measuring fire HRR in situations where conventional calorimetric methods are impracticable. Specifically, the AI-image fire calorimetry method proposed here can successfully identify transient fire HRR based solely on fire scene images. This research provides positive suggestions for integrating deep learning into intelligent firefighting systems.

This study's [15] objective is to create a more potent early detection system to lessen the increasing incidence of forest fires in India. Although currently in use, satellite-based systems have limited frequency and alert-sending capabilities. The research suggests using high-resolution surveillance cameras and GPS-equipped uncrewed aerial vehicles (UAVs) to detect forest fires more quickly and precisely. UAVs are expected to classify forest fires with a very high accuracy level—97.26 percent—by utilizing deep learning frameworks or, more precisely, improving upon MobileNet. The concept is centered on quickly providing state forest agencies with information about fire detection and its GPS locations so they may promptly deploy all essential firefighting resources. This technique makes it possible to detect forest fires earlier and more economically, which reduces the amount of property they are likely to destroy.

The automated fire extinguisher system developed in this research uses deep learning to monitor fires and put them out before they start. The method, which uses convolutional neural networks (CNNs) as its foundation, can locate people inside fire zones and identify active fires. In particular, we implement AlexNet architecture for human detection and build a learning network for fire warning. The model is assessed using various optimizers, activation functions, and learning rates to determine the most effective set. Wireless control and automatic settings are used to maneuver the robots. The setup that seems to function the best is chosen. In our scenario, the robot patrol and fire spot supervision are carried out in "automatic mode." Using built-in features that activate once the built-in model learns from the data may do auto-extinguished firefighting.

Using images of the surrounding forest region, this study [17] aims to evaluate the classification accuracy of several classifier models for efficiently recognizing forest fires. Deep neural networks (DNN) and conventional classifiers are assessed using landscape images from the Mendeley repository. Many parameters are used for comparison, including accuracy, sensitivity, specificity, precision, and false negative rate. The DNN-3 classifier achieves impressive results with ResNet50 deep features extracted from photos: 97.11% accuracy, 96.84% sensitivity, 3.16% false negative rate, 97.37% specificity, and 97.35% precision. The recommended ResNet50+DNN-3 model performs exceptionally well when combined with real-time IoT and embedded system applications, and it might end up in expert systems supporting forest monitoring and protection units.

3 Methodologies

Our methodology involves a few vital phases, namely data preprocessing, segmentation model creation, and classifier model creation, and then merging the two into one final pipeline for better tumor segmenting.

Data Collection and Preprocessing:

The study's dataset came from two primary sources: The folders "fire_images" and "non-fire_images," which were used to represent the photos of 755 outdoor fires (some of them were very smoky), and 244 nature images, which showed the diversity of landscapes. To ensure the depiction of two conditions, namely fire and non-fire, are presented in a well-balanced manner, this photo set was prepared carefully. Then, the dataset was thrown into two training and testing sets, with approximately 20% for testing and 80% for training purposes. The images went through the MobileNetV2 preprocessing function; this means scaling and normalizing and subsequently reducing to a size of 224X224 pixels before training.

Model Architecture:

The MobileNetV2 convolutional neural network, a popular pre-trained model for image classification tasks, was the foundation for the model design. The selection of MobileNetV2 was based on how well it handled image data. The top layers of the pre-trained MobileNetV2 model were loaded with frozen states to take advantage of the features learned from an extensive dataset. Subsequent layers were incorporated to optimize the model for the particular purpose of detecting fires. These extra layers consisted of dropout layers to stop overfitting and fully connected dense layers with ReLU activation functions. To output the probabilities of each class (fire or non-fire) in the input image, a dense layer with softmax activation comprises the final output layer.

MobileNet Architecture:

Convolutional neural networks (CNNs) with efficient topologies like MobileNet are geared at embedded and mobile vision applications. Google researchers created it to solve the problem of implementing deep learning models on devices with limited resources, like tablets, smartphones, and Internet of Things gadgets. The MobileNet architecture is well-suited for real-time inference on devices with constrained computational resources because it strikes a compromise between model size, computational complexity, and accuracy.

Depthwise separable convolutions, made up of depthwise and pointwise convolutions, are the primary innovation of MobileNet. Depthwise Convolutions: A conventional convolutional layer involves many computations because each filter works on the whole input volume. Conversely, depthwise convolutions apply a different convolutional filter to each input channel. This drastically lowers the computing cost by reducing the number of procedures and parameters. Pointwise Convolutions: The outputs from the depthwise convolutional filters are combined using pointwise convolutions, also called 1x1 convolutions, applied after depthwise convolutions. Using 1x1 filters, pointwise convolutions efficiently blend and change the information that depthwise convolutions have learned by performing channel-wise linear transformations.

Training and Optimization:

The model was trained using categorical cross-entropy as the loss function and the Adam optimizer with a learning rate of 0.0001. Three callback functions were used to monitor the training process and prevent overfitting: TensorBoard was used to visualize training metrics, ModelCheckpoint was used to save the optimal model weights based on validation accuracy, and EarlyStopping was used to stop training if the validation loss did not improve for a predetermined number of epochs. The model was trained using a batch size 32 and ran for 100 epochs. Its performance was assessed on both training and validation datasets.

Evaluation metrics:

The model was assessed for performance using a variety of measures after training was completed. The two main measures considered were accuracy and loss, which provide information about the model's generalization performance and predictive power. A confusion matrix was created to show the categorization findings and highlight instances of inaccuracy visually. The model's performance in several categories was assessed by computing precision, recall, and F1-score metrics for each class (fire and non-fire). Lastly, once the Reports were completed, we aimed to thoroughly summarize the model's advantages and disadvantages and analyze its performance based on various evaluation indicators.

Classification metrics:

Accuracy is determined by dividing the number of correctly stratified instances by the total number of cases. It gives a general picture of how well the model performs in determining which brain MRI imaging regions are tumorous and which are not.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where:

TP: True Positives

TN: True Negatives

FP: False Positives

FN: False Negatives

Confusion Matrix: The confusion matrix offers a comprehensive analysis of the model predictions by displaying, among other things, true positives, false positives, true negatives, and false negatives. The confusion matrix also provides us with other measures, including recall, precision, and precision-recall (F1-scores).

Precision, also known as positive predictive value, is the percentage of accurate optimistic forecasts among the model's positive estimates. It demonstrates how well the model removes false positives.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

where:

TP: True Positives

FP: False Positives

Recall (also called sensitivity): The percentage of true positive predictions among all actual positive samples in the dataset is measured by recall, also called sensitivity. It measures how well the model can identify good examples.

F1-Score: This balanced indicator of the model's performance is calculated as the harmonic mean of precision and recall. It is appropriate for imbalanced datasets since it considers false positives and negatives.

$$F1\ score = 2 \times \frac{Precison \times Recall}{Precision+Recall} \tag{3}$$

4 Results

The classifier model successfully distinguished between photos with and without fires, as seen by its excellent accuracy of almost 98% on the test set. A thorough examination of the confusion matrix validated the model's performance, showing few misclassifications. As in Figure 1, a comparison between the training loss and validation loss was made, while Figure 2 shows the training accuracy and validation accuracy results; in Figure 3, a confusion matrix was visualized to show how well the model classified the tumors.

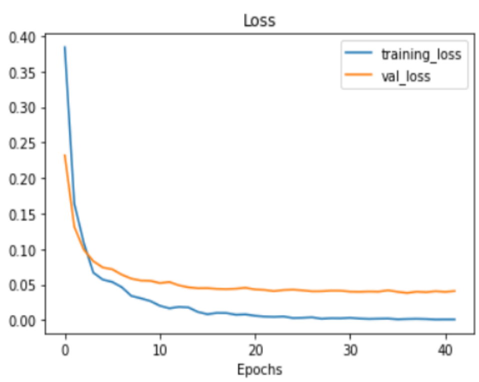

Fig. 1: training and validation loss results.

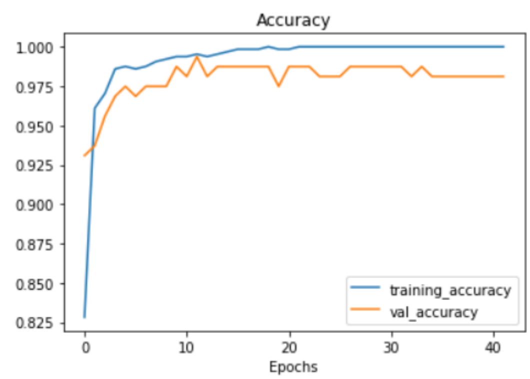

Fig. 2: training and validation accuracy results.

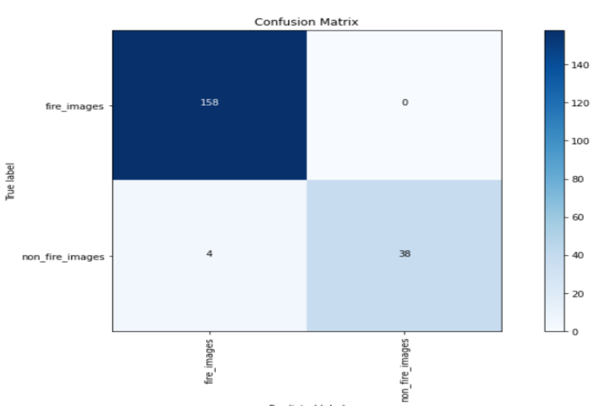

Fig. 3: Confusion matrix of the proposed model.

	precision	recall	f1-score	support
fire_images	0.98	1.00	0.99	158
non_fire_images	1.00	0.90	0.95	42
accuracy			0.98	200
macro avg	0.99	0.95	0.97	200
weighted avg	0.98	0.98	0.98	200

Fig. 4: Classification report.

5 Conclusions

The main goal of this research remains to classify forest fires using visual data using MobileNetV2, the latest neural network methodology. A large dataset containing only two types of photographs (with and without fire) was used. As a result of applying meticulous preprocessing and augmentation methods, the model was enhanced and developed consistently.

In our experiments, this model performed well, as can be seen by the % obtained on the test dataset. The loss curves, confusion matrix plots, and the access to precision, recall, and F1-score metrics in the classification report have clarified the training course and classification performance. It is foreseen that these findings will ensure better access to early warning systems and emergency response operations as it will enhance automatic fire detection. To improve forest fire management and prevention measures, further research could improve the model architecture, investigate different preprocessing methods, and continuously incorporate real-time data streams to monitor fire-prone areas.

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