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Automatic Outdoor Fire Detection Using Machine Learning and Deep Learning

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Abstract

Fire, which also poses a major threat to human safety and life, is one of the unfortunate phenomena that contributes to environmental disasters. This is especially true when it is not detected by sensor-based fire detection systems. In order to significantly speed up the detection of fires, specific areas can be equipped with affordable, effective sensors. The three key characteristics of fire are color, movement, and form (or fire shape), and these characteristics are utilized by vision-based fire detection systems. Systems for detecting smoke and fire have been developed using security camera footage. In this study, features are extracted from fire photographs before inputs are made. SVM-based on machine learning and CNN-based on deep learning are used to one of the classification strategies. Experimental evaluations were carried out based on two machine learning methods and deep learning method. The same data set was used in the two proposed approaches which consisted of (3894) images and the data was divided into the same percentage as well, which was 20% for testing and 80% for training and this was the best percentage after trying all percentages. The CNN deep learning model works efficiently based on a high accuracy of 90%

Keywords: Fire detection, Machine learning, Deep Learning. Image processing.

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1. Introduction

Abnormal events represent the most serious threat to human life, such as floods, earthquakes, accidents - combat, medical emergencies, and fires, which lead to a threat to safety and public health. Fires are the most common of other events[1]. The timely detection of fire or smoke is of utmost importance in order to enable prompt intervention and prevent extensive damage. Numerous techniques and instruments have been employed to detect the presence of fire or smoke in visual imagery. The majority of conventional detection techniques employ instruments and sensors that are designed to identify the existence of smoke or flame [2]. All traditional methods of early warning of fires have major drawbacks because they are prone to malfunctions, require regular maintenance, and can only identify flames or flames near places where installed in it and does not provide sufficient information about the direction of the fire, its initial location, size and many other defects [3].

The shortcomings of conventional approaches were addressed by a number of video and image-based solutions. These methods make use of photos and videos that cameras, which may be deployed in any interior setting, have produced. Additionally, the external system may determine whether a pixel is smoke or not using a variety of methods, such are the diffusion-based dynamic choice rule and the color-based static decision rule. [4] [5]. Also, there are techniques that use blurring boundaries and flare to detect fire and flames, as well as the video-based luminous flux technique [6].

The primary objective of the aforementioned techniques is to develop a rule-based algorithm that relies on specialized knowledge or specified human-crafted qualities, which serve as the principal indicators of smoke and fire, contingent upon various factors such as composition, texture, color, and motion. This renders the task intricate and challenging. In order for these algorithms to achieve high accuracy, in recent years another approach has been used to achieve a step towards detecting fires in videos and images utilizing machine learning and deep learning. In the deep learning approach, artificial neural networks were used, which achieved exceptional goals in different cases.

In addition to computer vision to overcome the shortcomings of the current regulation and provide a correct and accurate fire detection system as quickly as possible and is able to operate in a variety of environments It can recognize and extract key color and smoke elements from pictures and movies. Convolutional neural networks (CNN), in particular, have produced great results when used to solve visual identification problems and have made a significant contribution to the detection of fires.[7].

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2.Related works

Sebastien Frizzi et al. 2016 [8] The usefulness of deep learning target detection technology to identify forest fires was shown by the use of the convolutional neural network (CNN) to detect fires by segmenting the full picture into numerous tiny sections .

Zhang Qixing et al. [9] A proposed methodology involves augmenting the training set by extending the synthetic smoke image. Based on this premise, the implementation of Fast-RCNN smoke detection was proposed. Nonetheless, the utilization of the aforementioned technique is restricted to stationary data within a singular image, thereby limiting the overall system's capacity for generalization.

Guohua Wang et al. [10] this proposed method employes dynamic background modeling and deep learning to avoid the unreal alarms of smoke and SVM is used to complete the detection of smoke. Despite of its effectiveness, this system showed instability in complex outdoor scenes.

Almeida R. V. et al. [11] To find forest fires, the commercial technology Bee2Fire was introduced. Regular cameras and deep artificial neural networks will be used to fight fires. After training this network, it uses the picture classification method to look for smoke plumes over the horizon. The precision was (82%).

Wiame Benzekri et al. [12] This paper presents an early warning system for forest fires. When compared to the likes of lookout towers and satellite monitoring, this technique provides a higher degree of accuracy. The suggested system gathers forest environmental wireless sensor network data and uses AI, namely Deep Learning (DL) models, to forecast when a forest fire may break out. The integration of an Internet of Things (IoT) framework involves the utilization of a Low Power Wide Area Network (LPWAN), along with stationary or mobile sensors, and a proficient deep learning model. The evaluation and comparison of multiple deep learning models have demonstrated the potential of an autonomous and real-time environmental monitoring platform for identifying dynamic risk factors associated with forest fires.

Xu R. et al. [13] In this paper, a unique ensemble learning method for spotting forest fires in various environments is presented. The proposed method specifically integrates Yolo v5 and Efficient Net, two different learners, to boost the accuracy of the fire detection process. Another instance involves individual students using the Efficient Net to lessen the possibility of false positives. The incidence of false positives was reduced by 51.3% while the detection efficacy showed improvements ranging from 2.5% to 10.9%, all without an increase in delay time.

Abdul Bari et al. [14] This study demonstrates the significant efficacy of recent advancements in Deep Learning within the realm of computer vision. The utilization of Transfer Learning, a deep learning methodology, has proven to be highly advantageous for applications that suffer from a lack of available training data. The researchers employed Transfer Learning methodology to utilize pre-trained Deep Learning models on the Image Net Dataset. They improved these models using our own curated dataset, which comprises of movies that were retrieved from the internet and their own recorded footage, to address the fire detection problem. For transfer learning and in-between comparison, they specifically selected pre-trained InceptionV3 and MobileNetV2 models. On the same data set, they have also demonstrated comparisons between transfer learning and complete model training. When trained on a small dataset, they discovered that transfer learned models outperform fully trained models. Additionally, our models outperformed the hand-crafted features-based state-of-the-art fire detection system.

Seyd Teymoor seydi et al. [15] They suggested using the Fire-Net Imagery-trained Landsat-8 deep learning framework, which produces a more realistic depiction by combining optical (red, green, and blue) and thermal approaches from photographs. to detect current fires and biomass burning. Warp blocks and leftover warp blocks were also used. deeper features may be recovered from the dataset thanks to separable data.

3. Materials and Methods

3.1 Convolutional Neural Network (CNN)

A deep learning algorithm called CNN employs filters has learned to automatically extract complicated information from inputs in order to distinguish between 2D inputs. Figure(1) illustrates the CNN's fundamental modeling [16].

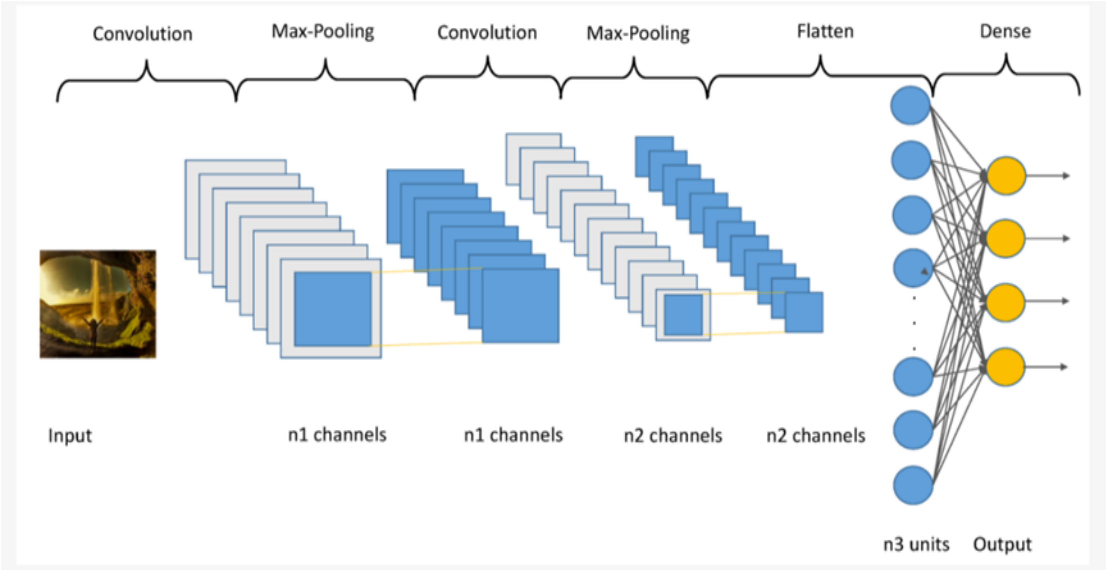

Fig. 1 The General Structure of the CNN System [16].

The three basic neural layers that make up CNN in general are convolutional layers, pooling layers, and fully connected layers. Using this method, CNN gets the complete picture. A feature map refers to each layer of the CNN. Add a feature layer with a 3D pixel density matrix for the color channels that were highlighted. What characterizes the inner layer map? An image created through a number of channels can have a specific feature exhibited in each of its "pixels." Each neuron has connections to a number of particular neurons from the layer above [17] .

CNN is made for education. Through the use of back-propagation of numerous building blocks, such as convolutional classes, fully connected classes (fully connected classes), pooling classes, and activation functions such as LLM (ReLU) and CNN, the spatial hierarchy of features is automatically generated and adjustable. It has been applied to driving robots and driver less vehicles, as well as picture recognition and visual amplification [18]. Traditional neural networks and CNNs differ significantly in several ways. (NNs). Due to these variations, CNN is the finest; among its benefits are the following:

1_ While NN input is only a 1D matrix, CNN input can handle 3D, 2D, and 2D with focus setups and parameters.

2_ Compared to a typical neural network, CNN lists more layers.

4. Machine learning

Given the enormous impact of AI applications like Alpha Go, machine learning is one of the most essential academic topics. Machine learning is a branch of artificial intelligence and computer science. It stands for a field that use particular distinctive algorithms to "learn" computer systems with particular data without complicated programming. Machine learning is the study of computers for the acquisition of new knowledge and skills and the realignment of existing expertise. In particular, it is a technique that aids computer systems or computers to perceive, observe, understand, and forecast the world such as a human existence[19].

4.1 Support Vector Machines (SVM)

The technique was developed in 1995. and it was first used to address particular classification and regression issues. The statistical learning approach is the foundation of this approach . The hyper-optimal level that optimizes category margin is defined. One of the most well-liked synthesis techniques is SVM. One of the supervised classification techniques, the input string and labels are provided. Structures that are determined by these sources' vector features. In order to completely separate these categories, this algorithm creates a super level that can be used to differentiate between the two classes. Two vectors that are parallel to the classifier and move through various phases are shown in Figure (2). The margin is the separation between these two parallel lines. Support vectors are the points on border vectors [20].

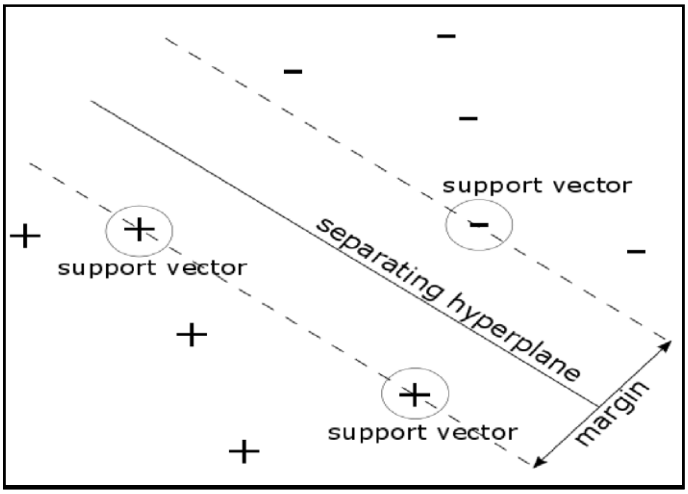

Fig.2 The SVM hyperplane between two classes [20].

- ## Linear SVM

If the super vector machine is described as a linear SVM, the linear SVM hyperplane, for instance, is defined by the direct equation if z represents pairings training (xi, yi) when i=1,2...z and with category labels y (1,-1).

$$w * y + b = 0 \qquad (1)$$

Where W=W1, W2,..., Wn, b is a bias, and x represents characteristics [18], w is a vector of weights. The third chapter will make use of this equation[21].

- ## Non-Linear SVM

In most cases, the linear classification fails to take into consideration the nonlinear kernel function that would be applied in these situations. which is the classification strategy that is suitable for the nonlinear classification [20]. Although linear SVM is simple to apply and quick to train, it appears to perform poorly on complex datasets because it has a large number of training examples but few features. Even though it lacks critical strength, nonlinear SVM can often be favored in many applications because of its greater consistency in quality across various problems[22].

5. PROPOSED APPROACH

5.1 Image Dataset

The fire detection dataset was used detection dataset, which was utilized to develop the suggested system (Automatic Outdoor Fire detection using Deep learning)[23]. and the data set type is (.jpg) pictures; it has two categories, Fire and Non-Fire; the total number of photos in the data set is (3894); There are (1241 total photographs in the non-fire category, compared to (2653 total images) in the fire category. Samples of the data set shown in Fig. 3 are as follows:

The proposed system includes five basic stages:

1- Dataset.
2- Preprocessing
3- Data splitting
4- build the model.
5- Evaluate and compare.

There are steps in every stage. The suggested system's main layout is seen in Fig. 4.

Fig. 3 Example images from the Set A image dataset: a) fire images; b) Non-Fir

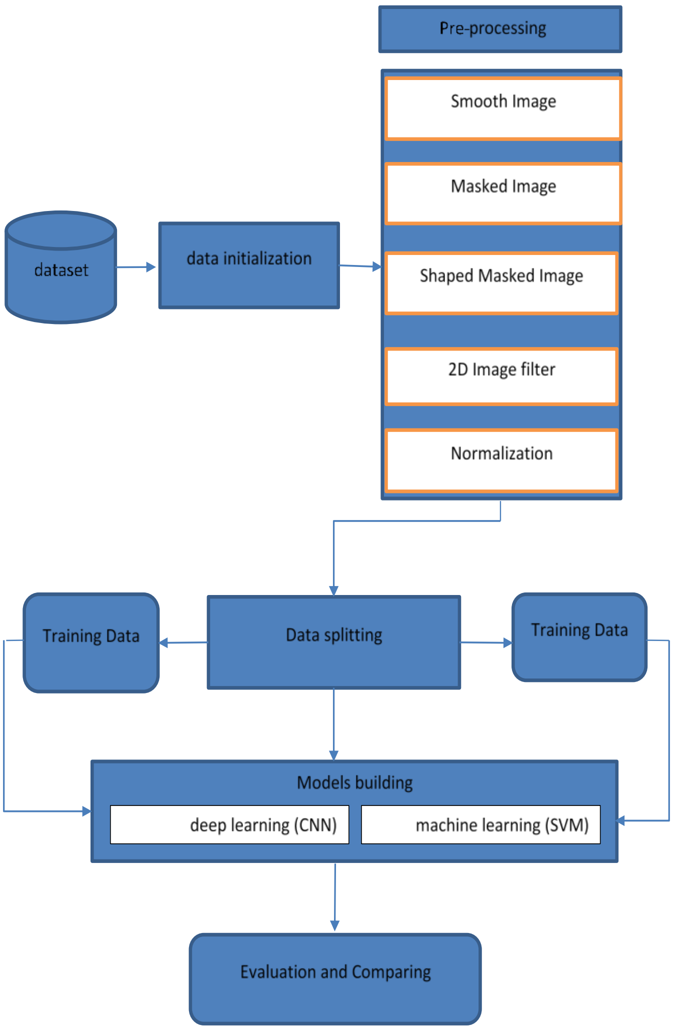

Fig. 4 Block Diagram of General Proposed System

Table (1) SVM model parameters

Model structure	Parameters
SVC //standard pipline//	(kernel="poly", degree=3, =5)

6.Training model with data

The training model procedure is split into two phases.

1. Gathering and pre-processing of data.

2. A machine learning and deep learning model for detecting building fires. Images were obtained for the problem statement in the first step. Fire and non-fire are the two classifications in the dataset. Train and test images are separated from the dataset. Currently, there are 1241 non-fire photographs and 2653 fire images in the collection, both of which came from Google.

7.SVM machine learning model

This procedure was previously described in Section 3. After carrying out the activities, the training process for images is carried out using an SVM method in order to later detect the fire in the testing stage. The SVM parameters are shown in Table (1).

The confusion matrix in Table (2) is utilized to reflect the average overall accuracy of all classes for the training period (69.33), which is used to illustrate the accuracy of training results for each class.

8.Results and Discussion

In this section, the obtained results from the proposed system have been presented and discussed. To evaluate the performance of the proposed model, the accuracy has been measured according to the TP, TF, FT and FP. Figs, 4, 5 shows the confusion matrix for both models.

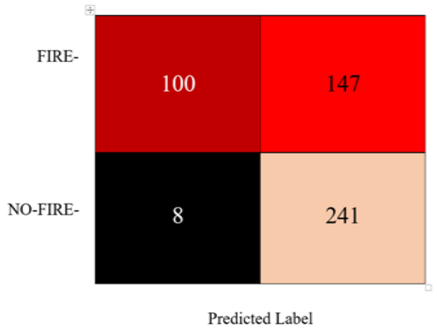

Fig. 4 The confusion Metrex of SVM model

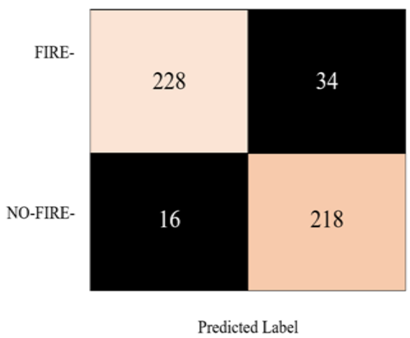

Fig. 5 The confusion Metrix of CNN model

However, the performance of the proposed models was compared with the related work, and the best accuracy was recorded with our deep learning model as shown in bellow table.

Table 2 the comparison of the proposed models with the related work

Ref.	Models	Accuracy
Almeida R. V. et al. [11]	Deep Artificial Neural Networks	82%
Dimitropoulos et al. [19]	Support Vector Machine	84.25%
Our proposed models 2023	SVM	69%
	CNN	90 %

9.Conclusions

The detection of fire images is the focus of this thesis. Our models base two approaches which are frames images and real-time testing, and considering the outcomes, it came to the following conclusions:

1. In frame images: the experimental evaluations were performed on two machine learning approaches which are traditional machine learning SVM and deep learning CNN.
2. All of the proposed methods employ the same dataset, which is split into the same proportions (20% for training and 80% for testing); this split was determined to be the most effective after experimenting with all other percentages.
3. In this work, the deep learning model based on CNN works efficiently and achieved a good result with accuracy of 90%.
4. The proposed methodology is a robust approach that utilizes modern technologies and computer facilities to detect and classify fires accurately and rapidly.
5. The suggested approach is quite effective in detecting both fire and no fire, and it may be applied to real-world situations. The initial options for places where the suggested approach might be helpful include supermarkets, schools, universities, hospitals, and airports.

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