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ORIGINAL PAPER

Robust stacking-based ensemble learning model for forest fire detection

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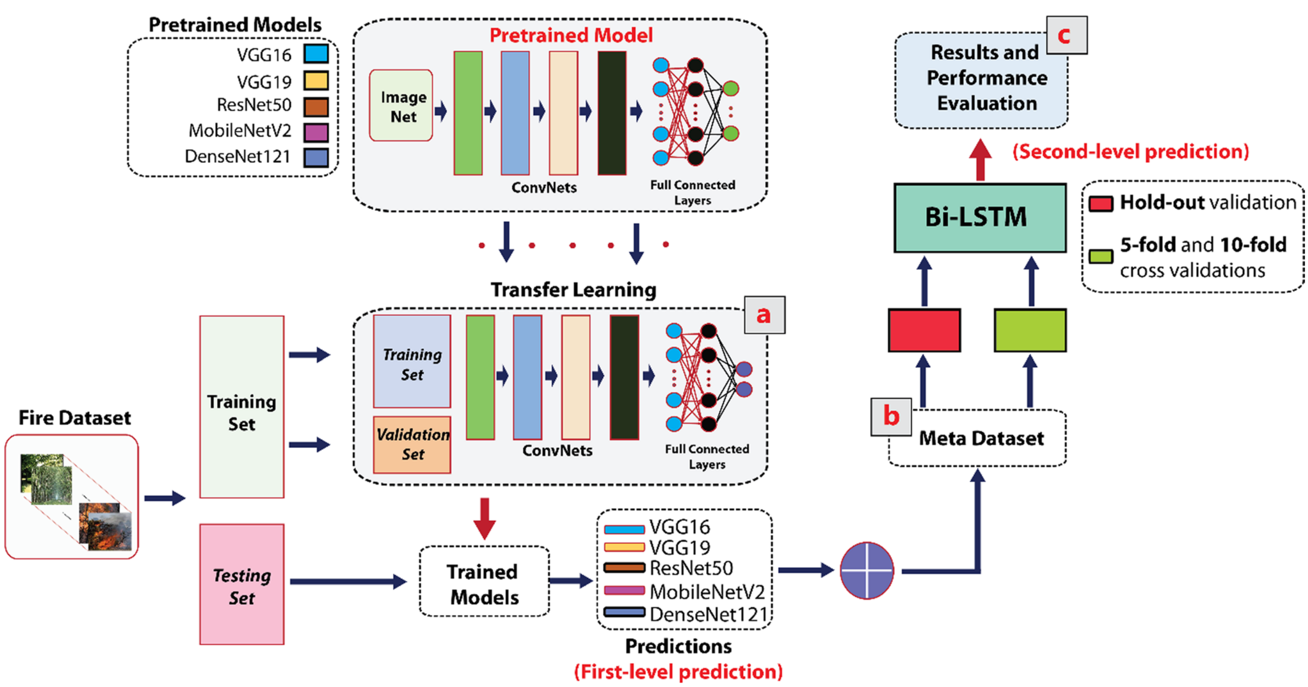
Abstract
Forests reduce soil erosion and prevent drought, wind, and other natural disasters. Forest fires, which threaten millions of hectares of forest area yearly, destroy these precious resources. This study aims to design a deep learning model with high accuracy to intervene in forest fires at an early stage. A stacked-based ensemble learning model is proposed for fire detection from forest landscape images in this context. This model offers high test accuracies of 97.37%, 95.79%, and 95.79% with hold-out validation, fivefold cross-validation, and tenfold cross-validation experiments, respectively. The artificial intelligence model developed in this study could be used in real-time systems run on unmanned aerial vehicles to prevent potential disasters in forest areas.

Graphical abstract
Block diagram of the proposed model



Keywords Forest fire · Computer vision · Deep learning · Stacking ensemble model · Bi-directional long short-term memory

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Introduction

Forests are important ecological resources that play an irreplaceable role in the sustainability of environmental balance in the terrestrial biosphere (Jaiswal and Banka 2017; Chen et al. 2017). Forests have effects on climate with the potential to reduce soil erosion and prevent natural disasters (Wang et al. 2012). Forest fires have profoundly affected ecosystems' soil, water, biota resources, atmosphere, and air quality. Moreover, forest fires reduce tree cover, increase our planet's gas emissions, and also reason for about 20% of CO_2 emissions in the atmosphere (Bouabdellaha et al. 2013). Because of serious environmental and public health burdens (Sannigrahi et al. 2022), forest fires are one of the main causes of ecological degradation (Šerić et al. 2011). Wildfires have received increased attention recently due to their enormous effect on the environment, people and wildlife, ecosystem function, weather, and climate (Abuelgasim and Fraser 2002). As a result, forest fires have social, economic, and environmental effects (Martinez-de Dios et al. 2008). Millions of hectares of forest area are threatened around the world each year (Veraverbeke et al. 2012; Zheng et al. 2020). Areas affected by wildfires are prone to high erosion. This usually occurs immediately after forest fires when the bare surface and an ash bed are current (Lucas-Borja et al. 2019). On the other hand, massive landslides can form after a forest fire in a landslide environment (Fernandez-Steeger et al. 2010), which is the most severe geological danger in mountainous locations (Turcotte and Malamud 2004; Hussain et al. 2022). As a result, forest protection is very important for the continuation of life in forests that are the source of oxygen (Cui 2020). Detecting fires at an early stage and preventing their spread is quite essential for our world. For fast and powerful detection of fires, it is very important to get a satisfactory level of equipment and trained active workers to the source of the flame as soon as possible (Sudhakar et al. 2020). Due to the importance of the subject, several studies have been brought to the literature so far. For example, Sannigrahi et al. presented a study in which the emissions caused by forest fires can significantly increase air pollution, and forest fires play a critical role when they occur during epidemic and pandemic crises (Sannigrahi et al. 2022). Nasirzadehdizaji and Akyuz (2022) investigated the hydrological results of forest fires and their effects on sediment load under different combustion scenarios. Tuyen et al. (2021) examined potential relationships between historical fires and nine causative factors. The authors revealed that the distances to roads and residential areas are more significant in fire occurrence using the Correlation Attribute Assessment feature selection method. Si et al. (2022) reported that elevation, slope, aspect, mean daily temperature, and mean daily relative humidity parameters were significantly related to forest fire occurrence using the optimal Logistic Regression model. Sivrikaya ve Küçük (2022) introduced a fire risk map based on the Analytic Hierarchy Process and Statistical Index methods. Müller et al. (2020) developed the Web-Geographic Information System prototype of the integrated Fire Hazard Assessment System that included daily fire weather index data, human activities, lightning, a high-resolution fuel type map, and a topography-based estimate of fire hazards. Kalabokidis et al. (2013) developed a web-based Geographic Information System platform called Virtual Fire, including easy, valid, fast sharing and using information and tools for fighting forest fires. Krüll et al. (2012) introduced a high-sensitivity smoke aspiration detector, two gas sensors, a microwave radiometer, and detection algorithms in the laboratory environment for early detection of forest fire. Hu et al. (2022) presented a study that determined the direction of the fire source and was also able to specifically extract the color and smoke texture. Besides, studies based on sensor data and the Internet of Things (IoT) are also available. For example, Peinl (2021) developed an IoT-based system, which includes using sensor and mobile communication technologies and analyzing data in a cloud environment for early detection and prevention of forest fires. Garcia-Jimenez et al. (2017) introduced wireless sensor network-based systems for forest fire detection. Varela et al. (2020) presented a study using a wireless sensor network and information aggregation methods to detect forest fires. Bolourchi and Uysal (2013) presented a fuzzy logic-based survey on wireless sensor networks for automatic fire detection in large forest areas. Bernabeu et al. (2004) proposed a prediction and detection system based on passive infrared sensors for automatic forest fire detection. Šerić et al. (2011) presented a study using experience and specific weather information to detect wildfires early and predict wildfire risk. The authors analyzed images and meteorological data. Li et al. (2022) aimed to reduce the information loss from smoke images and noise caused by blurred images for fast forest fire smoke detection. They proposed an IoT-based system to detect smoke.

Artificial intelligence-based approaches for wildfire detection have been particularly subject to deep learning research and widespread adoption. For example, Achu et al. (2021) modeled forest fire susceptibility using machine learning techniques on various geographic data to determine the boundaries of forest fire-sensitive regions. Singh et al. (2021) developed the Weather Forecast Index and a parallel support vector machine model fed by some weather parameters to predict wildfires. Fernandes et al. (2004) proposed a new method using committee machines composed of neural networks to classify lidar signals. Alonso-Betanzos et al. (2002) trained neural networks on the 125,156 meteorological data they collected from five meteorological stations and tested the network on the 13,906-test data. Zhang et al. (2018) detected forest fire smoke using a faster region-based CNN model. The authors generated real and synthetic smoke images to solve the problem of lack of training data to be used in model training step. They trained the model on the synthetic images and tested it on actual fire images. Liu et al. used deep learning methods for forest fire detection. The authors generated forest fire images with General Advanced Networks to solve the small dataset problem. Then, they measured the performances of several classifiers on the Histogram of Oriented Gradients-based features (Liu et al. 2020). Almeida et al. reported that their proposed CNN model classified forest fires more successfully than the state-of-the-art pre-trained models (Almeida et al. 2023). Chatragadda et al. (2022) worked with deep learning architectures such as CNN, VGG19, and DenseNet for wildfire detection and reported that DenseNet-201 outperformed others. Jagatheesaperumal et al. (2023) performed parameter tuning in the layers of the CNN model configured with Adam optimizer and softmax activation in the robot system they designed to detect and prevent fire accidents in their early stages. They also used the Alex-Net architecture for human detection in the fire area. Ghosh and Kumar extracted features from images using convolutional neural networks and recurrent neural networks to detect wildfire. They proposed a new hybrid deep learning model that uses two fully connected neurons in the last layer for classification (Ghosh and Kumar 2022). Majid et al. presented a framework for detecting fires using state-of-the-art CNNs trained on real-world firefighting images and transfer learning. The authors used an attention mechanism in their proposed model, which significantly helped the network achieve better performance, and reported that the EfficientNetB0 model offers quite good test accuracy (Majid et al. 2022). Khan and Khan (2022) added fully connected layers to the pre-trained MobileNetV2 architecture to solve the forest fire recognition problem and achieved 98.42% accuracy on the dataset used in this study. Today, unmanned aerial vehicle (UAV) has been used in many subjects, such as rice seedling detection (Asiri 2023), bridge crack detection (Li et al. 2023) and exposed steel rebars detection (Santos et al. 2022), so far. Some of the artificial intelligence-based UAV solutions introduced for the forest fire problem are as follows: Khan et al. (2022,) examined the success of various machine learning algorithms in their classification study for the artificial intelligence model required for the UAV-based forest fire extinguishing system. They reported that the VGG19 model gave 95% mean classification accuracy. Zhan et al. (2022) constructed an UAV-IoT that processes aerial images or video datasets of objects to detect forest fire smoke with low cost and high sensitivity. Reis and Türk have done a comprehensive study with various deep learning models on the images obtained by the unmanned aerial vehicle. They achieved very high accuracy with the InceptionV3 + GRU hybrid model they proposed (Reis and Turk 2023). As a result, many studies deal with the forest fire subject in the literature. Putting out late-detected forest fires requires equipment, and more trained human resources. Early fire detection cannot be made in regions or countries lacking decision support systems capable of automatically detecting forest fires. Therefore, forest fires have significant devastating effects on nature. Since the damage of forest fires is indescribable, they are a significant problem today. Considering the damages and losses caused by forest fires, early fire detection is vital in extinguishing the fire before it reaches destructive dimensions and preventing losses (Reis and Turk 2023).

An efficient monitoring system can help us detect and prevent wildfires so damage is prevented. Because uncontrollable fires are more difficult to see in their early stages, a faster and more precise detection approach can help reduce the incidence of the damage they cause (Chatragadda et al. 2022). It is also a fact that avoiding the potential effects of catastrophic events as much as possible requires the development of the right strategies, modeling, and forecasting of severe conditions (Mohajane et al. 2021). For this reason, there is a need for alternative computer-aided systems to analyze the field image with comparatively faster and inexpensive methods and to respond to fires at an early stage. Image processing-based methods that automatically detect fire images in forest areas in real-time systems have been intensively researched for the last few years. It is inevitable to use artificial intelligence-based models that offer high accuracy for UAV to fly over the terrains and send the fire emergency warning code to the decision centers in the IoT environment. Deep learning-based models could have an essential role in emergency warning systems that will undoubtedly support the field authority with the diagnosis of fire or not from forest landscape images. With this perspective, the primary motivation of this study is to propose a deep learning model that is different from the studies in the literature for detecting forest fires. This study offers an alternative computer vision-based method for automatic real-time identification and classification of forest fires. The proposed model has not been explored extensively for forest fire identification from landscape images. The novelty of the current study is that it includes a stacking ensemble modeling approach with highly accurate classification and a low false-negative rate. The proposed model uses pre-trained deep learning models as base learners to extract features representing images and predict target class in the first stage and uses the Bi-LSTM network as a meta-learner for final classification with high accuracy in the second stage. While the base learners classify the forest landscape images in the first stage, Bi-LSTM performs the final classification on the meta dataset that is composed of the predictions of the base learners in the second stage. The contributions of this paper to the literature could be summarized as follows:

- The performances of state-of-the-art CNN models are examined to detect forest fires.
- The training and testing phases of the Bi-LSTM network are performed on the meta-dataset that includes the predictions of the state-of-the-art CNN models.
- The model proposed in this study could be given a role in artificial intelligence-based expert systems.

The remainder of this paper is organized as follows. In "Materials and methods" section describes the dataset and gives information about the methodology used in this study. In "Experiments" section introduces the experiments in detail. In "Results and discussion" section presents experimental results and also discusses some studies in the literature. Finally, "Conclusion" section concludes with remarks.

Materials and methods

This study proposes a robust stacked ensemble learning model including base learners and meta-learner to detect forest fires. Figure 1 shows the block diagram of the proposed model. The first stage of the proposed model includes the training and testing of different pre-trained CNN models, such as DenseNet121, MobileNetV2, ResNet50, VGG16, and VGG19. Base learners classify the forest images at the first stage (Fig. 1a). In the second stage, the meta-dataset is composed by concatenating the classification results of these learners (Fig. 1b). Then, the Bi-LSTM network performs the final prediction with both validation rules (Fig. 1c). The proposed model takes advantage of the feature extraction and classification capabilities of state-of-the-art pre-trained CNN models and the superior classification capability of Bi-LSTM.

The rest of this section introduces the dataset used to validate the performance of the proposed model. In addition,

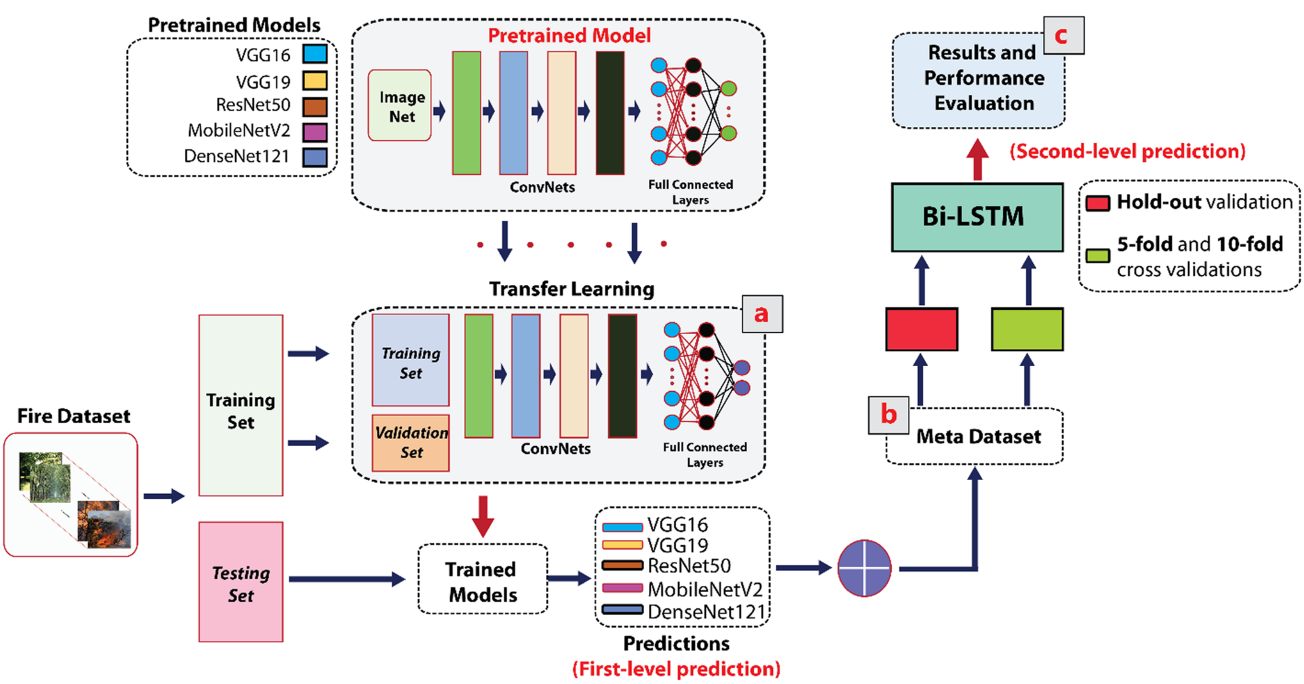

Fig. 1 Block diagram of the proposed model

Fig. 2 Sample forest landscape images; From top to bottom; **a** no-fire, **b** fire

transfer learning, Bi-LSTM, stacking ensemble learning, and performance metrics are briefly explained in this section.

Dataset

The dataset used to validate the performance of the model proposed in this study was composed and published by Khan and Hassan (2020) using various search terms on multiple search engines for forest fire problems. This balanced dataset consists of 1900 images, with 950 images belonging to each class. The images in the dataset are 250×250 spatial resolution with three channels. The authors ensured that the fire images included only the relevant fire area. Moreover, the authors divided the dataset into training and testing sets with a ratio of 80:20, respectively. Accordingly, 760 images from each class were reserved for training and 190 for testing. Figure 2 presents exemplary forest landscape images.

Transfer learning

Using pre-trained Convolutional Neural Networks (CNN) on any problem is called the transfer learning approach, and it is a reliable technique for learning (Shanmugam et al. 2022). A CNN model trained on large datasets is effectively reused for new target problems by making necessary changes, known as fine-tuning. This model provides a time advantage and allows successful results on small datasets. A pre-trained CNN model is weighted best on a large image dataset and therefore is used to obtain better results when compared to CNN from scratch having random weights (Khademi et al. 2022).

Bi-directional long short-term memory (Bi-LSTM)

Long short-term memory (LSTM) uses previous data to take inputs backward through hidden states (Joshi et al. 2022). Bi-LSTM is an enhanced version of LSTM networks and includes two LSTMs that consider the values of the input's backward direction and forward direction and then combine the outputs (Rehman et al. 2020). In other words, a Bi-LSTM consists of forward LSTM and backward LSTM layers. In this way, Bi-LSTM learns the effect of both previous and subsequent data for each datum point. The architecture of this network is shown in Fig. 3. Here, σ is the sigmoid function, $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ are independent of each other and indicate the LSTM hidden vector of the forward LSTM layer and backward LSTM layer, respectively, at time t. The weighted connection of these two hidden layers gives the

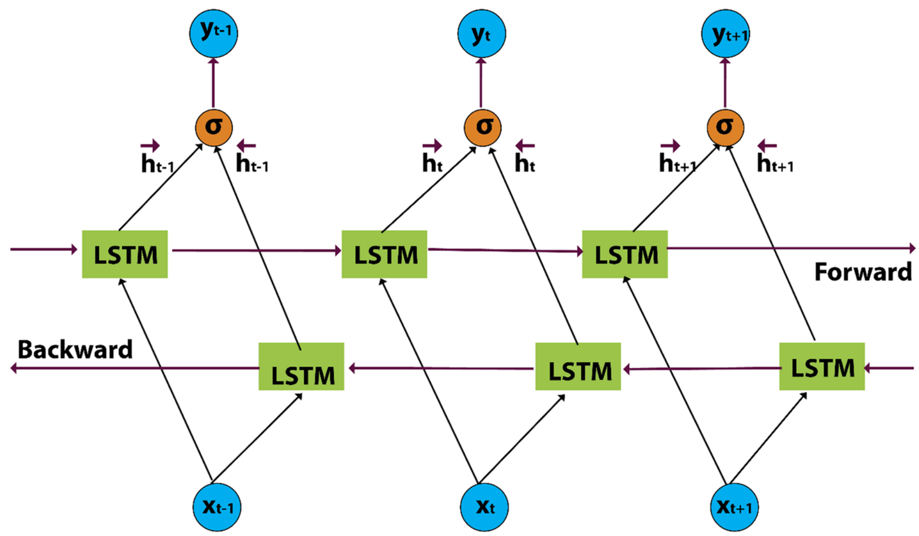

Fig. 3 Architecture of Bi-directional LSTM

output of Bi-LSTM (y_t). The process can be described as given between Eq. 1 and Eq. 3 (Huang et al. 2022):

$$\overrightarrow{h}_t = \mathrm{LSTM}\left(x_t, \overrightarrow{h}_{t-1}\right) \tag{1}$$

$$\overleftarrow{h}_t = \mathrm{LSTM}\left(x_t, \overleftarrow{h}_{t+1}\right) \tag{2}$$

$$y_t = \delta\left(W_{\overrightarrow{h}_y}\overrightarrow{h}_t + W_{\overleftarrow{h}_y}\overleftarrow{h}_t + b_y\right) \tag{3}$$

Here LSTM(.) represents the LSTM network, $W_{\overrightarrow{h}_t}$ and $W_{\overleftarrow{h}_t}$ are the weight of the forward and backward LSTM layer at time t, respectively. In addition, the b_y and $\delta(.)$ indicate the bias and activation function of the output layer, respectively (Huang et al. 2022).

Stacking ensemble learning

Stacking ensemble learning architecture includes base learners and meta-learner. A base learner indicates the first level machine learning algorithm, and a meta-learner indicates the second level in this architecture (Wolpert 1992). Base learners are separately trained as individual predictors in the first level, and their predictions are concatenated in a stacked ensemble learning strategy. So, the prediction results of the base learners are sent to the meta-learner, the final predictor, for classification in the second level.

Performance validation

The dataset has two classes in which 'fire' and 'no-fire' are labeled as positive and negative, respectively, used in this study. In a two-classes dataset, the performances of the models are measured using the basic criteria True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which are the parameters of the confusion matrix. 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 tested using the hold-out validation and k-fold cross-validation through Accuracy (Acc), Sensitivity (Sen), Specificity (Spe), Precision (Pre), and F1-score metrics. These metrics are given in between Eq. 4 and Eq. 8, respectively. The hold-out validation is performed by dividing the dataset as training and testing sets in some ratios. The k-fold cross-validation technique divides the dataset into k parts, one for testing and the remaining k-1 parts for

Table 1 Pre-trained CNN parameters settings

Parameter	Value
Optimizer	RMSprop
Learning rate	0.001
Activation function	*Softmax* in output layer
Epoch	30
Batch size	8

training (James et al. 2013). With this technique, the performance of any model is tested on all samples in the dataset, and the average performance of the k-fold cross-validation is reported as the overall modeling performance (Vu et al. 2022).

$$\text{Sen} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

$$\text{Spe} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{5}$$

$$\text{Acc} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}} \tag{6}$$

$$\text{Pre} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{7}$$

$$F1 - \text{score} = 2 \times \frac{\text{Pre} \times \text{Rec}}{\text{Pre} + \text{Rec}} \tag{8}$$

Table 2 Bi-LSTM parameters settings

Parameter	Value
Optimizer	Adam
Activation function	*Softmax* in output layer
Epoch	30
Batch size	8
Unit	4
Dropout	0.05
Recurrent dropout	0.05

Experiments

Model training and testing

All experiments used the Keras framework on the Google Colab environment having Tesla P100-PCI-E-16 GB GPU,

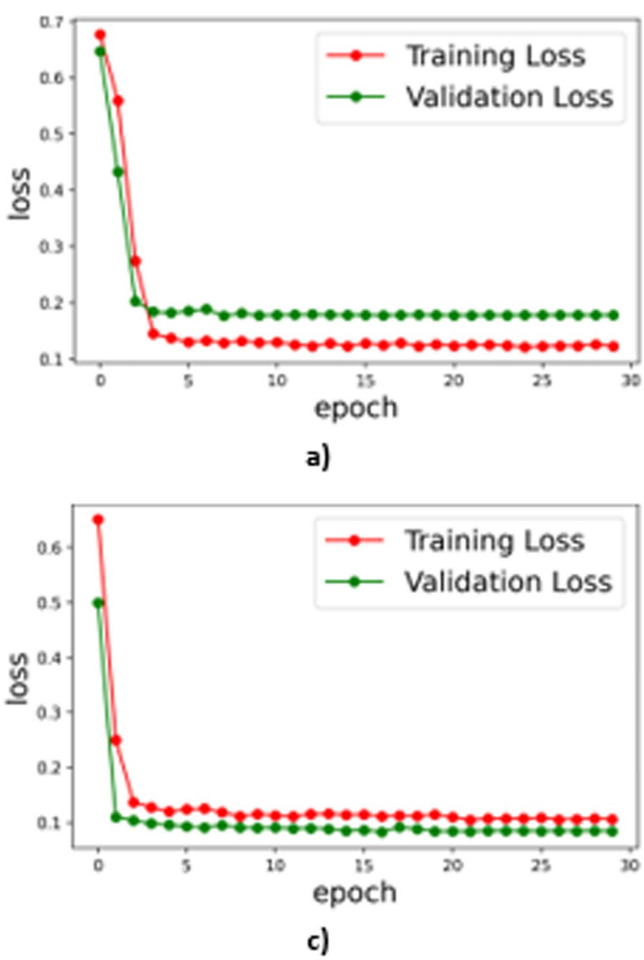

Fig. 4 Loss plots of some experiments; **a** Hold-out validation, **b** fold #3 in the fivefold cross-validation, **c** fold #8 in the tenfold cross-validation

Table 3 Hold-out validation results of pretrained CNN models

	TP	FN	TN	FP	Sen	Spe	Pre	F1-score	Acc
VGG16	177	13	173	17	93.16	91.05	91.24	92.19	92.11
VGG19	171	19	150	40	90.0	78.95	81.04	85.29	84.47
ResNet50	182	8	174	16	95.79	91.58	91.92	93.82	93.68
MobileNetV2	190	0	162	28	100.0	85.26	87.16	93.14	92.63
DenseNet121	171	19	182	8	90.0	95.79	95.53	92.68	92.89

Table 4 Hold-out validation and k-fold cross-validation results of the Bi-LSTM

		TN	FP	TP	FN	Sen	Spe	Pre	F1-score	Acc
Hold-out		36	2	38	0	**100.0**	**94.74**	**95.0**	**97.44**	**97.37**
$k=5$	Fold #1	34	4	36	2	94.74	89.47	90.0	92.31	92.11
	Fold #2	36	2	37	1	97.37	94.74	94.87	96.1	96.05
	Fold #3	34	4	37	1	97.37	89.47	90.24	93.67	93.42
	Fold #4	37	1	37	1	97.37	97.37	97.37	97.37	97.37
	Fold #5	38	0	38	0	100.0	100.0	100.0	100.0	100.0
	Average					**97.37**	**94.21**	**94.5**	**95.89**	**95.79**
$k=10$	Fold #1	19	0	18	1	94.74	100.0	100.0	97.3	97.37
	Fold #2	18	1	19	0	100.0	94.74	95.0	97.44	97.37
	Fold #3	18	1	19	0	100.0	94.74	95.0	97.44	97.37
	Fold #4	16	3	18	1	94.74	84.21	85.71	90.0	89.47
	Fold #5	18	1	19	0	100.0	94.74	95.0	97.44	97.37
	Fold #6	18	1	19	0	100.0	94.74	95.0	97.44	97.37
	Fold #7	18	1	18	1	94.74	94.74	94.74	94.74	94.74
	Fold #8	17	2	17	2	89.47	89.47	89.47	89.47	89.47
	Fold #9	19	0	19	0	100.0	100.0	100.0	100.0	100.0
	Fold #10	18	1	19	0	100.0	94.74	95.0	97.44	97.37
	Average					**97.37**	**94.21**	**94.49**	**95.87**	**95.79**

Bold fonts indicate the hold-out validation results and k-fold cross-validation average results

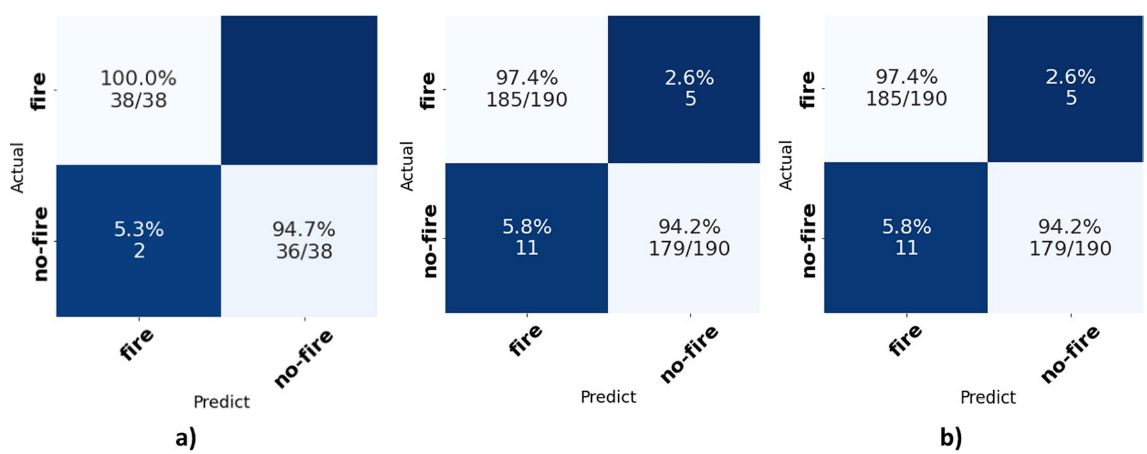

Fig. 5 Confusion matrices; **a** Hold-out validation, **b** Overlapped confusion matrix of fivefold cross-validation, **b** Overlapped confusion matrix of tenfold cross-validation

Intel(R) Xeon(R) 2.30 GHz CPU, and 25 GB RAM. The trainable parameters were set to 'True' to update the neurons' weights of the pre-trained models according to the forest landscape images. In the first stage, training and testing of pre-trained CNN models were conducted on the training and testing sets published by Khan and Hassan (Khan and Hassan 2020). In addition, 20% of the training set was reserved for the validation set in the experiments. Some parameters of pre-trained CNN models are listed in Table 1.

The training and testing of the Bi-LSTM were carried out on the meta dataset, composed of the prediction results of the state-of-the-art CNN models on the test images in the second stage. The meta-dataset was split into training, validation, and testing sets according to the validation rules. Experiments of the Bi-LSTM network were performed with the hold-out validation and k-fold cross-validation ($k=5$ and $k=10$) techniques. For example, 80% of the dataset is reserved for the training set, and 20% for the testing set for the k value is 5. In addition, the validation set includes 20% of the training set. Thus, the performances of the Bi-LSTM network were examined on different test sets for each fold. As a result, this network conducted predictions on all images in the testing set separated for first-level classification. Some loss plots of the training of the Bi-LSTM model are shown in Fig. 4. To avoid the presentation of repetitive figures and thus improve readability, only three loss figures were presented here. Also, some parameters of the Bi-LSTM network are listed in Table 2.

Results and discussion

This study introduced the stacking-based ensemble learning model for forest fire detection. Table 3 presents the hold-out results of state-of-the-art pre-trained CNN models that are base learners. According to the results, Resnet50, which offered higher classification performance than others in the first stage, correctly classified 182 out of 190 fire images and 174 out of 190 no-fire images. This network provided 93.63% accuracy, 95.79% sensitivity, 91.58% specificity, 91.92% precision, and 93.82% F1 score on the testing data. Table 4 presents the hold-out, fivefold cross-validation, and tenfold cross-validation results of the Bi-LSTM network, the meta-learner in the second stage. Figure 5 presents overlapped confusion matrices of the

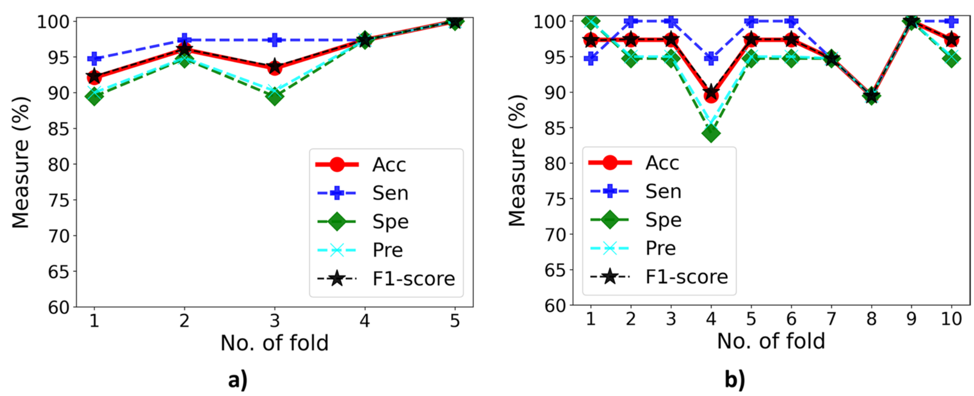

Fig. 6 The results of the Bi-LSTM network; **a** fivefold cross validation, **b** tenfold cross validation

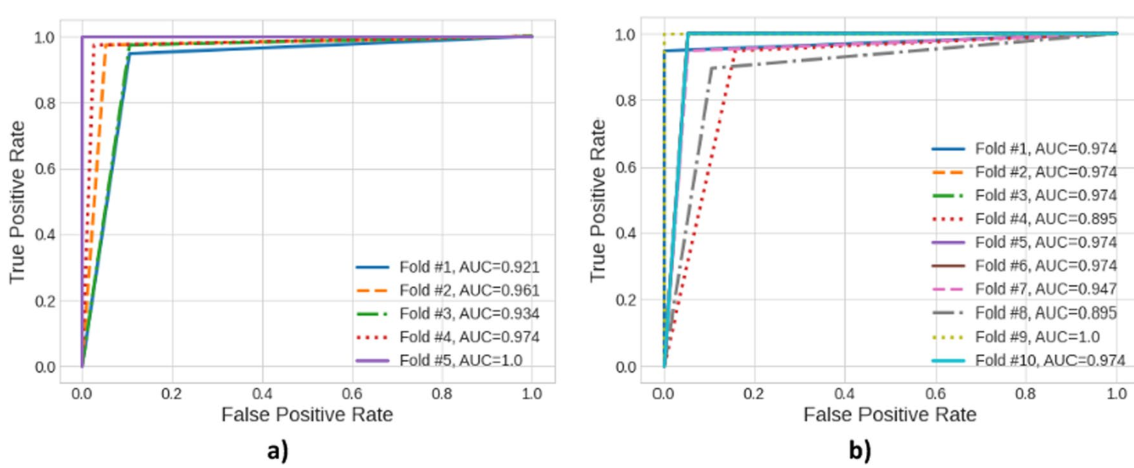

Fig. 7 ROC curves of the k-fold cross-validation experiments; **a** fivefold cross-validation, **b** tenfold cross-validation

Bi-LSTM. Accordingly, using the hold-out validation, the Bi-LSTM network correctly classified all fire images and 36 of 38 no-fire images and offered a very high classification performance with 97.37% accuracy, %100.0 sensitivity, %94.74 specificity, %95.0 precision, and %97.44 F1-score with this validation. Moreover, the Bi-LSTM network classified 185 of 190 fire images correctly and 5 of them incorrectly, while 179 of 190 no-fire images were classified correctly in the experiments with fivefold cross-validation and tenfold cross-validation experiments. The Bi-LSTM network classified fire and no-fire images with 95.79% average accuracy with fivefold cross-validation and tenfold cross-validation. This network presented a 97.37% average sensitivity, 94.21% average specificity, %94.5 average precision, and %95.89 F1-score on the testing data using fivefold cross-validation. Furthermore, this network offers a 2.11% to 11.32% improvement over the general classification accuracies compared to the base learners in the fivefold. Besides, this network's fivefold cross-validation and tenfold cross-validation experiments are similar. Figure 6 demonstrates the performance measures of the Bi-LSTM network. The total number of misclassified examples of this model is 16 in fivefold cross-validation and tenfold cross-validation. Moreover, the number of the model's false predictions is less than the number of misclassified samples by base learners. According to the results, the proposed model, which includes the Bi-LSTM network fed with the predictions of the pre-trained CNN models, presents an improved classification performance.

Moreover, Fig. 7 shows the proposed model's ROC curves and AUC values. This model presented an average 0.958 AUC value in fivefold cross-validation and tenfold cross-validation experiments. As a result, experiments with both validation techniques show that the Bi-LSTM network is quite successful on the meta dataset containing the predictions of pre-trained CNN models. Thus, this model could be evaluated as stable and robust for detecting forest fires.

There are studies in the literature that processed meteorological data, sensor data, and lidar signals for fire detection. Remote sensing provides detailed information on various earth parameters, including climate, vegetation, and forest variables (Kumar et al. 2022). The fact that sensor data are valid for specific regions and the necessity to be installed at a point close to the fire makes sensor data-based studies very costly (Pundir and Raman 2019). Today, computer vision-based analysis of forested field imagery is a subject that scientists work very hard. Table 5 summarizes the previous studies and the proposed study, which was performed based on CNN for detecting forest fires. CNN fine-tuning, CNN optimization, feature extraction and classification, CNN with attention mechanism approaches were used ofttimes. Computer vision-based detection of forest fires has a vital role in decision support systems. With this respect, using CNN in computer vision-based studies on images is very popular. Unlike studies in the literature, the proposed model showed very high classification performance with 97.37% and 95.79% accuracies, respectively, using hold-out and k-fold cross-validation techniques in the experiments. This artificial intelligence model, which detects the presence or absence of forest fire from landscape images, has

Table 5 Comparison of the proposed model and the studies in literature

Study	Method	Dataset	Validation	Acc (%)
Muhammad et al. (2018)	CNN with fine tuning	Other	Hold-out	94.39
Peng and Wang (2019)	Optimized SqueezeNet network	Other	Hold-out	97.124
Liu et al. (2020)	CNN and support vector machine	Other	Hold-out	97.6
Ghosh and Kumar (2022)	CNN and RNN	Other	Hold-out	99.10
Majid et al. (2022)	EfficientNetB0 with Attention mechanism	Other	Hold-out	95.40
Almeida et al. (2023)	CNN model	Other	Hold-out	95.41
Reis and Türk (2023)	InceptionV3 + GRU	Other	Hold-out	99.32
Jagatheesaperumal et al. (2023)	CNN with hyperparameter tuning	Other	Hold-out	89.64
Khan et al. (2022)	VGG19	Same	10-fold cv*	95
Khan and Khan (2022)	MobileNetV2	Same	Hold-out	98.42
Chatragadda et al. (2022)	DenseNet-201	Same	Hold-out	97
This study	Stacked-ensemble modeling	Same	**Hold-out** **k-fold cv*** **(k = 5, k = 10)**	**97.37** **95.79**

*cv cross-validation in the second level of the stacked ensemble learning model

The result of the proposed study is in bold the potential to play an essential role in decision support systems embedded in UAVs. However, this study has some limitations. For example, the factor analysis technique was not applied to the features extracted by deep learning networks, which are included in the proposed model in this study. This technique, which combines the correlated features, is used in many studies, such as climate change (Līcīte et al. 2022), time series (Kozisek et al. 2023), and medical data (Kaya and Kuncan 2022). In addition, the parameters of the deep learning networks used in this study have not been fine-tuned. Bio-inspired optimization algorithms could be used for this task. These algorithms were used to solve many problems, such as boosting energy production (Yu et al. 2020), shop visit balancing (Xia et al. 2023), traffic flow modeling of long and short trucks (Oyeyemi Olayode et al. 2023), and health state estimation (Liu et al. 2022). Lastly, although the dataset used in experimental studies is balanced and contains enough examples, validating the success of deep learning models on a dataset is the limitation of this study.

Conclusion

Studies that lack artificial intelligence-based systems and carry out delays cause negative results in the fight against forest fires. Therefore, artificial intelligence models are needed to support the authorities. In this context, this research study proposes an alternative computer vision-based model that can be practically applied in real-time applications for automatically identifying and classifying forest fires. The stacked modeling approach inspires the proposed model and considers the deep features of forest landscape images for forest fire detection. The main point here, and the part that differs from other studies in the literature, is the training and validation of the performance of the Bi-LSTM network on the meta-dataset consisting of the predictions of state-of-the-art deep learning models. Experimental studies include training and validating this model with hold-out and k-fold cross-validation techniques. Moreover, this model could play an essential role in the expert decision support systems to be designed with the aim of early detection and prevention of forest fires for the continuity of the forest ecosystem, which is very important for our world. The proposed model could play a key role in reporting the fire diagnosis to the command and operations center in the Internet of Things environment, thus preventing possible disasters. Therefore, the proposed model could contribute to the firefighting efforts of forest firefighters to avoid forest fires and minimize fire damage by being integrated into today's unmanned aerial vehicles. The proposed model is thought to encourage using deep learning models in unmanned aerial vehicles that will participate in forest fire detection and supports researchers in developing their ideas on this subject. It is planned to obtain a model that can be generalized to more than one dataset by conducting experimental studies on different datasets related to forest fires. Finally, a decision support system that uses the artificial intelligence-based model, which is the core component of this study, and another system that uses meteorological data will be more helpful in predicting fire risk.

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Declarations

Conflict of interest The author declares that he has no conflicts of interest.

Ethical approval and informed consent This research did not require ethics approval.

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