Fire and Smoke Detection Using Deep Learning

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Abstract: From large urban areas to dense forests, fires and wildfires are a major threat around the world. While the detection system can reduce these hazards, their high cost, low alarms, need for special construction, and overall lack of reliability have hindered mass adoption. This research focuses on manipulating electricity and smoke in images through the power of deep learning. Deep learning using neural networks has been incredibly successful in many fields, including computer vision. Our goal is to solve the limitations of current systems and provide effective and efficient solutions to premature electricity and smog in many areas, ultimately saving countless lives and natural limited resources.

Key Words: - Fire and Smoke accidents, Fire and Smoke detection, Surveillance images, Machine learning, Deep Learning.

I. INTRODUCTION

India has seen a high rate of fire incidents, which are a major hazard to industry. These kinds of events could endanger human and animal lives in addition to causing harm to property and the environment. Insurgency, terrorism, and corruption were surpassed by fire to rank third in the most recent National Risk Survey Report [1], indicating a serious threat to the people and economy of our nation. The recent forest fires in Australia, which claimed millions of lives and caused billions of dollars' worth of damage, served as a stark reminder to people throughout the world of the power of fire and the impending ecological disaster.

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Early fire incident identification can prevent irreversible infrastructure damage to properties and the ensuing financial losses, as well as save countless lives. Local surveillance is a required and effective means of detecting threats in densely populated areas while maintaining high accuracy and robustness. The following are some of the primary drawbacks of traditional opto-electronic fire detection systems: frequent maintenance, fault-prone hardware, the need for separate and frequently redundant systems, false alarms, and so forth. It is also not feasible to use sensors in hot, dusty industrial environments. Therefore, replacing current systems with surveillance video streams is one of the most practical and affordable ways to detect fires without having to establish or invest in huge infrastructure. For the current video-based machine learning models to work, feature engineering and domain expertise are crucial.

Creation of a classification model to identify fires in pictures and video frames using Deep Learning and Transfer Learning ([6][11]) in order to guarantee early detection and reduce manual labour. Images and videos from surveillance cameras can be utilized to identify fires using this methodology. Unlike hardware-based solutions, which require particular infrastructure for setup, this system doesn't require domain knowledge or prohibitively expensive computation for wholesome development.

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II. RELATED WORK

Convolutional Neural Networks (CNNs), Transfer Learning, Deep Learning, and Artificial Neural Networks (ANNs) are four popular computer-based fire detection methods ([14][28]). The Levenberg-Marquardt training algorithm is used to an Artificial Neural Network technique in the study presented in [2], resulting in a fast processing solution. This algorithm's accuracy ranges between 61% and 92%, with 8% to 51% of false positives.This approach demands substantial expertise but offers high accuracy and a low rate of false positives.

In contrast, the papers [3], [12], and [13] criticize current hardware-based detection systems for their low accuracy and high rate of false alarms, especially in broad regions such as dense-forests, buildings, crops, mountains, malls, or industries.The authors propose a streamlined variant of the YOLO model, comprising 12 different layers. They employ image augmentation methodologies encompassing contrast adjustment, rotation, saturation correction, zooming, and aspect ratio manipulation, resulting in the creation of multiple image instances totaling 1720.
The main aim of this model is to accurately draw bounding boxes around flame regions and surpass bounding boxes containing flame regions. Fire detection methods have been

outlined in [26], focusing on cases where flame color characteristics differ from those in the training dataset. The first method leverages Transfer Learning, using models like Xception, Inception V3, and ResNet-50, which are pretrained on the ImageNet dataset. This approach achieved an accuracy of up to 96%. The second method combines Xgboost and LightGBM, resulting in an AUC of 0.996.The Transfer learning models greatly reduces the training time and require smaller datasets. Both methods are advantageous as they do not necessitate domain-specific knowledge. According to studies [7], [8], and [29], the Deep CNN technique has also been employed to detect and localize fires, achieving accuracy rates between 90% and 97%. However, this method is time-intensive and was trained using an Nvidia GTX Titan X with 12 GB of memory.

In contrast, classic machine learning approaches based on human feature extraction provide excellent accuracy and a low false positive rate. Nonetheless, they require a thorough understanding of domain-specific aspects such as flame color models, color spaces, patterns, and motion vectors. Furthermore, they are subject to model reconfiguration when the observed objects change.

The advent of automated feature engineering, as elucidated in references [3] and [5], circumvents these challenges by automatically deriving salient features that are both interpretable and impervious to data leakage, facilitating their applicability across a spectrum of problem domains. Moreover, the adoption of Transfer Learning obviates the need to build models from scratch, allowing for the commencement from pre-existing models, such as Inception V3 and Inception-ResNet-V2, directly procurable from the Keras library. This strategic choice substantially diminishes computational overhead, thereby obviating the necessity for high-end GPUs. Notably, Inception V3 and Inception-ResNet-V2 have demonstrated efficacy in feature extraction for fire detection scenarios, yielding outcomes characterized by high accuracy.

The system's passive components include scripts for feature engineering, data preparation, and model selection. These were used to train and build a 96% accurate machine learning model ([15][17]).On the other hand, the second method focuses on flame feature extraction, fusion, and Transfer Learning, which is the process of fine-tuning pretrained models on the ImageNet dataset, including Xception, Inception V3, and ResNet-50.

Passive system components include feature engineering specification, data preparation, and model selection. This was used to train and create a 96% machine learning model ([15][17]). On the other hand, the second method focuses on flaming, fusing and transferring learning, which is a clear learning process. Deploy pre-trained models on ImageNet datasets, including Xception, Inception V3, and ResNet-50.

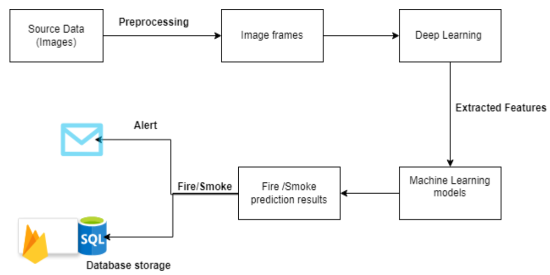

Fig.1 System Architecture

Figure 1 shows how source/input data, which is photographs, is divided into frames and pre-processed into a format that can be used as an input for models that have already been constructed for feature extraction. A feature vector that is frequently referred to as bottleneck features in transfer learning is produced by the deep learning model.
After processing the bottleneck features through a classification algorithm, a result—which might be smoke or fire—is obtained. The training data set was used to build the classification model.

In Figure 2 it depicts CNNs made up of several layers of neurons, including convolutional, pooling, and fully coupled layers. Convolutional layers use convolution methods to find patterns and characteristics in input images. While pooling layers minimize the spatial dimensions of the feature maps produced by the convolutional layers, fully connected layers perform the final classification or regression tasks.

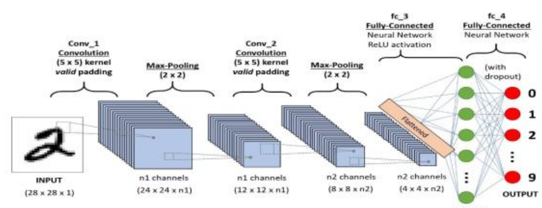

Fig. 2. CNN Architecture

In figure.3, the classification result is presented to the user, and subsequent actions are determined based on the outcome. If the result indicates fire, an alert email is sent to designated stakeholders, including the video frame and a timestamp. Users have the option to modify the recipient email addresses. Additionally, each fire detection event is logged in a cloud database for further analysis.

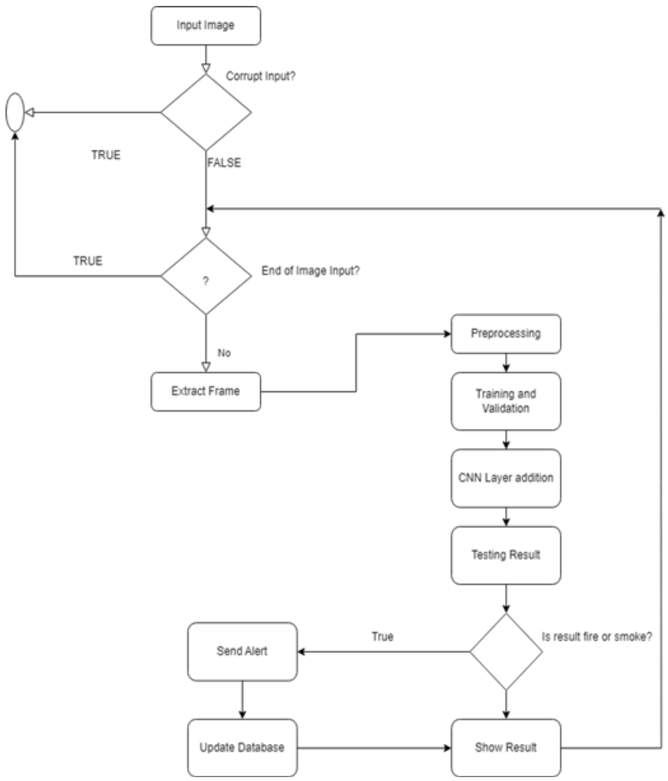

Fig. 3 Activity Diagram

IV METHODOLOGY

The model is divided into two parts -

A. Gathering and Preparing Data.

B. Developing a Deep Learning Model for Fire and Smoke Detection.

A. Gathering and Preparing Data.

The first step involves collecting image frames relevant to the problem statement, which includes two categories: fire and smoke. Positive samples are composed of images showing actual fire and smoke, while false positives are images with objects that appear similar to fire and smoke but are not. Since false positives are easier to gather, it is crucial to collect a diverse range of video frames to enhance the accuracy of fire detection. The assembled dataset is divided into training and validation sets. Currently, the dataset comprises 12,360 image frames of fire and 1,373 of smoke, all sourced from Google due to the absence of a standardized dataset.

B.Developing a Deep Learning Model for Fire and Smoke Detection.

The selection of the model architecture centered on Convolutional Neural Networks [25] fire detection (CNNs) because of their proven success in image classification tasks [20]. We chose ResNet-50, InceptionV3, and InceptionResNetV2 due to their robust structures and established performance records. These models, which include convolutional layers, ReLU activation functions, and pooling layers, were modified by removing their final fully connected layers to extract feature vectors. We used pre-trained models based on ImageNet to leverage their well-developed features and fine-tuned them on our specific dataset of fire and smoke image frames. Training, validation, and test sets of the dataset were created, and hyperparameters such as batch size and learning rate were tuned. During the training phase, the model weights were modified and accuracy was increased using optimization approaches such as SGD or Adam, and categorical cross-entropy was used as the loss function.

Table 1: Various Model Accuracy

Network	Algorithm	Accuracy
Inception Net V2 [27]	Decision Tree	90.51%
	Naive Bayes	94.32%
	Logistic Regression	96.81%
	SVM	96.25%
Inception V3 [29]	Decision Tree	92.58%
	Naive Bayes	94.71%
	Logistic Regression	97.17%
	SVM	96.51%
Resnet 50 [16]	Decision Tree	94.78%
	Naive Bayes	93.17%

	Logistic Regression	97.73%
	SVM	97.80%

V EXPERIMENTS AND RESULTS

Table 2: Fire and Smoke Result

Image Description	Expected Output	Actual Output	Status
a boy playing with toy	No - fire	No-fire	Paas
Men riding a horse during sunset	No- fire	Fire	Fail
men taking selfie toward sunset.	No-fire	No-fire	Pass
crowded NewYork City	No-fire	No-fire	Pass
forest Mist	No-Smoke	Smoke	Fail
two people talking to each other in a hall	No-fire	No-fire	Pass
Fireplace	Fire	Fire	Pass
burning candle	Fire	Fire	Pass
Images of streets, mountains, forest during winter season	No-smoke	No-smoke	Pass
men doing cycle race	No-fire	No-fire	Pass

Qualitative Results: Show example detections with both successful and failed cases, providing visual insight into the model's performance.

We conducted tests in Table 1 to assess how well feature extraction, fine-tuning, and continuous learning performed with pre-trained models. Since the suggested models are deep, we trained with GPU-capable kernels from Kaggle. For this method, we used the TensorFlow and Keras packages. Table 1 displays the tuned values that produced the best training outcomes for the models that were trained with the optimal hyperparameters. We employed early stopping, a technique where training ends when there is no more improvement in validation accuracy or decrease in validation loss, even though the models were programmed to run for 100 epochs. We replaced the models' pre-existing classifiers with our own in each example. To VGG16, we added a SoftMax layer and two fully connected layers. We used one SoftMax layer and one fully connected layer for Xception and InceptionV3. We retrained the top 5, 8, and 7 layers of VGG16, InceptionV3, and Xception, respectively, throughout the fine-tuning procedure.

Table3: Accuracy of Our Model

Network	Training Accuracy	Validation Accuracy
CNN Model	97.28%	99.71%

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Based on the accuracy in Table 2, our CNN model has an accuracy of 97.28% on the training data, whereas the accuracy on the validation data is 99.71%. When comparing our CNN model with existing pre-trained models, it is clear that our CNN model has good accuracy

Here in the fig.4 graph showing the training and validation accuracy of the model as described below.

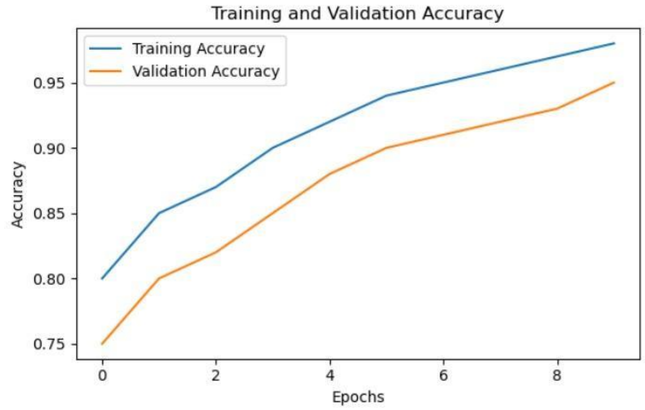

Fig. 4 Training and Validation Accuracy

We evaluated the models on the test data to determine how well they performed. Table 1 summarizes how effectively each of the proposed models have been tested and validated.

VI CONCLUSION AND FUTURE SCOPE

Advances in processing, computation, and algorithms have had a substantial impact on many sectors, including the analysis of surveillance video streams to detect anomalous or unexpected events. The rising frequency of fire accidents, which cause extensive death and destruction around the world, emphasizes the critical need for an accurate, timely, and cost-effective fire detection system. As a result, we developed a fire detection model for films and image frames using transfer learning in deep learning. In order to extract important features from video frames, pretrained models like ResNet-50, InceptionV3, and Inception-ResNet-V2 are utilized. These features are examined using a variety of machine learning techniques, including Support Vector Machine (SVM), Logistic Regression, Naive Bayes, and Decision Trees, in order to precisely identify fire.

As deep learning algorithms continue to evolve, they will enable more accurate and faster real-time detection of fires and smoke, significantly reducing response times and improving safety. These systems will achieve higher precision, effectively distinguishing between actual fire/smoke incidents and false positives such as fog or dust. Early detection capabilities will be enhanced, allowing for the identification of fires at their inception, potentially even before they are visible to the human eye. Moreover, the integration of multi-modal data from various sensors, such as infrared and thermal cameras, will bolster the robustness and reliability of these detection systems. Cloud integration will further enhance these systems by leveraging extensive computational resources for the continuous improvement and updating of detection algorithms. In the broader context of smart cities, fire detection systems will become an integral part of urban infrastructure, providing real-time data to emergency services and contributing to overall urban safety management.

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