Int. J. Nonlinear Anal. Appl. 13 (2022) 1, 2053-2063
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2022.5899

A real-time forest fire and smoke detection system using deep learning

Raghad K. Mohammed[a,*]

[a]*Department of Basic Sciences, College of Dentistry, University of Baghdad, Baghdad, Iraq*

(Communicated by Madjid Eshaghi Gordji)

Abstract

Large parts of the world's forests are threatened by fires. These fires happen continuously every month around the globe. They are very costly to society and cause serious damage to the ecosystem. This raises the necessity to build a detection system to intervene early and take action. Fire and smoke have various colours, textures, and shapes, which are challenging to detect. In the modern world, neural networks are used extensively in most fields of human activities. For the detection of fire and smoke, we suggest a deep learning technology using transfer learning to extract features of forest fire and smoke. We used a pre-trained Inception-ResNet-v2 network on the ImageNet dataset to be trained on our dataset which consists of 1,102 images for each fire and smoke class. The classification accuracy, precision, recall, F1-Score, and specificity were 99.09%, 100%, 98.08%, 99.09%, and 98.30%, respectively. This model has been deployed on a Raspberry Pi device with a camera. For real-time detection, we used the Open CV library to read the camera stream frame by frame and predict the probability of fire or smoke.

Keywords: Convolutional neural networks, deep learning, object detection, smoke detection, fire detection, transfer learning.

1. Introduction

Forest fire is a widespread and critical factor in the earth's ecosystem. Every month of the year it occurs continuously around the globe [5]. Therefore, it presents a serious threat and heavy cost to society and acts as a driving key of ecosystem changes [18]. About 2.3% of the land areas around the globe were burned every year, so it has a considerable effect on human's livelihoods and

*Corresponding author
Email address: Raghad_meme@codental.uobaghdad.edu.iq (Raghad K. Mohammed)

Received: September 2021 *Accepted:* November 2021

ecosystems [21]. Forest fires cause the loss of millions of hectares every year, which are lost as oxygen sources. Their loss is a significant factor in rising carbon dioxide that causes earth climate changes. Furthermore, forest fires are predicted to increase around the earth due to climate change [24].

The most effective and vital solution is early detection fights fires to preserve natural resources and protect living creatures. Traditionally, sensors are used to detect fires, smoke, heat, and carbon monoxide. They are effective in indoor places but hard to implement and not effective if used outdoors [9]. The spread of forest fires usually happens too fast to be contained or controlled in a short time. Consequently, it is crucial to construct an early forest fire detection system to stop the fire before it spreads. The drawbacks in traditional sensors detecting systems [26] demonstrate the need to find a more effective and accurate method to help in the prevention and control of forest fires [14].

The field of object detection in computer vision overcomes the drawbacks of traditional outdoor methods. Fire detection based on image analysis has advantages, such as the possibility to be used in wide-open areas, lower cost of installation, and visual confirmation of the alarm by operators. The deep learning and machine learning techniques can be used to deploy such a system [16]. Deep convolutional neural networks have led to a major development in image classification [11, 4]. The success of machine learning in accomplishing target tasks relies on its ability to extract meaningful features from data or images. Conventionally, experts design task-related feature extraction based on their experience in the target domain, which would be difficult for non-experts. Meanwhile, deep learning makes feature extraction easier and adopts this step into a learning step. That is, deep learning needs just a dataset with simple pre-processing (sometimes it is not even necessary) to extract important features instead of a hand-designed procedure. So, the heavy job of feature engineering and feature extraction have been shifted from humans to the computer, and non-experts can use machine learning in their applications and research [20].

Many deep learning algorithms are being used for image analysis because they help computers perform feature extraction for classification. Convolutional neural networks (CNNs) were used extensively in image analysis problems [23]. With convolutional filters, CNNs convert each image into one decision variable. To successfully train a network, a large number of images are needed. However, since sometimes it is not possible to have the required number of images, another proposed solution is transfer learning [25]. In transfer learning, we do not need to build a new model from scratch. Instead, we used a developed pre-trained model for solving this training issue. The benefit of transfer learning depends on the ability to adapt a pre-trained model to new images, so this technique has been adopted in many works [1, 2, 22].

The purpose of this paper is to build a real-time forest fire and smoke detection system via deep learning CNNs and transfer learning. The contributions of this paper include:

1. The proposed system can be implemented easily on surveillance cameras and drones to cover a wide area of forests and will release an alarm in case of fire.
2. It detects not just fire but smoke as well with higher accuracy than other available models and a very low probability of false alarms.
3. The very low latency time (less than 0.01 sec. per image, which represents a video frame) in detection helps prevent the spread of fire and decreases the losses caused by forest fires significantly.
4. The software used is free and open source. It can be installed on a Raspberry Pi device connected to a Raspberry Pi camera with a high coverage area. The suggested system appears in Fig. 1.

The rest of this paper is organized as follows. Section 2 highlights the related work. Section 3 demonstrates the proposed methodology. Section 4 explains the experimental results and the findings of the proposed method. Finally, Section 5 concludes the work and suggests some future works.

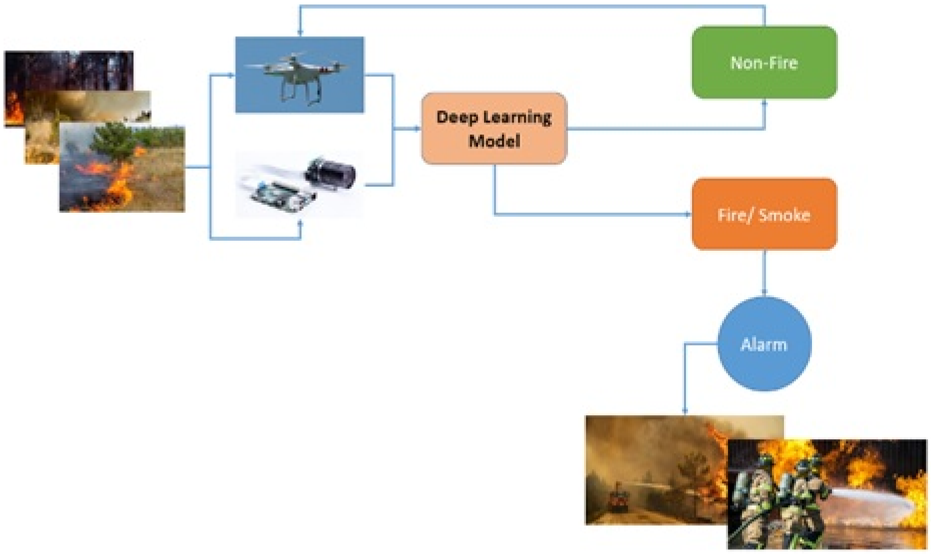

Figure 1: The proposed method of forest fire/ smoke detection using drones or a surveillance camera connected to a Raspberry Pi

1.1. Transfer learning based on deep convolutional network

For fire and smoke detection, a popular pre-trained deep learning model is Inception-ResNet-v2 CNN, implemented in Keras [23]. This model was pre-trained on the ImageNet dataset [8]. The architecture of Inception-ResNet-v2 is a combination of grid reduction modules following residual inception modules. Figure 2shows the architecture. The ResNet-v2 network has achieved the highest accuracy on the ImageNet dataset which contains 1.2 million labelled images [23]. The classes of the ImageNet dataset consist of daily requirements, fruits, and animals. For many image classification problems (including medical images), this dataset was successfully used for transfer learning [12]. In our research, this network was used for feature extraction from our dataset. During training, the CNN layers typically learn high and low-level features, while ResNet layers learn residuals to avoid the vanishing of weights [10].

Average pooling layers are used to reduce the convolutional layers' dimensionality, while Dropout layers are used to avoid overfitting. Finally, the classification layer with Softmax as activation functions.

2. Related works

Recently, many proposals have been presented by researchers to develop an ideal system that can detect forest fire early to stop the spread of the fire and avoid significant losses. For instance, [26] used the Efficient Netimage classifier by integrating Yolov5 and Efficient Det. They used a collected dataset of 10,581 images (2,976 forest fire and 7,605 non-fire), and after sufficient training, their model achieved 99.6% accuracy on 476 fire images and 99.7% accuracy on 676 fire-like images.

However, this work did not consider smoke detection, which is essential for early detection systems. [15] used image processing for feature extraction and a small deep neural network model to detect images from surveillance cameras and process them frame by frame. They used the SqueezeNet network for smoke detection only, and they achieved 97.124% accuracy on the test set. [3] used a two-stage method. They used sensor-based risk identification in the first stage and processed the surveillance images in the second stage. Then, they used MATLAB software with Arduino as a hardware-based system with CNN. They reached 87.1% accuracy after 10,000 epochs.

[6] suggested a deep learning network algorithm for fire detection using a large-scale YOLOv3 to process the images received from unmanned aerial vehicles (UAV) in real-time with a high-performance computer on the ground station. This algorithm reached a 91% detection.

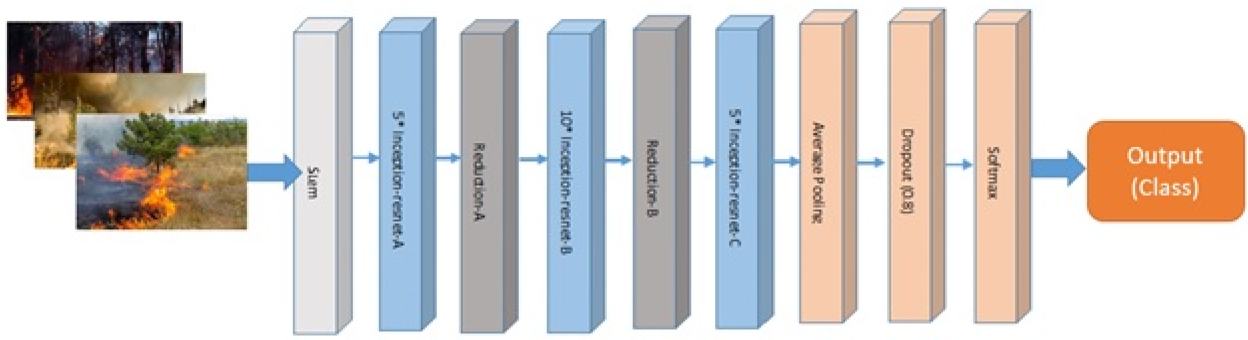

Figure 2: Inception-ResNet-v2 network architecture

The fusion deep network (with pre-trained ImageNet weights) reached an accuracy rate of 94.67%. [27] examined the Camp Fire (California, USA) area using a convolutional neural network for forest fire detection. They also used multispectral images from Landsat 8 which is an American Earth observation satellite and the theory of recognition of multispectral images with statistical methods to reach a 94.27% accuracy. [7] established an algorithm to detect forest fire by using YOLOv3 on UAV-based aerial images. A small-scale CNN is deployed according to the available computation power of the onboard hardware. The recognition rate was about 83% of the testing results of this algorithm. [17] suggested a method of image recognition based on CNN. They fine-tuned the Resnet50 network and added convolutional layers with Relu as the activation function. The output layer was a binary classification layer.

The training accuracy was 92.27%, and the test accuracy was 89.57%. [19] developed a deep learning method based on a U-Net network to extract fire masks from video frames. They used a dataset collected by drones during piled burning in an Arizona pine forest. Using infrared cameras, they collected video recordings and thermal heat maps and then annotated and labelled them to apply the algorithm. Their method approached 92% and a recall of 84%.

3. Methodology

The proposed framework aims to detect smoke and fire based on the images received from the video stream from the Raspberry Pi camera (or any video camera). The actions will be taken depending on the obtained result. Figure 3 summarises the suggested methodology of this paper. Inception-ResNet-v2 network was used to train, validate, and test the images dataset. The methodology of this paper is described as in the following.

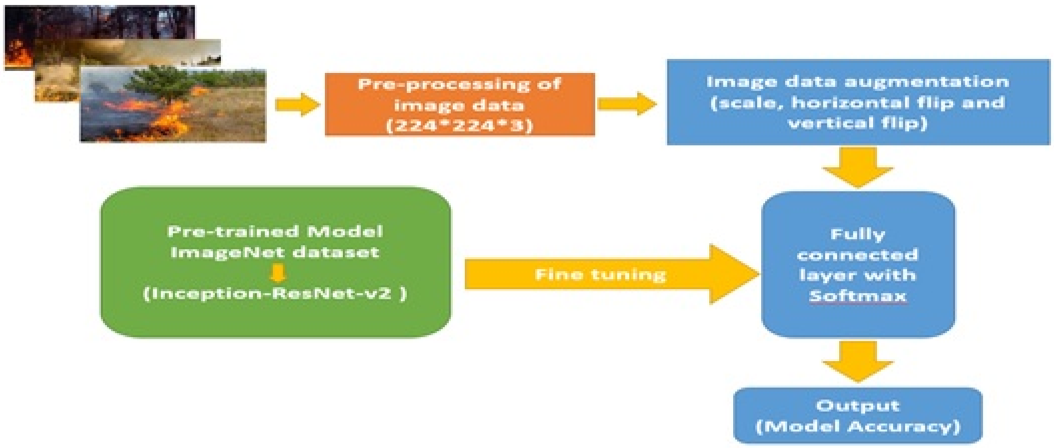

Figure 3: Overview of the methodology

3.1. Dataset

In this study, a forest images dataset of fire and smoke is used, which consists of 1,102 images with fire and 1,102 images with smoke. This dataset was collected from various internet sites including a dataset of forest fire on Kaggle (`https://www.kaggle.com/kutaykutlu/forest-fire`. Figure 4 shows some samples of the dataset images with their labels.

Figure 4: Fire and smoke image samples from the used dataset

3.2. Pre-processing and augmentation

We avoided a biased model by using data with a similar number of images for each class (balanced dataset). Additionally, we did not want to perform excessive image pre-processing to avoid any extra computational cost, which in turn slows down the process of detection. The only image pre-processing that we have done is the resizing of the images to fit in the Inception-ResNet-v2 network. On the other hand, image augmentation was used to give us more images to train our model and help to avoid overfitting. We used scaling, horizontal flipping, and vertical flipping in our work for image augmentation. The scaling operation is the process of reduction or magnification of the image by 2.5% to 10%, and horizontal flipping and vertical flipping were done by flipping images horizontally and vertically by 10% to 25%.

3.3. Image classification

As mentioned earlier, transfer learning is widely used to leverage knowledge from pre-trained models to solve new problems in another related field [25]. The weights of Inception-ResNet-v2, which trained on the ImageNet dataset are transferred into our task, and then these weights were optimized using the Adam optimizer. The pre-trained model can already extract useful and powerful features, and it can reduce the training time significantly. The model was trained using 80% of the total dataset randomly selected images (20% of this training set were utilized for validation to avoid overfitting), and 10% of the total dataset was used for testing and evaluating the model on data that it never trained on. The process of training can be summarized as follows.

1. Split the dataset into a train, validate, and test sets.
2. Specify the hyper-parameter initial values (e.g., epoch number, learning rate, loss function, etc.).
3. Use callbacks to save the best model and reduce the learning rate by 0.5 if there is no improvement in validation loss after two epochs. Use early stopping to stop training if there is no improvement after four epochs to avoid overfitting.
4. Through the learning process, use the validation set to evaluate the network performance.
5. Repeat steps 3 and 4 ten times (the number of epochs), and quit if any callbacks conditions were achieved.
6. Save the best model with the lowest loss of the validation data.
7. Evaluate the performance of the model on a dataset that has not been trained on test data by using the specified performance matrices.

The model was built with Keras library and Python 3.8 on a computer with Intel(R) Core (TM) i7-10750H CPU @ 2.60GHz with 2.59 GHz, 32.0 Gigabyte of RAM, and a display adapter from NVIDIA GeForce GTX 1650 Ti. The Adam optimizer was used with an initial learning rate of 0.001, batch size of 55 images, a dropout rate of 0.45, a momentum update rate of 0.99, categorical cross-entropy as the loss function, 10 backpropagation epochs, and a callback of early stopping with a threshold of 2. After saving the best model, we uploaded it and used it to predict the probability of fire and smoke in any picture. Since our model just trained on images that contain fire or smoke, it would not recognize images without them, and it always will classify an image as a smoke or fire image, even if the probability of both classes is very low. To solve this issue, we wrote a function that measures the probability of each class and sets a threshold value.When the probability of fire or smoke is less than this value (0.043 in our model), the image will be considered Non-fire and no reaction will be taken. We implemented our model on a Raspberry Pi and used the Open CV library to read the video stream from the camera frame by frame and used the model to predict the probability of fire or smoke. This technique removed the need for segmentation or other methods, which detected if there was fire or smoke first and then classified them. This method reduced the computing time significantly (less than 0.01 sec. per image), which is important to build a fast detection system.

3.4. Model evaluation and performance matrices

In this study, after the training process, the performance of the model on the testing set (10% of the whole dataset) was evaluated using seven performance measurements, which include accuracy rate, recall (sensitivity), F1-Score, precision, specificity, and area under the curve (AUC).AUC is the probability of classifying a random positive image sample by the model higher than a random negative image sample. It is estimated by calculating the true positive rate (TPR) and false-positive rate (FPR), which are calculated using different thresholds. The last measure used is the precision-recall curve. Equations (3.1)-(3.5) indicate the first quantitative measures:

$$\text{Classification accuracy rate} = \frac{(T_p\ +\ T_n)}{(T_p\ +\ T_n + F_p\ +\ F_n)}, \tag{3.1}$$

$$\text{Recall (Sensitivity)} = \frac{T_p}{(T_p +\ F_n)}, \tag{3.2}$$

$$F1 - \text{Score} = 2\ X\frac{(Precision\ X\ Recall)}{Precision\ +\ Recall}, \tag{3.3}$$

$$\text{Precision} = \frac{T_p}{(T_p\ +\ F_p)}, \tag{3.4}$$

$$\text{Specificity} = \frac{T_n}{(T_n + F_p)} \tag{3.5}$$

where T_p(true positive) is the number of images correctly classified as fire images, T_n(true negative)represents the number of images correctly classified as smoke images, F_n(false negative) represents the number of fire images which misclassified as smoke andF_p(false positive)represents the number of smoke images which misclassified as fire.

4. Results

In this section, we explain the performance of the suggested network applied to validation data. The performance matrices values are explained in Table 1.

Table 1: The performance of the suggested model using the explained performance matrices.

Performance matrices	***Value***
Accuracy	***99.09***
Precision	***100.00***
Sensitivity	***98.08***
F1-Score	***99.09***
Specificity	***98.30***

Figure 5 shows the area under the curve (AUC) / receiver operating characteristic (ROC) curve. While accuracy is based on one specific point, ROC tries all possible points to plot the sensitivity and specificity. The AUC of our model achieved 99%.

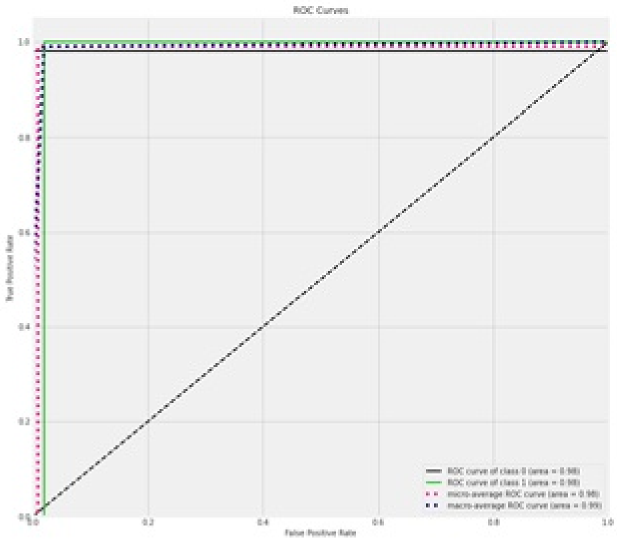

Figure 5: ROC curve of the model on the test.

Figure 6 illustrates the confusion matrix for the model. Out of 52 fire images of the test data, only one was misclassified as smoke.

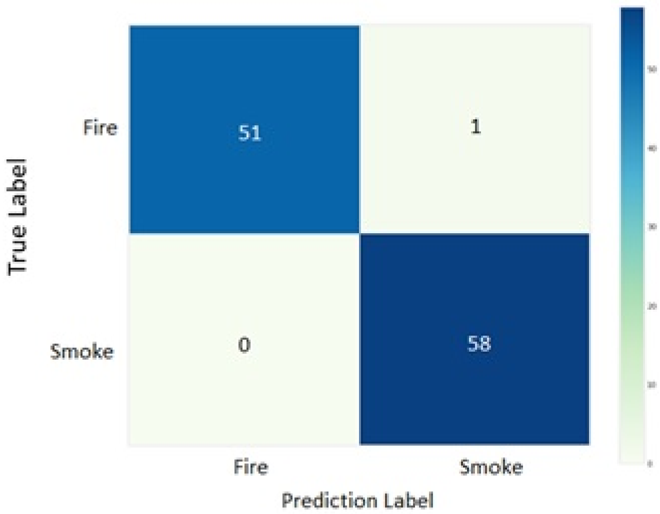

Figure 6: Model's confusion matrix.

Figure 7 illustrates the training and validation accuracy and loss per epoch for the model. The model reached and stabilized with the highest accuracy after 3 epochs and reached the lowest loss after 9 epochs.

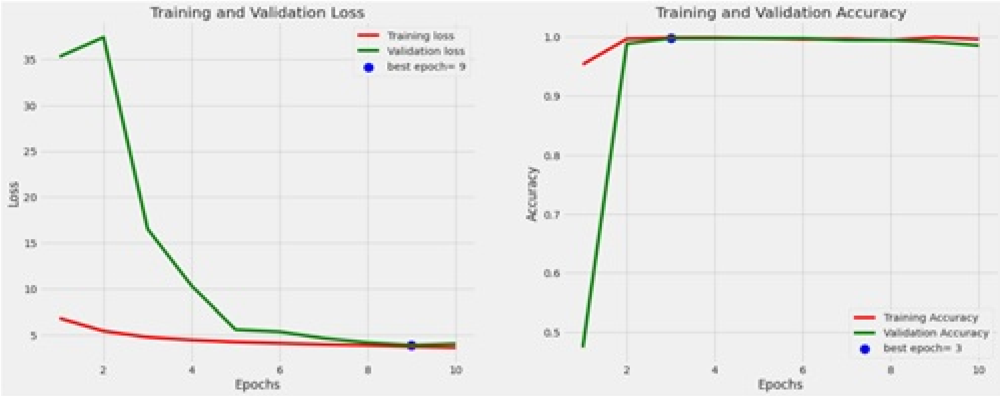

Figure 7: Training and validation losses and accuracy per epoch.

In Figure 8, the different thresholds have been taken to evaluate the trade-off between recall and precision, which is called the precision-recall curve. Hence, high precision indicates a low false-positive rate, high recall indicates a low false rate and a higher area under the curve indicates higher precision and recall.

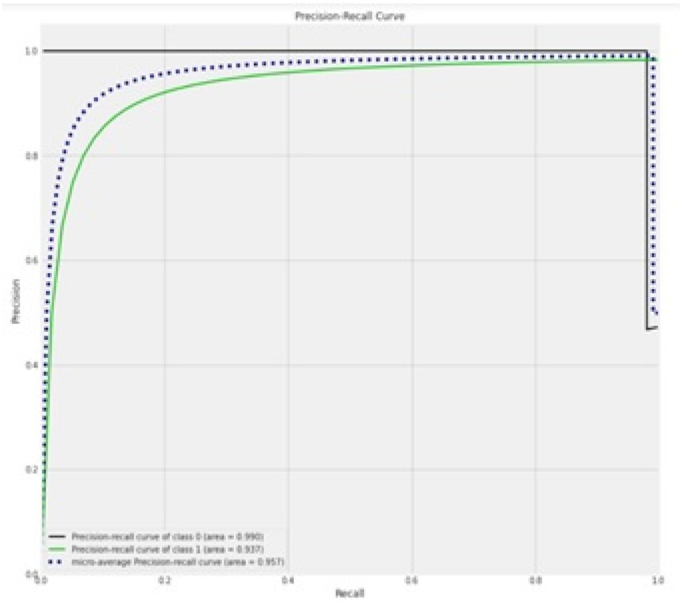

Figure 8: Precision - Recall curve.

5. Discussion

This study aimed to build a forest fire and smoke detection system using deep learning. We used transfer learning with an Inception ResNetv2 pre-trained model. The used dataset consists of 1,102 images for each class (fire and smoke). The pre-trained model was used to extract features from the images, and then a classification layer was used to classify the images. We obtained 99.09%, 100%, 98.08%, 99.09%, and 98.30% for accuracy, precision, recall, F1-Score, and specificity, respectively. Most other studies obtained more or less accuracy detecting either fire or smoke, while our model detects both. Table 2 explains the model's accuracy for related work with the detection type and used dataset.

Table 2: Comparison among some of the related works and our proposed model.

Study	Dataset	Detection type	Accuracy %
(Xu et al., 2021)	10,581 images	Fire only	99.7
(Peng & Wang, 2019)	Image processing for feature extraction	Smoke only	97.124
(Cui, 2020)	3,000	Fire only	87.1
(Jiao et al., 2020)	57,000 steps, and 64 images are used in each step.	Fire only	91
(Liu et al., 2019)	5,984 frames of video, has 3,526 smoke frames.	Smoke only	94.67
Our proposed model	1,102 fire images and 1,102 smoke images	Fire and smoke	99.09

6. Conclusions and future work

As the threat of forest fires increases due to climate changes, the need for finding a detection system increases. Deep learning algorithms proved their efficiency in detecting different objects. The process of fire and smoke detection is challenging due to their behaviour. In this work, we designed a real-time detection system using transfer learning with the InceptionResNetv2 network. We trained this network on a dataset containing images of smoke and fire and reached 99.07% accuracy. In case of fire or smoke detection in image frames streamed by a surveillance camera, an alarm will be sounded. This suggested system is very effective, inexpensive, and easy to apply. It can also save a significant number of trees and forest creatures that might be lost every year around the globe due to delayed detection.

For future work, we suggest training the model on more types of data, not in forests only but in other areas to build an early fire detection system for cities. Alternatively, it could use the same structure but train on satellite imagery, which covers a wider area to more quickly detect fires.

References

[1] M. Byra, *Discriminant analysis of neural style representations for breast lesion classification in ultrasound*, Biocyber. Biomed. Engin. 38(3) (2018) 684–690.

[2] J. Z. Cheng, D. Ni, Y.H. Chou, J. Qin, C.M. Tiu, Y.C. Chang, C.S. Huang, D. Shen and C.M. Chen, *Computer-aided diagnosis with deep learning architecture: Applications to breast lesions in US images and pulmonary ndules in CT scans*, Scientific Rep. 6(1) (2016) 1–13.

[3] F. Cui, *Deployment and integration of smart sensors with IoT devices detecting fire disasters in huge forest environment*, Computer Commun. 150 (2020) 818–827.

[4] K. He, X. Zhang, S. Ren and J. Sun, *Deep residual learning for image recognition*, Proc. IEEE Computer Soc. Conf. Computer Vision and Pattern Recogn. (2016) 770–778.

[5] P. Jain, S.C.P. Coogan, S.G. Subramanian, M. Crowley, S. Taylor and M.D. Flannigan, *A review of machine learning applications in wildfire science and management*, In Environmental Reviews, 28(4) (2020) 478–505.

[6] Z. Jiao, Y. Zhang, L. Mu, J. Xin, S. Jiao, H. Liu and D. Liu, *A YOLOv3-based Learning Strategy for Real-time UAV-based Forest Fire Detection*, Proc. 32nd Chinese Control Decision Conf., IEEE, (2020) 4963–4967.

[7] Z. Jiao, Y. Zhang, J. Xin, L. Mu, Y. Yi, H. Liu and D. Liu, *A Deep learning based forest fire detection approach using uav and yolov3*, 1st Int. Conf. Indust. Artif. Intell. (2019) 1–5.

[8] A. Krizhevsky, I. Sutskever and G.E. Hinton, *ImageNet classification with deep convolutional neural networks*, Commun. ACM, 60(6) (2017) 84–90.

[9] S.B. Kukuk and Z.H. Kilimci, *Comprehensive analysis of forest fire detection using deep learning models and conventional machine learning algorithms*, Int. J. Comput. Experimental Sci. Engin. 7(2) (2021) 84–94.

[10] Y. LeCun, K. Kavukcuoglu and C. Farabet, *Convolutional networks and applications in vision*, ISCAS 2010-2010 IEEE Int. Symp. Circ. Syst.: Nano-Bio Circuit Fabrics Syst. (2010) 253–256.
[11] T. Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan and S. Belongie, *Feature pyramid networks for object detection*, Proc. 30th IEEE Conf. Computer Vision and Pattern Recogn. Janua 2017 936–944.
[12] G. Litjens, T. Kooi, B.E. Bejnordi, A.A.A. Setio, F. Ciompi, M. Ghafoorian, J.A.W.M. van der Laak, B. van Ginneken and C.I. Sánchez, *A survey on deep learning in medical image analysis*, Medical Image Anal. 42 (2017) 60–88.
[13] T. Liu, J. Cheng, X. Du, X. Luo,L. Zhang, B. Cheng and Y. Wang, *Video smoke detection method based on change-cumulative image and fusion deep network*, Sensors 19(23) (2019) 50–60.
[14] B.S. Negara, R. Kurniawan, M.Z.A. Nazri, S.N.H.S. Abdullah, R.W. Saputraand and A. Ismanto, *Riau forest fire prediction using supervised machine learning*, J. Phys.: Conf. Ser. 1566(1) (2020) 12–20.
[15] Y. Peng and Y. Wang,*Real-time forest smoke detection using hand-designed features and deep learning*, Comput. Electr. Agricul. 167 (2019) 105029.
[16] H. Pranamurti, A. Murti and C. Setianingsih, *Fire Detection Use CCTV with Image Processing Based Raspberry Pi*, J. Phys.: Conf. Ser. 1201(1) (2019) 012015.
[17] M. Rahul, K. Shiva Saketh, A. Sanjeet and N. Srinivas Naik, *Early detection of forest fire using deep learning*, IEEE Region 10 Annual Int. Conf. (2020) 1136–1140.
[18] T. Schoennagel, J.K. Balch, H. Brenkert-Smith, P.E. Dennison, B.J. Harvey, M.A. Krawchuk, N. Mietkiewicz, P. Morgan, M.A. Moritz, R. Rasker, M.G. Turner and C. Whitlock, *Adapt tomore wildfire in western North American forests as climate changes*, Proc. Nat. Acad. Sci. United States Amer. 114(18) (2017) 4582–4590.
[19] A. Shamsoshoara, F. Afghah, A. Razi, L. Zheng,P. Z. Fulé and E. Blasch, *Aerial imagery pile burn detection using deep learning: The FLAME dataset*, Computer Networks 193 (2021) 108001.
[20] D. Shen, G. Wu and H. Suk, *Deep Learning in Medical Image Analysis*, Annual Rev. Biomed. Engin. 19 (2017) 221–248.
[21] G. Shi, H. Yan, W. Zhang, J. Dodson, H. Heijnis and M. Burrows, *Rapid warming has resulted in more wildfires in northeastern Australia*, Sci. Total Envir. 771 (2020) 144888.
[22] H.C. Shin, H.R. Roth, M. Gao, L. Lu, Z. Xu, I. Nogues, J. Yao, D. Mollura and R.M. Summers, *Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning*, IEEE Trans. Medical Imag. 35(5) (2016) 1285-1298.
[23] C. Szegedy, S. Ioffe, V. Vanhoucke and A.A. Alemi, *Inception-v4, inception-ResNet and the impact of residual connections on learning*, 31st AAAI Conf. Artificial Intell. (2017) 4278–4284.
[24] L. Vilà-Vilardell, W. S. Keeton, D. Thom, C. Gyeltshen, K. Tshering and G. Gratzer, *Climate change effects on wildfire hazards in the wildland-urban-interface – Blue pine forests of Bhutan*, Forest Eco. Manag. 461 (2020) 117927.
[25] K. Weiss, T.M. Khoshgoftaar and D.D. Wang, *A survey of transfer learning*, J. Big Data 3(1) (2016) 1–40.
[26] R. Xu, H. Lin, K. Lu, L. Cao and Y. Liu, *A forest fire detection system based on ensemble learning*, Forests 12(2) (2021) 1–17.
[27] V. Yaloveha, D. Hlavcheva and A. Podorozhniak, *Usage of convolutional neural network for multispectral image processing applied to the problem of detecting fire hazardous forest areas*, Adv. Inf. Syst. 3(1) (2019) 116–120.