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Forest Fire Risk Assessment and Detection using Deep Learning Models

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Abstract

Background: There is a severe need to detect any kind of fire in a faster and accurate method, especially forest fires to stop huge losses to the human community and the environment losses. The main purpose of the proposal is to identify and evaluate the accuracy of the existing Artificial Intelligence (AI) methods for detecting fire and improve the methods to detect fire in real-world scenarios in faster and accurate methods. **Methods**: The proposal uses a dataset to train a model, and in addition uses a few test images from an existing database to test the models developed. We develop and test the following neural network models namely, Deep Neural Network (DNN), Recurrent Neural Network (RNN), Convolution Neural Network (CNN), and a combination of RNN and CNN. **Findings**: A conservative estimate of the yearly losses caused by forest fires in India for the entire nation is 440 crores INR. The loss of biodiversity, soil moisture, nutrients, and other intangible advantages is not factored in this assessment. The proposed models namely DNN, RNN, CNN, and RNN+CNN give an accuracy of 55%, 61%, 55% and 98% respectively. **Novelty and applications**: The RNN+CNN model proposed to have good accuracy which is much better compared to existing models. The model in addition can be used in real-time CCTV surveillance which can predict the fire in real-time with a faster alert duration of less than 30 sec.

Keywords: Fire detection; CNN; RNN; DNN; Artificial Intelligence (AI); Environment loss; Fire Losses

1 Introduction

To reduce damage produced by fire disasters, several traditional and leading-edge fire recognition approaches have been offered. Among these methods, vision and sensor-founded fire recognition systems have involved a lot of consideration from the scientific community. The fire detection approach is divided into five fundamental classes founded on the types and uses of sensors: light-sensitive, smoke-sensitive, gassensitive, temperature-sensitive, and combination[1]. Applications for machine learning include the identification and forecast of forest fires in any of the mentioned classes. Algorithms for detecting fires using machine learning depend on manually collecting observable information from photos. These features solely pay attention to the flame's surface features, which might cause data loss during manual extraction. Deep learning has the capability to autonomously extract and learn complex feature representations, in contrast to machine learning methods. With the proven results of CNNs in the classification of images and deep learning's revolutionary development in computer vision, research on the detection of fire is looking very promising. CNN-based techniques provide the prediction to a vigilant system after using frames as surveillance schemes as input[2].

There exists a notable trend toward the adoption of computer vision (image) founded systems for traditional fire detection, owing to swift developments in video and image treating methods in addition to digital camera technology[3]. Large, open environments are ideal for the recognition of fire using video-based techniques. Most locations nowadays have camera surveillance systems installed for both outdoor and indoor monitoring. In this case, developing a video-based fire warning system that could leverage the existing security cameras would be beneficial to detect and alert the fire in real time. Systems of this kind have various benefits over conventional detection techniques. Using such a type of detection is less expensive than using traditional methods and installing this kind of system is easier[4]. Secondly, compared to other traditional detection methods, a vision-found fire detection system reacts more swiftly. Since it can monitor a wide area and doesn't need any specific conditions to trigger the devices.

Even while CNN-based fire detection algorithms outperform conventional algorithms in terms of detection accuracy in complicated scenarios, there still exist some issues. First, the region proposal stage was disregarded in the indulgence of classifying picture fire detection as a classification job in most contemporary machine learning methods. The algorithms assign a class to the full picture[5]. But just a tiny portion of the image was engulfed in smoke and flame during the early stages of the fire. Using the whole image feature without region recommendations will reduce detection accuracy and cause a delay in fire detection and alarm activation if the smoke and flame feature is not immediately visible[6].

Research Gap:

It is challenging to conclude that the approaches that have been suggested so far are flawless. There may be false predictions of fire occurrence, this generally happens at night since a number of things have blurry images. Rainy nights may make it difficult to identify fires. One more major problem with the existing systems is the complete image is used as a ROI for detection of fire. Whereas in a real-time scenario, there exist only certain regions where fire exists. This may lead to false prediction of the fire using the AI model and the time for prediction is increased.

The solution to the first problem, we propose a better camera for capturing the images. In addition, we do image pre-processing steps such as a morphological operation for a clear pixelation of the image, through which the image contrast is increased. The solution to the second problem can be done by ROI detection. Therefore, in instructions to increase the algorithm's capacity for early detection, proposal zones should be identified prior to picture categorization. Second, by manually choosing characteristics and using CNNs to categorize proposal areas, some researchers created algorithms that generate proposal regions. Such a technique uses a lot of computation and slows down detection speed since it generates the proposal areas by calculating on a distinct basis rather than using CNNs for the global detection process[7].

The research mainly focuses on the following aspects:

- Collect a forest fire dataset that includes information on topographical, climatic, ecological, and human aspects that contribute to fire in the forest.
- Use the image pre-processing techniques to enhance the image in the night.
- Use the developed model to classify a real-time image, which is segmented into regions, instead of categorizing the complete image.
- Develop the DNN, CNN, and RNN models for testing the dataset.
- Extending the developed model to detect a live video stream (series of images).

2 Methodology

2.1 Dataset Used

The fire dataset was produced in 2018 as a portion of the NASA Space Challenge, with the intention of using it to train a model that would identify photos that included fire. It can be obtained from the Kaggle website[8]. The information is separated into two folders: the fire images folder has 755 outdoor fire photos, some of which have smoke in them; the non-fire images folder has 244 nature photos (such as those of trees, grass, rivers, people, foggy forests, lakes, animals, roads, and waterfalls). In this dataset, around one hundred images are castoff for the testing dataset and 800 are scaled and reshaped to create the training dataset. Convolution, activation functions, and max pooling are castoffs to train the model. The developed model remains trained with different batch dimensions and epoch settings to get better accuracy [8].

2.2 System Architecture

Frame Capturing - This is the initial stage that details the configuration of the webcam/USB camera with our program. Using the open-cv in Python, which assists in grabbing the live videos from a USB camera connected to the system. Further, through the utilization of frame grabbing approach the concerned frame from the video is extracted subsequently according to the set time given in seconds in the JPEG format. Finally, these continuous image frames are fed to the system to detect the fire [9].

Grayscale and Binary Conversion - The captured frames in the previous step are castoff for detecting fire where the primary component used is its color. The averaging of RGB color components and thresholding of pixels are utilized for realizing a heuristic approach and converting the frame into a gray-scale image. The threshold value, which is usually set at 180, is then castoff to verify the mean value of RGB which indicates the color of the fire. The numbers of pixels that are conforming to the threshold are counted. The count is then stored as the fire pixel count. This count is then further analyzed for the threshold count for the value decided by the system. If the count exceeds this threshold, then the frame is said to contain fire founded on the color and is labeled subsequently.

Co-Axial Ratio -This step of the procedure is utilized for the identification of the shape of the fire in the presented technique. This is achieved through the utilization of the Co-axial variance approach. In the proposed approach the ratio of the fire pixels obtained in the previous step is utilized for the calculation of Equation (1) and Equation (2). This is repeated for every pixel that is extracted in the previous step. The ratio stream obtained through these equations and the ratio represents the morphology vector or the shape vector of the fire. Figure 1 shows the overall system architecture of fire assessment and detection system.

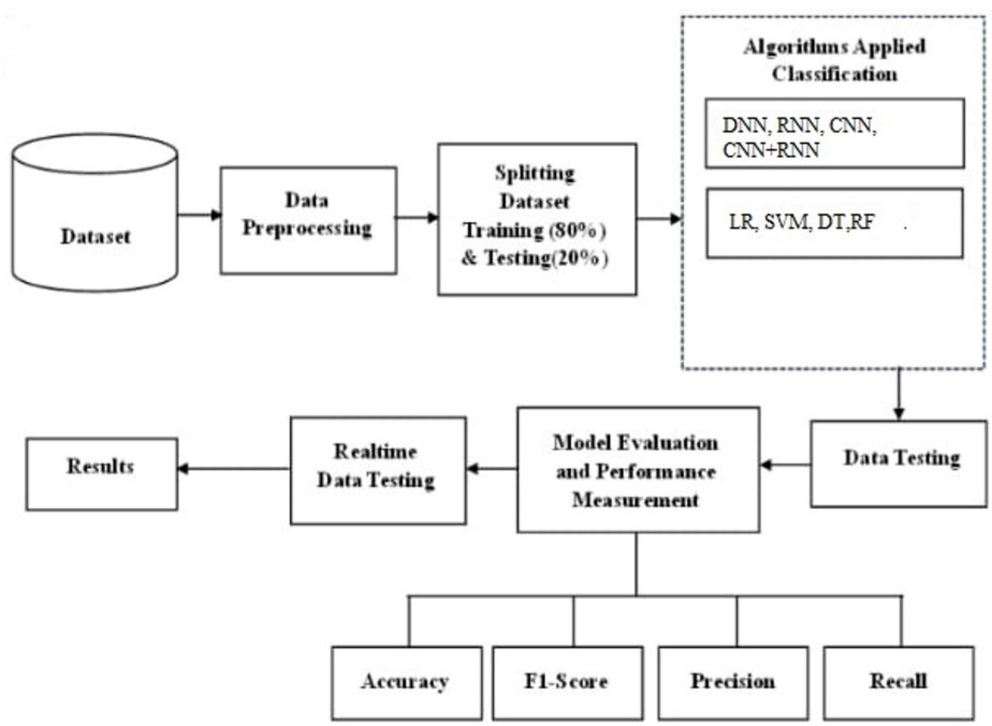

Fig 1. System Architecture

$$X\ (i) = \sum_{a=1}^{M} \frac{I(a,b)}{width} \tag{1}$$

$$Y\ (j) = \sum_{b=1}^{M} \frac{I(a,b)}{height} \tag{2}$$

Here, X(i) and Y(j) are the morphological operators being used to convolute the X-axis and Y-axis accordingly. I(a, b) is the each pixel value at position a and b and M represents the total pixels of the image.

Fire Motion Estimation - This remains the penultimate step that is involved in the fire detection that is used for the detection of motion of fire. For every time interval T frame grabbed is compared to the previous frame for a reference in the motion. The fire pixel values obtained in the previous steps are segregated into previous and current frames whose difference is then.

Fire Detection through Decision Tree - In this step of the procedure the false positives are eliminated through the utilization of the Decision Tree. The parameters obtained in the preceding steps are given as input to the Crisp Value Generator module. The parameters are the shape, motion, and color of the fire. These values are tagged in a Crisp value manner where the values range from zero to one. The crisp values that are obtained in the previous step of this procedure are segmented according to the ranges given below in Table 1.

Table 1. Threshold values used for fire alert

Fire Level	Value
Very Low Fire	Below 0.2
Low Fire	Between 0.2 and 0.4
Medium Fire	Between 0.4 and 0.6
High Fire	Between 0.8 and 0.8
Very High	Above 0.8

The segregation allows for the effective division of the values as the very low, low, and medium values are highly uncertain and are false and, therefore are discarded. The parameter values representing the high and very high are standards that are considered very likely to remain an indication of fire and are subsequently used to raise the alarm.

2.3 Classification and Model Comparison

As mentioned, we have developed and tested various machine-learning systems for detecting forest fires. Below are the ML algorithms used for testing the dataset. Key features in fire detection models often include smoke detection, heat signatures, and flame characteristics, each contributing uniquely to accurate detection. Smoke detection identifies subtle changes in particle density and color variations, while heat signature analysis captures infrared or thermal data to recognize abnormal temperature increases. Flame characteristics, such as shape, color, and movement patterns, further aid in distinguishing fire from non-fire events. The models process these features through layers of algorithms that assess and weigh the significance of each indicator, offering a transparent view of the model's decision-making, which can enhance reliability and interpretability in practical fire detection applications.

2.3.1 SVM

Eventually, once we have the hyperplane, we shall be using it to make predictions. It explains how certain training data have an influence. Data sets close to the separation line are taken into consideration due to the high gamma value. Likewise, while determining the separation line, low gamma value datasets that are farther away from it will also be considered. Table 2 describes the parameters obtained while the dataset is tested with the developed algorithm.

Table 2. Hyperparameter computed for SVM

Dataset	Recall	Precision	Support	F1-Score
Without Fire	0.29	0.65	69	0.40
Fire	0.87	0.61	87	0.72

2.3.2 CNN

Fire pictures from films are converted into frames and used to produce image datasets. A few photographs were added to the dataset that were obtained in the repository. Pictures should be categorized as either non-fire or fire. There exist 541 and 2316 photos in images of non-fire and fire, respectively. There are 2857 pictures in all. These photos are saved as a linear array after being scaled as (300X300) and further reshaped to (-1,300,300,1) [10]. This is supplied to the convolutional layer as an input. To create feature maps, several kernels of varying sizes are applied to input data into these procedures. There are 64 convolution filters in the model, each measuring 3 by 3. Features mappings pass via an activation function of ReLU. The feature map's positive section is updated quickly by this function. The subsequent process, known as max pooling, uses these feature maps as input. These feature maps undergo additional processing via a convolution layer and a pooling layer with a 3x3 kernel size. Subsequently, a layer known as "flatten" transforms 2D feature maps into a vector that may be sent to a fully linked layer. Of these three primary processes, neurons in the convolution and fully linked layers have weights that are learned and modified during the training phase to afford a better representation of the input data. An example of a matrix-vector multiplication is a dense layer. The trainable parameters, which are modified during backpropagation, are represented by the values in the matrix [11]. As a result, the output is a m-dimensional vector. Lastly, we have initiation functions to distinguish between fire and non-fire outputs, like Soft-max. A probability distribution that translates output to a 0–1 range is provided by the soft-max function. It serves as the last layer in the classification model for this reason. An Adam optimizer that offers an adjustable learning rate to regulate the unique learning rate of each parameter is used to construct the model. Since there exists only one expected outcome for this categorization, the unconditional cross-entropy loss formula is employed. Table 3 shows the accuracy of the CNN algorithm.

Table 3. Accuracy parameter computed for CNN

Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
0.99	0.03	0.96	0.60
Time Cost			0.005 Seconds

2.3.3 RNN

We modify the RNN in [12] in the study presented and stop calculating sequence outcomes in four directions. We compute the sequence results in only two directions. The proposed is a one-layer structure of RNN computations, and the sample pictures are for reference only; it is not a picture from the experiment dataset. Consider it an RNN model that is bidirectional. The hyperparameters used in RNN to enhance the accuracy of the RNN model are depicted in Table 4.

$$x \in R^{wxhxc} \tag{3}$$

If x is the original picture, then c stands for the quantity of color channels and other c for the number of filters (or convolution kernels). The edge, texture, and form of the picture determine the output of convolutional layers following the deconvolution procedure, according to [13]. As an outcome, the original picture with the original image slice of feature characteristics is the output of the convolution layer following filter processing.

Table 4. Hyperparameter computed for RNN

	Precision	Recall	F1-score	Support
NoFire	0.58	0.40	0.47	90
Fire	0.55	0.71	0.62	91

2.3.4 RNN+CNN

A two-dimensional function with a matching spectral function is the fundamental component of a convolution kernel. In the formula, F (u, v) represents a certain type of spectral function. The convolution of the picture takes the properties of various frequency bands inside the image. In actuality, the multiplication operation in the frequency domain segment and convolution operations in the time domain segment are equivalent [14]. Nevertheless, the Fourier transform is limited as it remains unable to describe the signal's local properties in the time domain and performs poorly on abrupt or non-stationary signals.

Therefore, employing a wavelet transform is preferable:

$$WT\,(a,t) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f\,(t) * \varphi\left(\frac{t-\tau}{a}\right) dt \tag{4}$$

where φ denotes a wavelet basis; this is distinct from ix e in regular Fourier transform in that it is a wavelet basis function that meets certain requirements rather than a straightforward positive or cosine wave basis function. Two-dimensional waves possess both sequence and local properties. As a result, this study extracts the two-dimensional wave's sequence characteristics using an RNN network and employs those features as a key component in determining picture categorization. Table 5 shows the combination of the RNN and CNN model.

Table 5. Hyperparameter computed for RNN and CNN combination

	Precision	Recall	F1-score	Support
NoFire	0.46	0.45	0.46	69
Fire	0.57	0.59	0.58	87

The hopping connection mechanism used by ResNet makes it possible to stack network layers deeply without experiencing the vanishing gradient problem[14–20]. However, this means that the depth of the ResNet model is not very deep. The ultimate full-connection network can be immediately connected to the characteristic of the middle layer output. ResNet is a neural network structure made up of many shallow CNNs. While the CNN-RNN approach in the study is unable to attain the same deep network structure as ResNet, it may link to the final full-connection layer using the distinct feature output of the middle layer.

The difference in support numbers between RNN and RNN+CNN outcomes arises because RNN focuses on capturing sequential dependencies, while RNN+CNN combines this with CNN's ability to extract local patterns or spatial features. The inclusion of CNN layers introduces richer feature representations, which may lead to some samples being reclassified differently, altering support numbers. These variations reflect the enhanced capacity of RNN+CNN to interpret data more comprehensively, not inconsistencies in the model.

In fire detection, evaluating model effectiveness with comprehensive metrics like precision, recall, F1-score, and false positive/negative rates is crucial. Precision helps measure the model's accuracy in identifying actual fire incidents without over-predicting, while recall assesses its capability to detect true fire events, minimizing the chance of missed detections. The F1 score, balancing precision and recall, provides an overall view of performance. Additionally, analyzing false positive rates (incorrectly signaling fire) and false negative rates (failing to detect fire) is essential for this application, as false alarms can cause unnecessary panic, and missed detections can lead to dangerous outcomes. These metrics collectively enable a thorough assessment of the model's reliability and safety in real-world fire detection.

3 Results and Discussion

Founded on the developed models, we created a simple User interface in Python, to test the images for all the models. Figure 2 displays a simple button to select the test image, do the preprocessing and buttons for classification and prediction. The figure also displays the accuracy of all the 4 models developed.

3.1 Fire detection for images

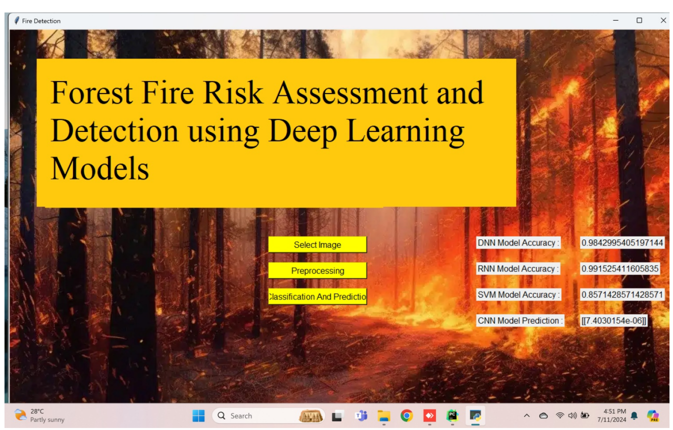

Fig 2. Image based Model accuracy

Table 6. Model accuracy and Prediction comparison Table as per NASA Dataset wise dataset

Sl. No	Model	Accuracy	Prediction
1	LR	55%	No Fire
2	SVM	61%	Fire
3	DT	51%	Fire
4	RF	58%	Fire

Table 7. Model accuracy and Prediction comparison Table as per Image based

Sl. No	Model	Accuracy	Prediction
1	DNN	91%	No Fire
2	RNN	98%	Fire
3	CNN	97%	Fire
4	RNN+CNN	99%	Fire

Table 6 describes the overall accuracy of all 4 algorithms used for fire prediction using the database method. We can observe that the SVM methods have remained obtained through the highest accuracy of 61%, as the database had a different variable parameter. It can be proven that for a features-based fire prediction, the SVM model is the best algorithm that can be utilized.

Table 7 discusses the overall accuracy of the real-time image found fire detection algorithms. We can observe that all the models have more than 90% accuracy. The RNN and CNN combination algorithm gave us the best accuracy of 99%, as the images were segmented and found on regions the accuracy has been improved. In addition, the speed of computation is also improved with this approach.

Table 8. Accuracy comparison of the existing models and the proposed model for the combination of classification and segmentation founded methods for surveillance monitoring and forest fire

Authors	Method	Year	Architecture	Accuracy
Zhao et al.	DCNN	2018	Deep CNN - Saliency	98%
Khryashchev et.al	CNN	2020	U-Net & ResNet34	46.5%
Ciprian-S´anchez ´et al.	CNN	2021	U-Net, FusionNet & VGG-16	92.63%
Ghali et al.	DCNN	2022	TransU-Net, TransFire,	98.9%
Proposed	CNN & RNN	2024	Decision tree, SVM	99.15%

Table 8 describes thecomparison of existing models using various CNN models and the respective architecture. We can observe here that the proposed model has a combination of two models and has given accuracy of up to 99%. To address the challenges in fire detection model accuracy, it is essential to consider factors like overfitting, model generalizability, and environmental performance. Overfitting occurs when a model performs well on training data but fails to generalize to new data, potentially reducing its effectiveness in real-world fire detection. Additionally, model robustness across diverse environments is crucial, as varying weather conditions and lighting can impact detection accuracy. Ensuring model adaptability to these conditions can improve reliability and decrease false alarms, enhancing its practical application across different scenarios.

4 Conclusion

Fire remains the most hazardous anomaly because, if allowed to spread unchecked, it may result in catastrophic events that harm the environment, humanity, and the economy. It remains possible to identify fire occurrences with the cameras. Thus, we suggested a CNN, DNN, and RNN method for camera-based fire detection here. With our method, the fire under video monitoring may be located and alerted.

The major novelty of the proposed model is that the model is capable of segmenting the region of interest in an accurate method as the morphological operation was very helpful. In addition, the method was capable of achieving maximum accuracy even in the image during the night, as we had targeted an improvement in this area as well.

Furthermore, by fine-tuning datasets, our suggested approach strikes a compromise between the size of the model in addition to the accuracy of the detection of fire. We have achieved 99% accuracy. The F-measure value is 0.95 as well. These numbers demonstrate how much better a forecast the model makes. Using datasets gathered from fire recordings, we do tests and compare the results to our suggested system. Given the CNN model's decent performance in detecting fires in addition to its size and false alarm rate, disaster management teams may find the system useful in quickly mitigating fire catastrophes, therefore preventing significant losses. The identification of fire scenarios under observation is the main objective of the paper.

The first observation, based on the research we carried out during the complete implementation of the algorithm, saw a few difficulties in getting a better dataset that could be used to improve the model. As we update the latest dataset with different kinds of images, the model will automatically improve its accuracy. We suggest such a future improvement in addition to our model. The second observation we found is that the models most of the time cannot be able to differentiate between the light and fire in an image taken during the night. Though we were able to achieve the maximum accuracy of such models as well, we suggest furthermore research can be done in this aspect.

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