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A comprehensive comparison study of traditional classifiers and deep neural networks for forest fire detection

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Abstract

Forest fires cause great harm to people, environment, and nature. Fire detection using forest landscape images can play a critical role in the design of expert systems required to solve the forest fire problem. The main aim of this study is to evaluate the classification accuracy of different classifier models for efficiently detecting forest fires and to present an effective and successful model. At this point, classification performances of traditional and deep neural networks (DNN) based classifiers were compared on landscape images dataset taken from the Mendeley repository within the frame of well-known metrics such as accuracy, sensitivity, specificity, precision and false negative rate. The DNN-3 classifier performed very well on the ResNet50 deep features extracted from images with 97.11% accuracy, 96.84% sensitivity, 3.16% false negative rate, 97.37% specificity, and 97.35% precision. This model (ResNet50+DNN-3) offered the most area under the curve with 0.971. In this context, it is thought that the proposed model could play an active role in the design of expert systems that will support the forest protection and monitoring units by easily integrating with real-time internet of things and embedded system applications.

Keywords Forest fires · Fire detection · Deep features · Deep neural networks

1 Introduction

Forests, which are the heart of wildlife, are undoubtedly the oxygen source of our nature [1]. Forests cover nearly 30% of the earth's surface and play an important role in the ecosystem's balance with the climate, and forest loss is a serious disaster [2]. Forest fire which is very dangerous for forests and people [3] is a global problem with strong negative impact on biodiversity [4]. A large-scale wildfire destroys the forest's flora, fauna, and vegetation while also posing a significant risk to the lives of humans and animals [5]. Some climatic conditions are considered as factors that have great impact on the occurrence of forest fires [3, 6]. Forest fire, which is the subject of intense research in the world, is one of the main causes of ecosystem losses and deterioration of human life [6, 7]. Early automatic detection of forest fires, which is one of the issues being researched to reduce disasters, can assist decision-makers in planning extinguishment efforts [8]. Forest fires are considered one of the urgent issues, and the negative effects of them are minimized as much as possible with the right strategies [7]. Intense forest fires devastate homes and wildlife, causing many negative effects and increasing global temperature [9]. On the other hand, it should not be forgotten that forest fires in village areas affect the livelihoods of the villagers. Village life is largely poverty-stricken and livelihoods are severely affected by the fire [10, 11]. As a result, fire threatens millions of hectares of forest areas around the world every year, with its highly destructive effect on forest ecosystems [12, 13]. Therefore, it is essential to monitor and protect forests and forest assets [1]. A forecasting system and remote sensing-based studies should be carried out to minimize losses from fire [12]. Reis et al. stated that the ability to predict where deforestation and fires are most likely to occur is important for designing policies for preventive action [14]. This information, as well as the related works introduced in Sect. 2, reveal the importance of the subject.

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Computer vision-based studies are carried out in order to provide decision support to field experts in medical sciences [15, 16], agricultural sciences [17, 18], forest sciences [19, 20], and other disciplines. Many computer-aided studies have been carried out for the detection of forest fires, so far. Traditional classifiers have some problems such as the complex background of images, low accuracy which will lead to a false positive rate, and poor generalization in image recognition. Pereira et al. indicated that hand-made feature sets for active fire thresholds can cause false positive or negative results, while deep learning techniques can encode more complex rules to improve this aspect [21]. Moreover, one difficulty in hand-made feature-based studies is the computation cost of a large number of features. This can make them computationally slow and memory shortage problems [22]. Developments in the field of artificial intelligence allow the establishment of computer-aided models that will contribute to the studies to be made regarding problems experienced in forests and many other areas. Deep learning automatically extracts the features required for detecting and classifying fire cases from the landscape images. Automatic recognition of forest fires by computer-assisted expert systems using these images is a promising solution to overcome this problem. These systems provide support to field experts in terms of time spent and subjective evaluation problems.

Using deep features extracted from the layers of deep learning architectures for image classification is quite common. Deep learning architectures which are popular recently present more successful results compared to traditional machine learning approaches in many studies. It can be concluded that the features obtained from CNN layers are more meaningful than hand-crafted features.

A global fire monitoring and alarm system is urgently needed due to ecological and humanitarian concerns. Specialized fire detection devices and satellites should be developed for this purpose [23]. According to Xie and Peng, people may miss important forest signals, so developing reliable predictive models for forest fire fighting is critical [19]. Addressing the same issue, Venâncio et al. stated that CNN is the most promising solution in the fight against forest fires, which is a very important task [24].

The main objective of this study is to propose a deep neural network model that performs the classification of forest fire images robustly and prosperously. In this context, effective and successful model research was carried out with a comprehensive comparison of the classification performances of different classifier models using deep features obtained with pre-trained deep learning architectures from forest landscape images. In this context, this study presents a model based on integrating the deep features extracted with pre-trained models, and deep neural networks for fire detection from forest landscapes. The deep neural network-based classifiers used in this study were built from scratch. The experiments were carried out with traditional classifiers as well in order to evaluate the performances of these classifiers. At this point, the best model developed in this study may have a core role in classifying forest landscape images by an expert system for forest fire detection. Moreover, this model could be used efficiently by easily integrating with the internet of things and embedded systems.

The remainder of this paper is organized as follows. Section 2 introduces a broad summary of the relevant studies. Section 3 introduces briefly the material and methods used in this study. Section 4 presents experiments and their results. Section 5 discusses this study with limitations and also evaluates some studies in the literature. Finally, the study is concluded with final remarks in Sect. 6.

2 Literature review

The literature on forest fire destruction, forest fire types, and forest fire risks can be summarized as sensor data-based internet of things (IoT) systems, terrain, humidity, and other attributes-based systems, and computer vision-based systems. For example, Akıncı and Akıncı applied machine learning techniques on the average annual temperature, average annual precipitation, and other attributes related to 545 forest fires between 2013 and 2021 in the Manavgat district of Antalya province in Turkey and obtained the best fire susceptibility map using the XGBoost model [25]. Arnett et al. estimated fire severity from forest area data compiled into a simple fire index and correlated it with selected set of common spectral vegetation indices. They then derived fire severity classes to map fire effects and estimate damage to the woody surface consumed [26]. Çolak and Sunar modeled fire risk using remote sensing technology. The authors integrated multi-time remote sensing data obtained before the fire with auxiliary data in the geographic information system to evaluate the spatial and temporal patterns of forest fire risk in the Menderes region of Izmir. They taken account six fire risk variables determined statistically in previous studies to obtain fire risk map [27]. Dampage et al. proposed a machine learning regression model with two classes, fire, and no-fire, for a successful fire detection system on temperature, relative humidity, light intensity level, and CO level data obtained from a wireless sensor network [6]. Dindaroğlu et al. examined the effects of forest fires using various indices related to water, combustion, terrain and vegetation, and current strength and curvature data. The authors carried out their studies on a 47.43 hectares of fire area in Kahramanmaraş, Andırın, Çınarpınar forest areas in Turkey [28].

Koetz et al. presented a study including support vector machines classifier, and combine of supplementary data and imaging spectrometry observations sampled in the air spatial and spectral domain to better classify land cover for forest fire management [29]. Mohajane et al. used 510 historical forest fire points as a forest fire inventory map for forest fire susceptibility modeling. They examined the performance of five new hybrid machine learning algorithms on ten independent causal factors such as altitude, slope, aspect, distance to roads, distance to residential areas, land use, normalized vegetation index, precipitation, temperature, and wind speed. According to their study, the Frequency Ratio-Random Forest ensemble model outperformed other models [7]. Prasanna et al. detected forest fires early with the help of cameras fixed to the towers. In their study, the Raspberry Pi embedded system integrated with the fire detection algorithm warns the forest control department in case of fire [9]. Reis et al. evaluated the potential deforestation and forest fires in the Amazon and showed that over a 31-year period forest fires occurred only during the years of extreme drought triggered by the El Nino hurricane [14]. Sannigrahi et al. focused on assessing the effects of forest fires on terrestrial ecosystem productivity in India between 2003 and 2017. To analyze the relationship between forest fires and ecosystem productivity, they estimated the spatial-temporal changes of combustion indices derived from remote sensing data for both fire and normal years [30]. Silva et al. discussed forest degradation caused by fire in bamboo-bearing areas in the eastern part of the Brazilian state of Acre based on a combination of forest inventory and satellite remote sensing data [31]. Singh et al. developed a parallel SVM model trained on weather forecast index and some weather parameters for predicting forest fire effectively [32]. Tang et al. studied forest fire susceptibility in Huichang County, China, due to forest values and frequent fire events. They analyzed forest fire using support vector machine classifier with hyperparameter tuning [33]. Yang et al. proposed an automated image annotation method called pixel-level kNN tagging to detect forest fire images. In their study, the authors used fast convex hull method to easily and accurately select samples in training the kNN classifier [34]. Zheng et al. proposed a model for determining fire risk levels based on the ant-miner algorithm. They tested the performance of their model on historical fire data between 2000 and 2018 years. The authors stated that their model could be used to predict the fire risk of forested regions in cloud-rich areas [12]. Sathishkumar et al. evaluated the performance of several pre-trained models based on feature extraction, fine-tuning, and learning without forgetting to detect fire and smoke from images. [8]. Mishra et al. analyzed forest fire trends and patterns in Nepal over the last two decades and proposed a deep learning model to assess forest fire vulnerability risk based on historical events throughout the country [35].

In recent years, deep learning techniques have achieved tremendous success in many areas, however, the uses of deep learning models for active fire detection are relatively limited. The following is a summary of CNN-based studies for forest fire detection. Bjånes et al. proposed a new ensemble model based on two deep learning networks previously presented in the literature, which achieved remarkable results regarding forest fire susceptibility and other environmental risks. In addition, they compared the performance of the proposed model based on deep learning networks with XGBoost and SVM machine learning algorithms they used in their studies [36]. Cui detected fire accidents in forest areas using the IoT. The author evaluated the performance of the model by comparing the Convolutional Neural Networks (CNN) based model for forest monitoring and anomaly detection to overcome forest fire risks with existing approaches and stated that deep CNN offers better performance than others [1]. Kalaivani and Chanthiya designed an optimized CNN within the layer to improve the accuracy and reduce the error rate in their work to identify wildfire images [37]. Liu et al. proposed a multi-level forest fire detection method based on deep learning. The authors first produced high-quality forest fire samples with general advanced networks to solve the problem of uneven distribution and a small number of samples. Second, they used Adaboost classifier based on the histogram of oriented gradients features to make the primary estimation of the forest fire image and then CNN and SVM to make the second estimation [38]. Pereira et al. showed that CNNs were more successful than hand-crafted algorithms on the hand-designed features extracted from image patches obtained from Landsat-8 images, which taken around the world in August and September 2020, including forest fires [21]. Permana et al. classified communication calls between birds by utilizing CNN to early detect forest fires in Indonesia, a tropical country where forest fires are common each year [39]. Shamsoshoara et al. presented a deep learning-based image segmentation study as well as a 2-class (fire and no-fire) fire classification study on a dataset containing video and images of fires taken with drones in Northern Arizona [40]. Venâncio et al. proposed a CNN-based fire detection system that is appropriate for low-power, resource-constrained devices [41]. In another study, Vencio et al. suggested an automatic hybrid fire detection system based on the CNN-based identification of potential fire events and the analysis of these events' temporal dynamics [24]. Vikram and Sinha proposed a Neuro-fuzzy classification-based Sensor model and a CNN-based framework to identify the forest fire-prone area. This framework predicts the state of the forest area based on data from sensors that detect the temperature, relative humidity, and drought status of that area, as well as camera sensors that simultaneously capture images of that area [42].

3 Materials and methods

3.1 Dataset

In this study, the dataset composed and published by Khan and Hassan [43] was used. Fire and non-fire landscape images are 250 $\times$ 250 pixels in RGB color space. There are 950 images for each class in the dataset. Figure 1 presents some fire and non-fire images in the dataset.

3.2 Deep features and transfer learning

Deep features in computer vision are expressed as meaningful features that represent the image in layers of the CNN network where images are given as input. Transfer learning is a knowledge transfer strategy that uses a pre-trained CNN model to solve a problem instead of training a CNN from scratch [44]. This strategy is implemented with two ways in many problems. First, deep features extracted from the convolutional layers of the pre-trained models are given as input to the classifier algorithms. Second, the pre-trained model is adapted to a specific problem, in other words, the pre-trained model is retrained and validated on the new dataset.

3.3 Classifiers

In machine learning, various classifier algorithms are used to classify features that represent the target class. In this study, Deep Neural Networks (DNN), Nave Bayes (NB), Support Vector Machine (SVM), and Logistic Regression (LR) were used. These classifiers are described briefly here. LR is a classification method used for binary or polynomial outcome variables [45]. NB is a classical probabilistic classifier based on Bayes' theorem, assuming class conditional independence [46]. SVM is a classification algorithm introduced by Vapnik [47] and later generalized to the nonlinear case by Cortes and Vapnik [48]. Neural Network is a machine learning technique inspired by and likened to the human brain nervous system. It consists of multiple hidden layers between input and output layers [49]. A typical DNN should have at least three hidden layers, which can be considered as the minimum number for effective implementation of layer-by-layer training [50].

3.4 Performance metrics

Evaluation of the model performance for binary classification is mainly based on the confusion matrix, which shows the ability of the model to predict real class labels [51]. True positive (TP), true negative (TN), false positive (FP), and false negative (FN) criteria in the confusion matrix are commonly taken into account in classification studies. Here, TP and TN denote the number of correctly classified fire and non-fire images, respectively. On the other hand, FN and FP refer to the number of misclassified fire and non-fire images, respectively. The performances of the models are measured by utilizing Accuracy (Acc),

Fig. 1 Sample images for each class; From top to bottom; **a** non-fire image samples, **b** fire image samples

False Negative Rate (FNR), Sensitivity (Sen), Specificity (Spe), and Precision (Pre) metrics. These metrics are given in Eqs. 1, 2, 3, 4 and 5, respectively. With regarding this study, the sensitivity or true positive rate (TPR) is the ratio of forest fire images correctly classified by the classifier to all forest fire images. FNR is the ratio of incorrectly estimated forest fire images to all forest fire images. Specificity or true negative rate (TNR) is the ratio of correctly classified non-forest fire images to all non-forest fire images. Precision is the ratio of correctly classified forest fire images to all images classified as forest fires. Accuracy is the ratio of correctly classified images in both classes to all images. Also, the area under receiver operating characteristic curve (AUC) another measure that demonstrates the effectiveness of the classifier models was taken into account to evaluate the predictive ability of the models. The AUC is calculated by plotting the true positive rate (TPR) versus the false positive rate (FPR) at various thresholds. The AUC area is expected to be as much as possible.

$$Acc = \frac{TN + TP}{TP + FN + TN + FP} \tag{1}$$

$$Sen(TPR) = \frac{TP}{TP + FN} \tag{2}$$

$$FNR = \frac{FN}{FN + TP} \tag{3}$$

$$Spe(TNR) = \frac{TN}{TN + FP} \tag{4}$$

$$Pre = \frac{TP}{TP + FP} \tag{5}$$

4 Experiments

4.1 Experimental enviroment

All experiments in this study were conducted with 64-bit Windows 11 Pro operating system with Intel I CoreI I7-8550U CPU 1.85 GHz and 8 GB of RAM. All codes were implemented in Python using Keras open-source library with Tensorflow backend.

4.2 Model training and testing

This paper proposes an efficient and reliable automatic classification method for forest fire detection using forest landscape images. Figure 2 presents the general framework of this study.

In this study, the dataset which consists of 1900 images was split to training and test sets with 80% and 20% ratios, respectively by Khan and Hassan [43]. Accordingly, there are 760 and 190 images in each class in the training and test datasets, respectively. In other words, 1520 images were reserved for training of the models, and the remaining 380 images were reserved for testing the performances of the models. The dataset is balanced since there is an equal number of images for each class. Images in RGB color space were resized to default sizes for each pre-trained model i.e., 299 × 299 for Xception and 224 × 224 for others. Table 1 summarizes the training and test sets.

The deep features required for training and testing of models were extracted from the images using pre-trained VGG16, ResNet50, DenseNet121, and Xception. Then, experimental studies were carried out on these features within the frame of two scenarios. In Scenario 1, deep features were sent to three different DNN classifiers. In Scenario 2, the deep features were sent as input data to NB, SVM, and LR classifiers. Thus, experiments were conducted within this context, and the performances of various models constructed are discussed.

The DNN classifiers used in this study consists of an input layer, three hidden layers, and finally an output layer with 2 neurons. The numbers of neurons in hidden layers of the DNN classifiers were set to 50xmodel_no, 100xmodel_no, and 50xmodel_no, respectively, where model_no is the digit in the label of the DNN classifiers. For example, DNN-1 refers to DNN model #1. The numbers of neurons in the hidden layers of this model are 50, 100, and 50 (50 × 1, 100 × 1, 50 × 1), respectively. Likewise, the numbers of neurons in the hidden layers of the DNN-2 and DNN-3 models are (100, 200, and 100) and (150, 300, and 150), respectively. In order to avoid the problem of overfitting, 10% of the neurons were reduced by the dropout technique before the output layer in each DNN model. While the ReLu activation function was used in the hidden layers, the softmax activation function was used in the output layer for each DNN-based model. The training of DNN classifiers, whose optimizer is Adam with a 0.001 learning rate, was performed with 100 epochs. In addition, 20% of the training set was reserved for the validation set and the early stopping technique (patience = 5) was used in model training. The performances of all models built were observed on the test set containing 380 images including fire and non-fire images. Some parameters of traditional and DNN-based classifiers used in this study are listed in Tables 2 and 3, respectively. All parameters of traditional classifiers were used with their default values.

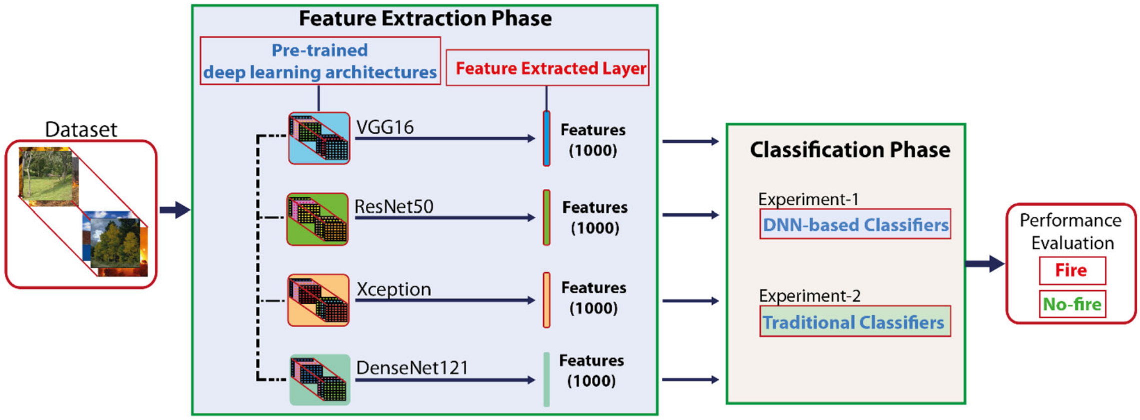

Fig. 2 General blog diagram of the study

Table 1 Training and testing datasets

Original dataset		Training set	Testing set	Total
Classes	Non-fire	760	190	950
	Fire	760	190	950
Total		1520	380	1800

Table 3 DNN parameters settings

Parameter	Value
Optimizer	Adam
Learning rate	0.001
Dropout	0.1
Activation function	*ReLu* in the hidden layers
	Softmax in the output layer
Epochs	100
Batch size	32

4.3 Results

The classification results performed with both traditional and DNN on the deep features extracted from pre-trained CNN layers to detect forest fire were summarized using confusion matrices, tables, and figures. The predictive ability of different classifier models in the testing phase was evaluated using confusion matrix for each model. Confusion matrices that demonstrate the best classification accuracies of DNN classifiers on the deep features were given in Fig. 3. As can be seen from this figure, the DNN-3 classifier, which is trained on the ResNet50 deep features, classified the fire class samples with 96.8% ratio and TP number is 184. Also, same classifier classified the non-fire class samples with 97.4% ratio on the same deep features and the TN number is 185.

As seen in Table 4, DNN-1, DNN-2, and DNN-3 classifiers gave high classification accuracies with 95.53%, 96.32%, and 97.11%, respectively on the ResNet50 deep features. In addition, two DNN models which offer good performance on these deep features were interpreted below.

a) The DNN-3 classifier offered the highest Sen with 96.84% on the ResNet50 deep features. Moreover, this classifier presented the low FNR of 3.16% on the same deep features. This classifier is the most successful model in this study with 97.37% Spe and 97.35% Pre.
b) The DNN-2 classifier presented a high Sen of 95.79%, high Spe of 96.84%, and high Pre of 96.81% on the ResNet50 deep features.

Table 2 Some parameters settings of the traditional classifiers

Classifier	Parameters with values
LR	penalty='l2', C = 1.0, fit_intercept = True, intercept_scaling = 1, solver='lbfgs', max_iter = 100, multi_class='auto'
NB	Priors = None, var_smoothing = 1e-9
SVM	C = 1.0, kernel='rbf', gamma='scale'

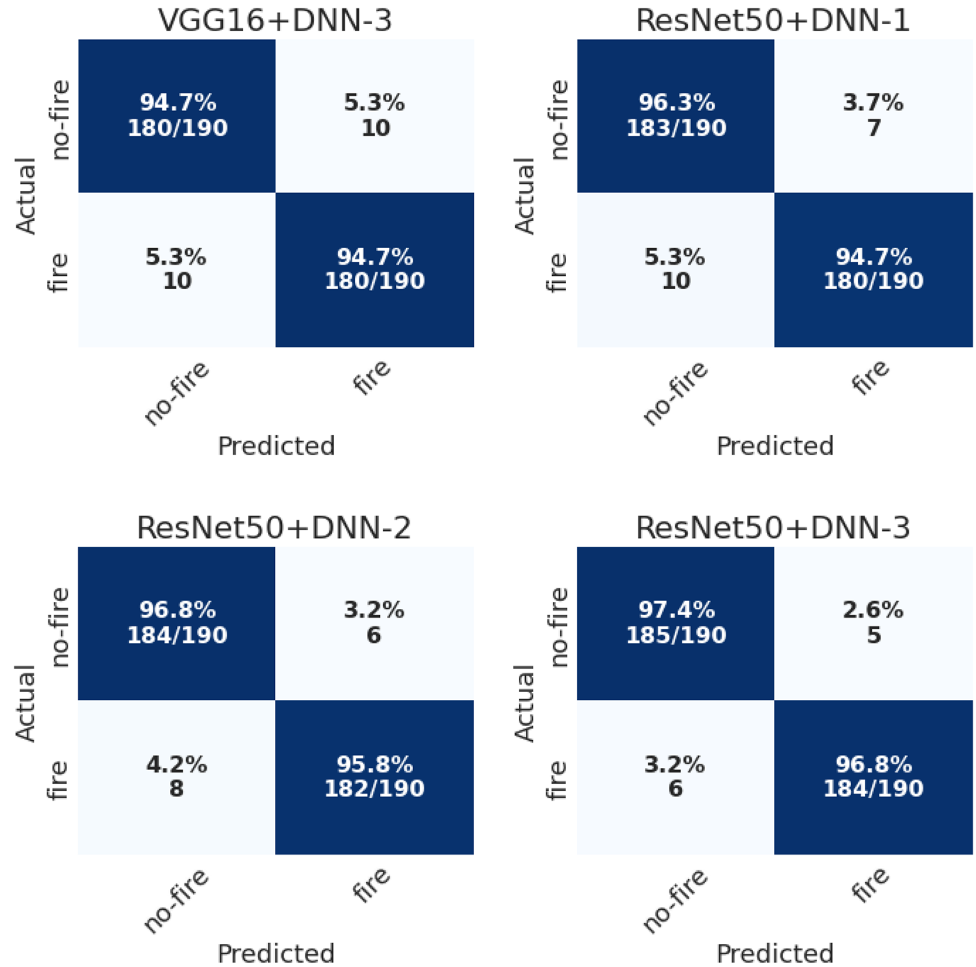

Fig. 3 Confusion matrices of the best performances by the three DNN classifiers

Table 4 The results of the DNN classifiers on the test dataset

Classifier	Deep features	Sen (%)	Spe (%)	Pre (%)	FNR (%)	Acc (%)
DNN-1	DenseNet121	97.37	40.0	61.87	2.63	68.68
	ResNet50	94.74	96.32	96.26	5.26	95.53
	VGG16	93.68	93.68	93.68	6.32	93.68
	Xception	86.84	42.11	60.0	13.16	64.47
DNN-2	DenseNet121	96.32	35.26	59.8	3.68	65.79
	ResNet50	95.79	96.84	96.81	4.21	96.32
	VGG16	93.68	94.74	94.68	6.32	94.21
	Xception	84.74	65.79	71.24	15.26	75.26
DNN-3	DenseNet121	97.89	40.0	62.0	2.11	68.95
	ResNet50	**96.84**	**97.37**	**97.35**	**3.16**	**97.11**
	VGG16	94.74	94.74	94.74	5.26	94.74
	Xception	77.89	74.21	75.13	22.11	76.05

Bold font indicates the best results in this study

In this context, the accuracy-loss graphs of the two best models were also presented in Fig. 4. Accordingly, the training of the DNN-2 model at the 25th epoch and the DNN-3 model at the 16th epoch were completed in the model training in which the Early stopping technique (patience = 5) was employed. It is also noted that approximately similar results were obtained in repeated experiments by DNN. This is normal due to the nature of DNN. Overall, the results obtained on the VGG16 and ResNet50 deep features were better than the Xception and DenseNet121 deep features in all experiments performed by DNN models.

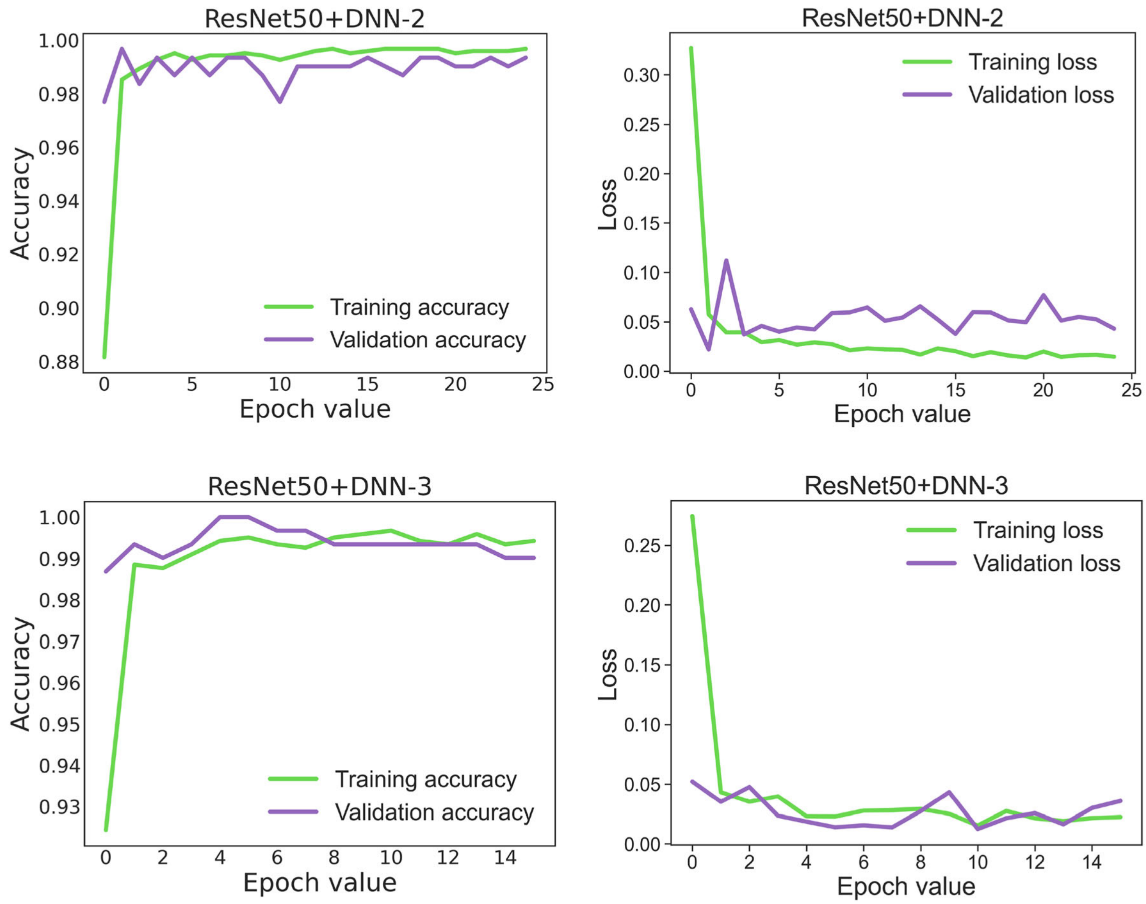

Fig. 4 Accuracy-loss graphs of two best DNN models

Fig. 5 General classification accuracies and elapsed time information of the DNN classifiers

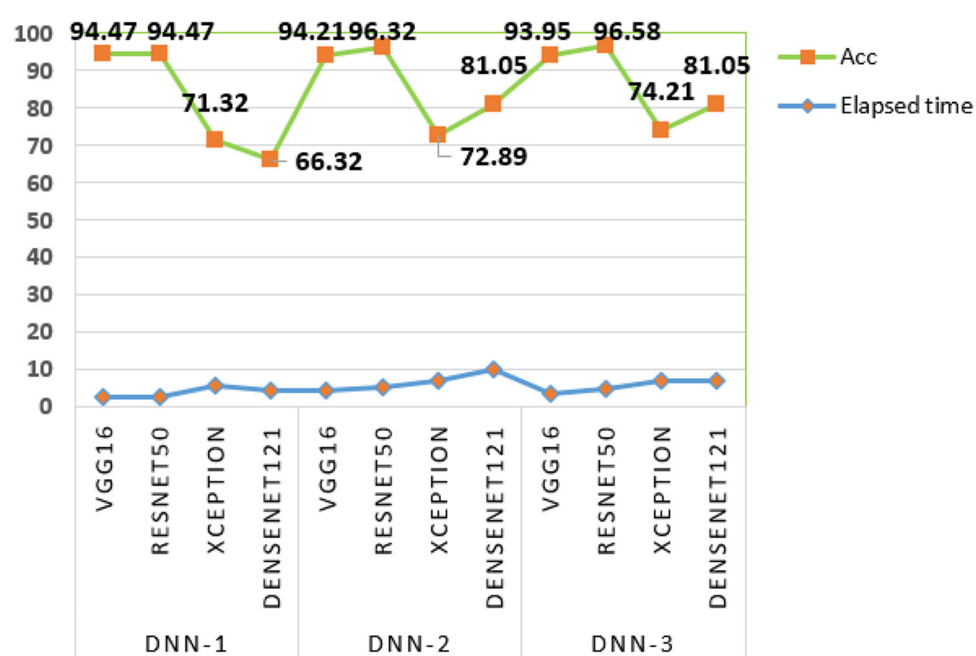

Figure 5 presents the elapsed time of DNN-based classifiers' training and testing processes and also their classification accuracies on the testing set. In the experiments, it is seen that especially general classification accuracies of the DNN models on the VGG16 and ResNet50 deep features are better than the others. DNN classifier (DNN-3) offered highest accuracy with 97.11% on the ResNet50 deep features. From this point of view, it is clearly seen that the overall classification performance of this model is pretty high on the ResNet50 deep features.

Confusion matrices that demonstrate the best performances of NB, SVM, and LR traditional classifiers were given in Fig. 6. As can be seen in this figure, the NB classifier among the traditional classifiers correctly classified most of the samples in the fire class with 93.2% ratio. This classification was obtained on the VGG16 deep features and the number of TP is 177. SVM classified correctly most of the samples in the non-fire class with 96.8% ratio. This classification was obtained on the ResNet50 deep features and the number of TN is 184.

As seen in Table 5, the NB and SVM presented high classification accuracies with 92.89%, while LR presented 91.58% classification accuracy. The successes of the models that present the highest measures regarding Sen, FNR, Spe, and Pre metrics are also interpreted below, respectively. According to this;

a) The NB classifier achieved high Sen with 96.84% and low FNR with 3.16% on the DenseNet121 deep features. However, the Spe value offered by this

Table 5 The results of the traditional classifiers on the test dataset

Classifier	Deep features	Sen	FNR	Spe	Pre	Acc
LR	DenseNet121	67.37	32.63	92.11	89.51	79.74
	ResNet50	86.84	13.16	96.32	95.93	91.58
	VGG16	87.89	12.11	93.16	92.78	90.53
	Xception	80.53	19.47	60.53	67.11	70.53
NB	DenseNet121	96.84	3.16	30.0	58.04	63.42
	ResNet50	92.11	7.89	55.26	67.31	73.68
	VGG16	93.16	6.84	92.63	92.67	92.89
	Xception	46.84	53.16	95.79	91.75	71.32
SVM	DenseNet121	71.05	28.95	83.68	81.33	77.37
	ResNet50	88.95	11.05	96.84	96.57	92.89
	VGG16	92.11	7.89	93.68	93.58	92.89
	Xception	78.42	21.58	61.58	67.12	70.0

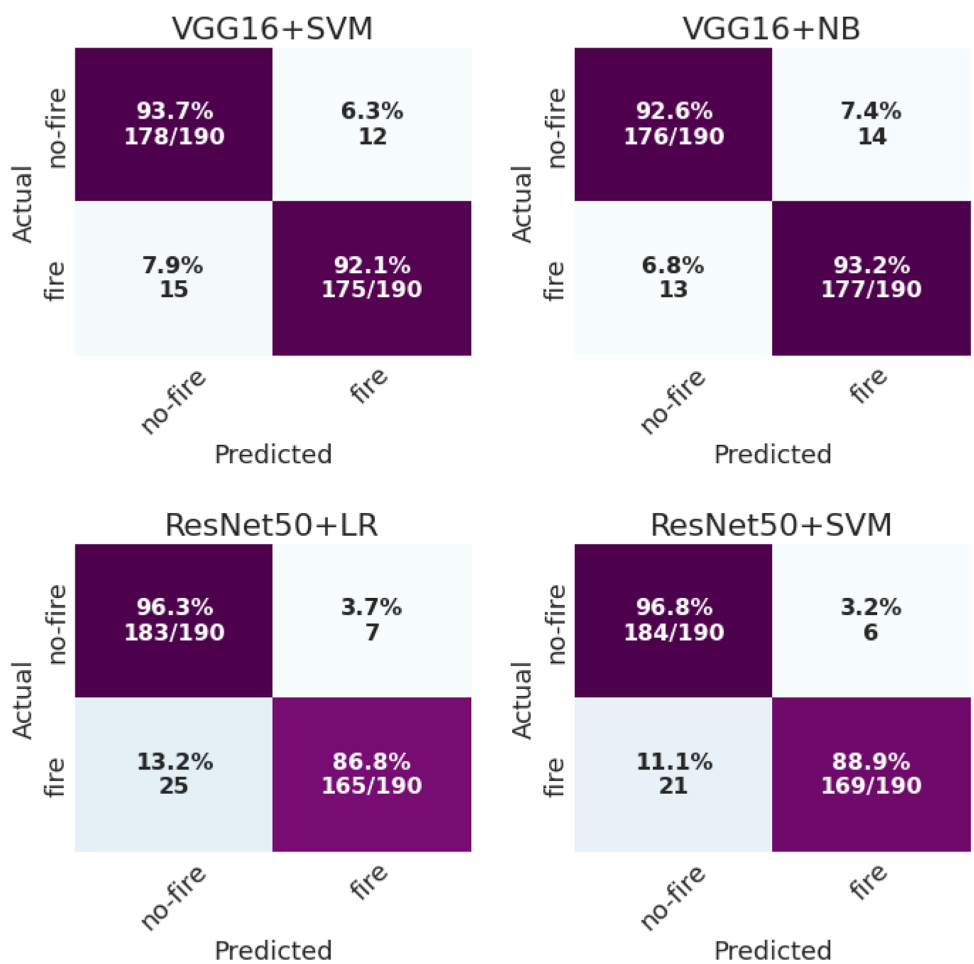

Fig. 6 Confusion matrices of the best performances of NB, SVM, and LR

classifier is very low at 30%. Moreover, the Pre measure of this classifier is also quite low.

b) The SVM classifier offered high Spe with 96.84% and high Pre with 96.57% on the ResNet50 deep features. This classifier can be considered successful with Sen of 88.95% and FNR of 11.05%.

Figure 7 presents the elapsed time of traditional classifiers' training and testing processes and also their classification accuracies on the testing set. As can be seen in Table 5; Fig. 6, NB only performed well on the VGG16 deep features, while LR and SVM performed well on the VGG16 and ResNet50 deep features. Also, the time taken to train and test of these classifiers is quite short. Considering the short-elapsed times for the performances of the models in the testing set, it is seen that a little more time is required for DNN models compared to others.

Figures 8 and 9 demonstrate the ROC curves with AUC values of the classifier models used in this study. As can be seen in these figures, the AUC values of traditional classifiers and DNN classifiers especially trained on the Xception and DenseNet121 deep features are relatively low compared to the VGG16 and ResNet50 deep features. Therefore, they were not able to successfully classify Xception and DenseNet121 deep features. Also, the AUC values of DNN classifiers which run on the deep features extracted with VGG16 and ResNet50 pre-trained architectures are over 0.9 and higher compared to traditional classifiers. The DNN-3 classifier achieved the best AUC with 0.971 on the deep features extracted from Resnet50 pre-trained model.

Images misclassified by the classifiers used in experimental studies were also examined and evaluated. In experiments where the best classification accuracies were obtained, the number of images misclassified by traditional classifiers is 27, and the number of images misclassified by DNN-3 is 11. Both NB and SVM classifiers, that were trained on the VGG16 deep features, misclassified 27 images. The NB classifier misclassified 14 non-fire images and 13 fire images. The SVM classifier misclassified 15 fire images and 12 non-fire images. Moreover, this classifier trained on the ResNet50 deep features misclassified 6 non-fire images and 21 fire images. DNN-3 classifier trained on the ResNet50 deep features misclassified only 6 fire images and 5 non-fire images. Also, it was observed that the traditional classifiers and DNN-based models have less success on the Xception and DenseNet121 deep features compared to other deep features. This indicates that Xception and DenseNet121 deep features are less meaningful than others for machine learning.

5 Discussion

Some studies in which detection of forest fire was carried out are summarized in Table 6. Bisquert et al. used artificial neural networks and logistic regression to predict forest fire hazards from remote sensing and fire history data [52]. Cui developed a system based on smart sensors and IoT devices to monitor anomalies in forest areas [1]. Kanakaraja et al. proposed an advanced forest fire detection

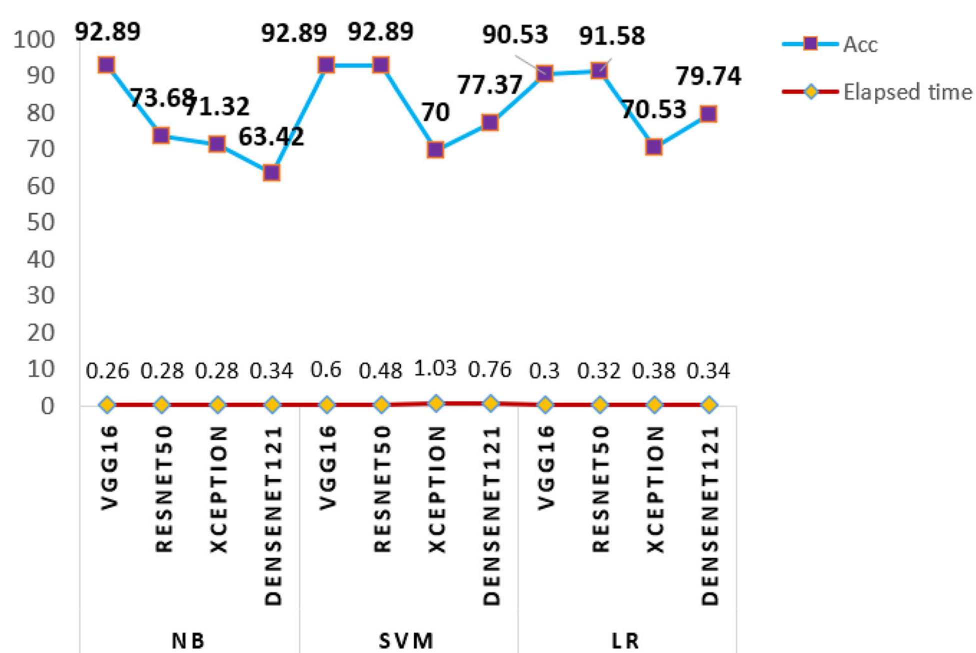

Fig. 7 General classification accuracies and elapsed time information of the traditional classifiers

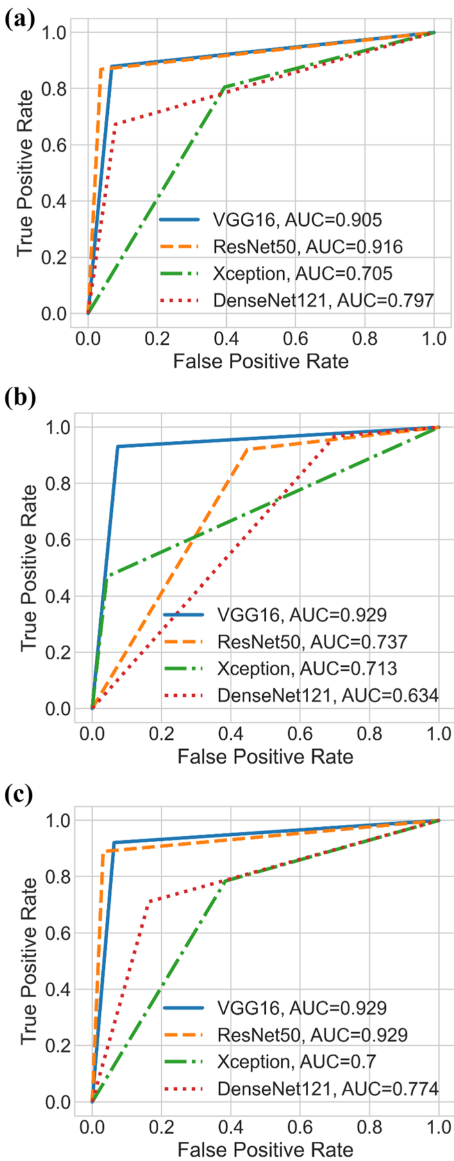

Fig. 8 ROC curves of each traditional classifier model used in this study; **a** LR, **b** NB, **c** SVM

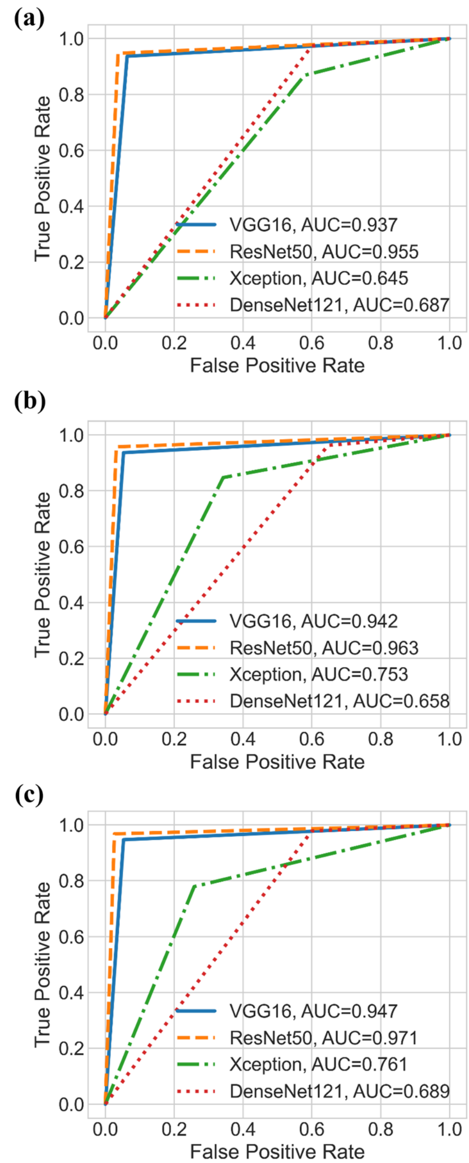

Fig. 9 ROC curves of DNN classifiers used in this study; **a** DNN-1, **b** DNN-2, **c** DNN-3

and monitoring system based on IoT. The authors used ESP32 board and rain, sound, DHT11, and PIR sensors in their study [53]. The disadvantage of sensor-based systems is that they must be installed at a point close to the fire. For this reason, the vision-based system, which employs security cameras with increased speed and robustness in detecting forest fires at great distances, comes to the fore [54].

Liu et al. first produced forest fire samples with General Advanced Networks and then employed CNN and SVM for forest fire prediction on the balanced dataset [38]. Peng and Wang used an optimized SqueezeNet network with deep separation convolution layers and bulk normalization layers to perform fast classification of images and improve the robustness of the detection algorithm using the hand-designed features they extracted from the images [55]. Shamsoshoara et al. trained the CNN model on a 2-class dataset they composed and obtained 76.23% accuracy [40]. Harkat et al. obtained 96.21% overall accuracy by using the SVM with Radial Basis Function kernel on the distinguishing features obtained with information-theoretic feature selection approaches for the classification of fire and non-fire pixels [56]. Dogan et al. proposed an ensemble ResNetV2 deep learning model based on feature extraction, feature selection, classification, and iterative hard majority voting to detect fires and obtained 99.15% classification accuracy [57]. Kukuk and Kilimci performed a comprehensive analysis of traditional machine learning

Table 6 Comparison of the proposed model and the studies in literature

Study	Method	Dataset	Acc (%)
Cui [1]	Arduino based IoT devices and CNN	Other	99.12
Bisquert et al. [52]	Neural network	Other	76
Liu et al. [38]	CNN and SVM	Other	97.6
Peng & Wang [55]	Optimized SqueezeNet network	Other	97.124
Shamsoshoara et al. [40]	CNN	Other	76.23
Harkat et al. [56]	Feature selection and SVM with Radyal Temel İşlev (RBF) kernel	Other	96.21
Dogan et al. [57]	Feature selection and ensemble learning	Other	99.15
Kukuk and Kilimci [58]	CNN	Other	99.32
This study	**ResNet50 deep features + DNN-3**	**Mendeley**	**97.11**

*The result of this study is in bold

algorithms, object detection techniques, and several deep learning models to detect forest fires and reported that convolutional neural networks outperform other methods with 99.32% accuracy [58].

The detection of forest fires, which cause significant losses due to their spread and expansion, is the subject of computer vision. Loss of life and property can be reduced with prompt and accurate fire identification [59]. At this point, the use of Unmanned Aerial Vehicles (UAVs) for fire monitoring is more appealing, as satellite images have low resolution and contain repetitive images constrained by satellite orbital patterns. Modern drones and UAVs, which can be outfitted with Tensor Processing Unit/Graphics Processing Unit platforms, use their camera equipment to process images from the field and detect forest fires early [40]. Computer vision-based models are run on mini-computer integrated UAVs for this purpose. With this perspective, this study presented a successful model that includes ResNet50 deep features extracted from forest landscape images and the DNN-3 classifier. The ResNet50 + DNN-3 model reached a very high level of success with a classification accuracy of 97.11% in this study. This model which misclassified six non-fire images and five fire images presented 96.84% high true positive ratio and 3.16% low false-negative ratio. A few misclassified images are a limitation of this study and will reveal the error of an expert decision support system. With a very highly accurate classification, this artificial intelligence model that has the potential to play a role in the decision support systems required for forest fire detection is very competitive. In addition, this model could be used in conjunction with other models in systems that require multiple decision support. Furthermore, this model and other artificial intelligence models could be used in ensemble learning approaches such as Stacking, Voting, and Bagging. Also, including other data such as humidity, temperature, etc. in the decision-making system will provide an opportunity for a more stable and robust intelligent decision support system.

6 Conclusion

Forests are oxygen production centers that are very important for living things. The damages caused by the sudden forest fire disasters to our nature are very high. Forest protection and monitoring systems which are good for human health and have an important place in wildlife, are one of the main research areas carried out recently. The detection of forest fires using computer vision is critical for surveillance systems. In this study, the features were extracted automatically from images by utilizing different deep learning architectures based on the transfer learning approach. The performances of different classifiers were comprehensively compared using these features. The ResNet50 + DNN-3 model showed the best performance of 97.11% Acc, 96.84% Sen, 97.37% Spe, and 97.35% Pre for fire detection and recognition. In addition, this model offered low false negative ratio with 3.16% compared to others. In the light of these results, the proposed model can be a very effective tool for analyzing and developing forest fire management and strategies. Moreover, this model with high classification accuracy and low false negative could be included in the early warning system which can be applied for the continuity of the forest ecosystem. Also, a more accurate and detailed assessment of forest fire susceptibility could be conducted by considering fire-related spectral indices.

In future studies, it is planned to design a user graphic interface including a deep learning model in the expert systems that instantaneously detect forest fires from the landscape image and provide support services to management units. The application of image preprocessing techniques on the landscape images taken from the environment and the construction of different deep learning models on the resulting images are among the objectives. In addition, it is planned to focus on exploring the hypothesis that the model proposed in this study and alternative approaches will perform well on different data sources for active fire detection. Moreover, it aims to make highly reliable predictions by producing solutions for environment-related problems and differences in image resolutions. Finally, early fire detection and segmentation methods conducted on forest fires especially ground fire, trunk fire, canopy fire, and also smoke imagery are among the planned studies. When considering the damages caused by forest fires to our nature, the design and implementation of these systems are inevitable. Courtesy of these systems, which will support the managers and field officials in charge of forest regions, forest fires can be managed and at least fires can be stopped before they spread to large areas.

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Declarations

Competing interests The author declares that he has no conflicts of interest.

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