Detecting Wildfire-Damaged Areas From Satellite Images Using Deep Learning

Esmanur Alican[1] and Caner Ozcan[2]

[1] Department of Computer Engineering, University of Karabuk, Karabuk, 78050, Turkiye
[2] Department of Software Engineering, University of Karabuk, Karabuk, 78050, Turkiye

Abstract

Rapid detection of forest fires is crucial to reduce their devastating impact on ecosystems and human lives. In this paper, we present an AI-based solution for forest fire detection using deep learning from satellite imagery using the ResNet50V2 convolutional neural network (CNN). The dataset used to train the model consists of 1,900 images (950 per class), carefully curated to reflect real-world scenarios of both active forest fires and undisturbed forests. Data preprocessing included image augmentation to reduce overfitting and enhance model performance. Transfer learning, model regularization, and reconstructed pooling layers were applied during training on this dataset, which was augmented with techniques such as random horizontal rotations, zooming, and cropping to improve model generalization. The model achieved 97.63% accuracy and 98.40% precision in detection. Forest fire detection using satellite images is very useful because CNN methods can detect and locate active fires more than once per hour. It is well known that the earlier a forest fire is detected, the more effective it is for people and the environment. This method can help to develop of new strategies for real-time fire monitoring systems, in addition to greatly enhancing wildfire management and prevention efforts. This study focuses not on early fire detection, but on identifying post-wildfire damage using deep learning techniques applied to satellite imagery.

Keywords

Forest; Forest fire; Detection; Deep Learning; ResNet50V2

1. Introduction

A forest is a closed area of trees, other plant species and animals at a certain level of closure, together with the invisible is defined as a living system and community in which organisms interact [1]. The world's forests cover a total cumulative area of a staggering 4.06 billion hectares, covering about 31% of the planet's land area [2]. Climate change is expected to have a particularly significant impact on boreal forests due to rapid and significant temperature increases in this region [3], as each additional degree of warming could result in a tripling of the area burned [4]. Therefore, the aim of this study is to determine how much land is destroyed after the fires are extinguished by using artificial intelligence (AI) integrated systems. By identifying affected regions after fire events, the proposed model can support post-disaster assessment and resource planning.

Deep learning, as a subset of AI, has the ability to enhance the detection rate of fires and other natural disasters using large datasets [5]. More specifically, image processing techniques have also been proposed that would benefit the response time by improving the ability to spot a forest wildfire in its early stages [6]. It is also noted that deep learning (DL) image classification models are able to successfully analyze visualization artifacts such as smoke and flames in order to determine the presence of fire [7]. DL models such as ResNet50v2 have recently achieved high accuracy rates in forest fire detection in remote sensing application systems.

ResNet50v2[8], a convolutional neural network model, effectively recognizes key details underlying images from image-trained data due to its layered structure. This model is particularly useful in building a forest fire detection system because it maintains its efficiency even with very large datasets [9]. The content of the image passes through the network with less distortion and easily through the use of "residual" connections, which enables ResNet50v2 to speed up the learning process, thus improving the

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esmnralicann@gmail.com (E. Alican); canerozcan@karabuk.edu.tr (C. Ozcan)
0009-0003-0575-7766 (E. Alican); 0000-0002-2854-4005 (C. Ozcan)

overall accuracy [10]. This characteristic feature combined with the strength of the neuron structure, allows ResNet50v2 to be useful in practical problems requiring high accuracy, such as fire detection.

Wildfires can have a devastating effect on ecosystems, people, and economies especially in areas vulnerable to wildfires. Current methods of fire remote sensing via satellite still struggle with offering timeliness, precision, or flexibility. Most of the traditional approaches depend on systematic monitoring (by humans) or use local sensor networks. This aids in scaling detection but isn't helpful in real-time detection over extensive areas. An AI-based method that utilizes satellite images to quickly pinpoint the exact location of the wildfires and assist with rapid aid is highly essential.

For this study, we used the Forest Fire Detection Dataset presented by Khan and Hassan[11] and available from Mendeley Data. This dataset contains a large number of images specifically selected for the purpose of forest fire detection. It is a balanced dataset consisting of 1900 images in total, with 950 images belonging to each class. The comprehensive size of such a dataset also makes it suitable for the effective development of a DL model that can positively contribute to the early detection and monitoring of forest fires.

The purpose of this paper is to recommend an AI-based approach for fast and effective detection of forest fires. In this regard, the authors trained the ResNet50v2 model which was prepared on a large dataset for forest fire detection and evaluated the model's performance. The focus of this research is to find possible extensions to current fire detection systems and to emphasize the use of AI in the management of environmental threats.

2. Related Works

Over the past few years, there has been significant attention towards the applications of AI and DL on detecting forest fires [12]. Attempts have been made on the researches front to build models that help in detection of wild fires in real time, through the usage of computer vision as well as machine learning. Several satellite imaging as well as ground sensors, and unmanned aerial vehicles have been integrated into the wildfire monitoring systems that help in detecting, analyzing, and responding to these events in real time [13]. The detection of wildfires has also been effectively done through various DL structures.

Harkat et al. and Yang et al. [14,15] have shown that DL does not perform adequately due to limited data, generalization, interpretability, and missing features, but integration of DL with other methods can improve efficiency. Sathishkumar et al. [16] used DL based forgetting learning technique for forest fire and smoke detection. VGG16, InceptionV3 and Xception models were trained with fine tuning and their performances were compared. They utilized deep learning-based learning for fire and smoke detection, highlighting the potential of AI in early fire detection systems. In another study, Best, et al. [17] compared frozen VGG, 4-layer CNN, and fully trainable VGG for UML diagram classification and showed that the frozen VGG achieved higher accuracy with reduced sample size and required less computation time compared to the fully trainable VGG.

Achieving efficient and fast operation of endpoint devices is one of the achievements of Peng et al. [18] with their proposed fire detection algorithm. An effective balance between accuracy and speed is achieved by using quantization-compatible activation functions, a QARep component, and image size optimization using a YOLOv8 algorithm. While image transfer has a positive impact on accuracy, there is an impact on accuracy with respect to INT8 quantization, resulting in some loss of accuracy. The study by Ginkal et al. [19] explores the use of AI methods for forest fire detection. The study provides an AI-based framework for early detection of forest fires. The framework uses machine learning techniques to perform fire detection by combining color, motion and shape features. Features such as color probabilities, color histograms and image moments are used for fire region segmentation, classification, and verification. Experiments show that the proposed framework works with high accuracy and provides real-time processing time.

Another research article by Titu et al. [20] explores the integration of lightweight DL models for real-time fire detection using drones and edge computing. Using knowledge distillation techniques, the study develops DL models such as Detection Transformer (DETR), Detectron2, and YOLOv8. Using this approach, the YOLOv8n model achieved the highest accuracy (95.21%). In another study in a similar area, Anh et al. [21] offer a different approach to detecting forest fires with UAVs, using different color spaces in combination with correlation coefficients to determine the actual fire area.

Liu et al. [22] propose two AI agents armed with large digital databases that autonomously control fiber optic temperature monitoring systems and DL algorithms to detect fires in large commercial spaces. The research examines the effectiveness and reliability of this combined approach and expresses how it can revolutionize fire safety measures when applied to large commercial spaces. In their work, Dampage et al. [23] propose the use of wireless sensor networks in conjunction with machine learning to detect wildfires at very non-extensive stages. Machine learning models are used to evaluate data gathered by sensor networks, so as to estimate the likelihood of a wildfire. In a second part, rechargeable batteries and a solar-powered power supply are used to ensure that the system remains energy efficient.

To summarize, previous research has shown that image-based wildfire detection can be performed with deep learning models VGG, Inception, and variants of YOLO. However, most of these works emphasize detection and monitoring using UAVs or ground sensors. Relatively few have attempted the post-wildfire damage identification using satellite images with high accuracy CNN architectures like ResNet50V2. Our study seeks to fill this gap by utilizing a powerful transfer learning technique for detecting wildfire damage using satellite imagery, providing a valuable resource for post-disaster evaluation and recovery design.

3. Methods

3.1. Data Collection and Data Pre-Processing

The dataset for forest fire detection is a comprehensive and carefully selected resource specifically designed to assist the development of algorithms for tasks such as forest fire detection and object detection. The images are the result of a search for different keywords in different search engines. As depicted in Fig. 1, designed for the binary problem, the dataset of 1,900 images (950 images per class) is divided into two main categories: The first category contains images documenting active forest fires, while the second category contains images of undisturbed, fire-free forest areas.

Figure 1: Dataset content examples [11].

To improve the performance of machine learning and DL models, all images in the dataset are three-channel with a spatial resolution of 250 × 250 and consistent formatting. Each image in the dataset is carefully reviewed and pre-processed to remove irrelevant elements, such as human activity or firefighting equipment, to focus only on fire and non-fire regions. This is important for the model that will be used for training, as it eliminates false positives when the model is asked to identify areas of the forest that have burned and those that have not.

This balanced division of the dataset is critical for the model used in training to accurately distinguish between fire-affected and burned areas in forested and unaffected areas. As shown in Table 1, the dataset is divided into three subsets; this separation allows the model to be effectively trained on a variety of samples while achieving higher accuracy rates on the test data.

Table 1
Train, validation, and test distribution in dataset.

Set	Class	Original Count	Augmented Count (Estimated)
Training	fire	608	19456
Training	nofire	608	19456
Validation	fire	152	0
Validation	nofire	152	0
Testing	fire	190	0
Testing	nofire	190	0

Augmentation was performed here because the number of data in the dataset is not sufficient for the ResNet architecture and would lead to overfitting of the model. Initially, 20% of the training data was reserved for validation. As shown in Fig. 2, augmentation was then applied at each step of the training: horizontal rotation of the images, random zooming, and certain cropping operations were applied separately for each data in the dataset. For the test data, the data was only scaled to "1./255". Applying the augmentation to the test data may not reflect the real performance of the model and may lead to misleading results.

Figure 2: Augmentation example.

3.2. ResNet50v2 Model Architecture

Convolutional Neural Networks (CNNs) are among the fundamental building blocks of DL methods, and they're popular in tasks such as image and computer vision [24]. CNNs are based on extracting local features from high-order inputs and passing them to lower layers for more complex features [25]. This process allows the model to learn and achieve more accurate results. However, CNNs frequently tend to have issues training deeper, especially in deep networks. This is where deep network architectures like ResNet50v2 can provide a solution. ResNet50v2 is a member of the Residual Networks family and adds an important innovation to the traditional structure of CNNs: residual or jump connections [26]. These structures help solve the problem of gradient loss as the depth of the network increases.

Using ResNet50V2 architecture involves opting for residual blocks which helps to bypass the issues of vanishing and exploding gradient problems during deep representation learning. The purpose of this residual block is captured in an equation that includes the image to be processed, pre-trained weights corresponding to the YOLO CNN, and skip connections. This method is superior at producing results when there are variations in dimension [27]. Furthermore a solution to the degradation is provided using DL framework where the mapping of the layer of the non-linear stack is treated as a 'cut' from the original input.

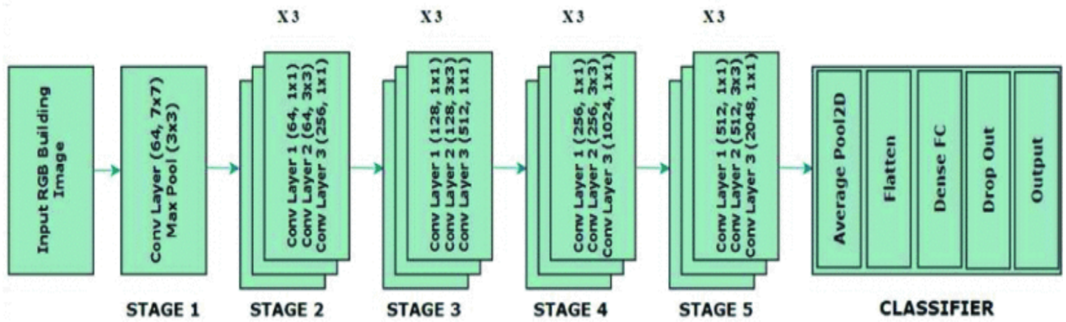

Figure 3: ResNet50v2 architecture.

The application of ResNet to computer vision has shown outstanding performance [28]. ResNet18, ResNet50, and ResNet101 are the most widely used types of ResNet networks. Among these network types, ResNet50 has achieved better identification accuracy and real-time performance [29]. The number 50 in its name represents the 50 layers that make up the ResNet50v2 architecture. These layers include the convolutional layer, the batch normalization layer, and the ReLU activation function [30].

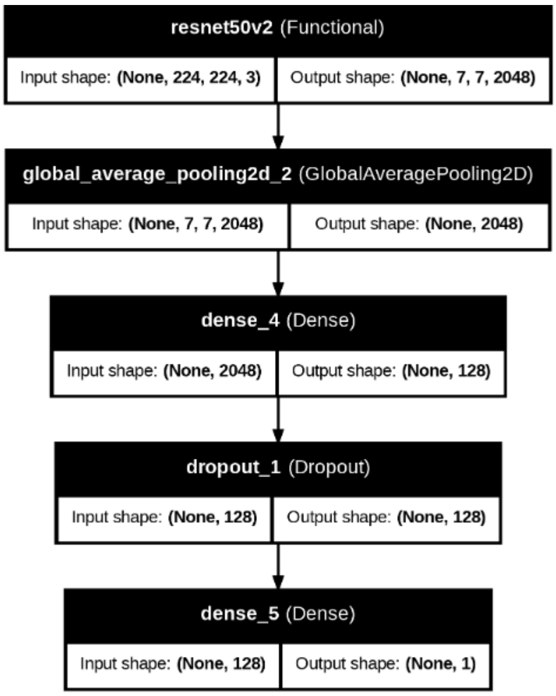

Figure 4: ResNet50v2 model architecture.

In this paper, the transfer learning method of the ResNet50v2 model is used to implement a DL model using the Keras library. In order for the model to efficiently extract features from the input data, ResNet50v2 is used as the base feature extractor with pre-trained weights on the ImageNet dataset. The model is loaded with a structure that excludes the classification headers, allowing only feature extraction. The architecture of the model as illustrated in Fig. 3, is built on top of ResNet50v2 as the base feature extractor and enriched with Global Average Pooling and Fully Connected (Dense) layers. This allows for a more compact feature set, greatly reducing the number of parameters required. The goal at this stage was to remove unnecessary complexity from the model.

The model is completed with Global Average Pooling and Fully Connected (Dense) layers. Global Average Pooling takes the average value of each feature map to create a more compact summary vector and reduce the number of parameters. This step increased the efficiency of the model. The resulting vector was transferred to a 128-neuron dense layer, where the risk of overfitting was reduced using the ReLU activation function and L2 regularization. In addition, a dropout layer was added and applied at 50% to increase the generalizability of the model. The output layer is built to perform binary classification using a sigmoid activation function and represents the model's classification decision as a value between 0 and 1.

4. Experimental Results

In this work, the ResNet50v2 model was transformed into a transfer learning model that was trained on a dataset defined as a forest fire detection dataset. The data was cleaned with fire and non-fire images in an equally weighted ratio. To increase variability and prevent overfitting in the data augmentation stage, random horizontal rotation, zooming, and cropping were applied during the training set hours to allow variability while ensuring that overfitting is contained. The validation and test sets did not require augmentation, although the test set was normalized to a range of 1/255.

The model was then modified to have a global mean pooling layer, a fully connected layer consisting of 128 neurons, an L2 regularization term with $\lambda = 0.01$, and a drop of 50%. The binary classification output layer had a sigmoid activation function reflecting the probability of firing. Training was done with the Adam optimizer. The learning rate was set to 0.0001 and the binary cross entropy loss was used. Early stopping was implemented to track accuracy loss, and training was terminated after observing 10 consecutive epochs in which there was no improvement.

Most academic research evaluates model performance not by a single measure, but rather by a combination of measures, including accuracy (1), recall (2), precision (3), and F1-score (4). These metrics allow for fair and comprehensive comparisons across tasks, in addition to providing a quantitative measure of model performance [32].

$$Accuracy = \frac{True\ Positive\,(TP) + True\ Negative\,(TN)}{True\ Positive\,(TP) + True\ Negative\,(TN) + False\ Positive\,(FP) + False\ Negat}, \tag{1}$$

$$Recall = \frac{True\ Positives\,(TP)}{True\ Positives\,(TP) + False\ Negatives\,(FN)}, \tag{2}$$

$$Precision = \frac{True\ Positives\,(TP)}{True\ Positives\,(TP) + False\ Positives\,(FP)}, \tag{3}$$

$$F1\ Score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \tag{4}$$

Table 2 presents the performance metrics of the model on the test data. The model performed well with an accuracy of 97.63%. This means that 97.63% of the samples tested were correctly classified. In addition, the precision of the model is 98.40%, meaning that 98.40% of all samples predicted to be fire were in fact correctly classified as fire. The recall rate is 96.84%, which means that most of the images containing fire are correctly recognized. The F1-score of the model is 97.61%, which is an important performance measure that reflects both the accuracy and the recall of the model in a balanced way. Overall, the model shows a high success rate and effective classification performance, with both false positives and negatives minimized.

Table 2
Model performance metrics on test data.

Metric	Value
Accuracy	97.63%
Precision	98.40%
Recall	96.84%
F1_Score	97.61%

There is a need to analyze the working of the model in a detailed manner, which can be done by analyzing certain different parameters. One of these metrics can be a confusion matrix as shown in Fig. 3. The confusion matrix protocol allows the user to more accurately determine the type of classes that have been solved compared to the others. In this way, it can be determined which fire class was correctly recognized and which was more prone to errors.

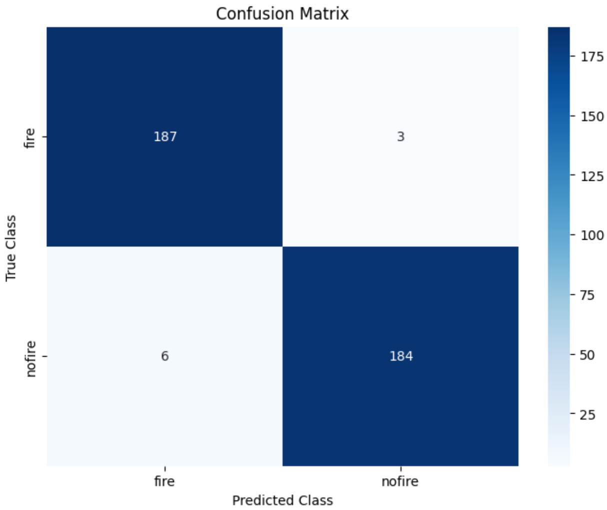

Figure 5: Confusion matrix of the model's fire classification.

5. Discussion

This article demonstrates a useful case of DL application for an important ecological problem: detecting wildfires. Applying the ResNet50V2 architecture together with small but cleverly augmented dataset results in 97.63\% accuracy and 98.40\% precision in locating wildfire affected regions from satellite images. With regard to transfer learning, the use of already trained ImageNet weights is one of the most notable advantages, as it allows for better results and faster convergence even when there isn't sufficient training data available. Data augmentation methods like horizontal flips, zooms, and crops help control overfitting, which is a serious problem when working with small datasets. Regularization techniques also improve the model's generalizability.

Still, the error analysis section would improve by providing more detail outside of the confusion matrix analysis. Determining if the true miss-classifications are false positives (areas without fire but marked as fire) or false negatives (burned areas that should have been marked but are not) is the most important part misclassification analysis. Examining those misclassified images could show the flaws in the model and the biases it holds.

Although many researchers use the ResNet50V2 architecture with transfer learning for image classification, our research is different. We customize the model to detect post-wildfire land damage using satellite images, an area not previously investigated. Unlike most prior work on real-time fire or smoke detection, our focus is on identifying areas of fire damage in forests. Moreover, unlike other more sophisticated solutions such as the dual-agent detection system described in [22], our model is less complicated while achieving the same high accuracy, thus better tailored for environments with constrained resources. To address the problem of limited datasets, we applied specific augmentation strategies, dropout, and L2 regularization. These methods help ensure robustness and generalization. The modular architecture and training pipeline enhance central and edge-based fire monitoring practicality.

Furthermore, examining the practical aspects of the proposed methods would greatly increase the impact of the study. For example, in what ways could this model be used with current wildfire monitoring systems? What are the implications for safeguarding the environment, saving money, and improving response time? Trying to answer these questions would reiterate the importance of the topic while enhancing the discussion providently.

6. Conclusion

Using the ResNet50V2 architecture, the model achieved a remarkable accuracy of 97.63% when classifying satellite images into wildfire and non-wildfire categories. The model's accuracy, coupled with its capacity to spot forest fires, makes it an invaluable asset for prompt fire detection and prevention. Adopting an approach based on DL and satellite imagery provides the opportunity to enhance the detection of fires' earliest stages, thus enabling quicker, more efficient actions. In addition, these real-time assessments can aid in firefighting efforts on a personal and communal level.

The use of satellite information for instant evaluation can have supportive implications in helping onlookers assess the location of fire activity. This is important in determining the location to dispatch firefighting teams to, hence optimizing resource use and reducing damage.

In addition, this study helps refine the general approach to managing forest fires. As the current version of the model improves, further steps can look into testing other augmentation strategies to increase the model's strength, new fine-tuning adjustments to improve performance, or even other neural network designs that are better intended for certain satellite images or regions geography. Such changes would greatly improve the range of applications of the model so that it can be configured to work in varying environmental and geographical regions, including those that are untapped. This development may enhance the capacity to monitor and prevent wildfires in different ecosystems around the world.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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