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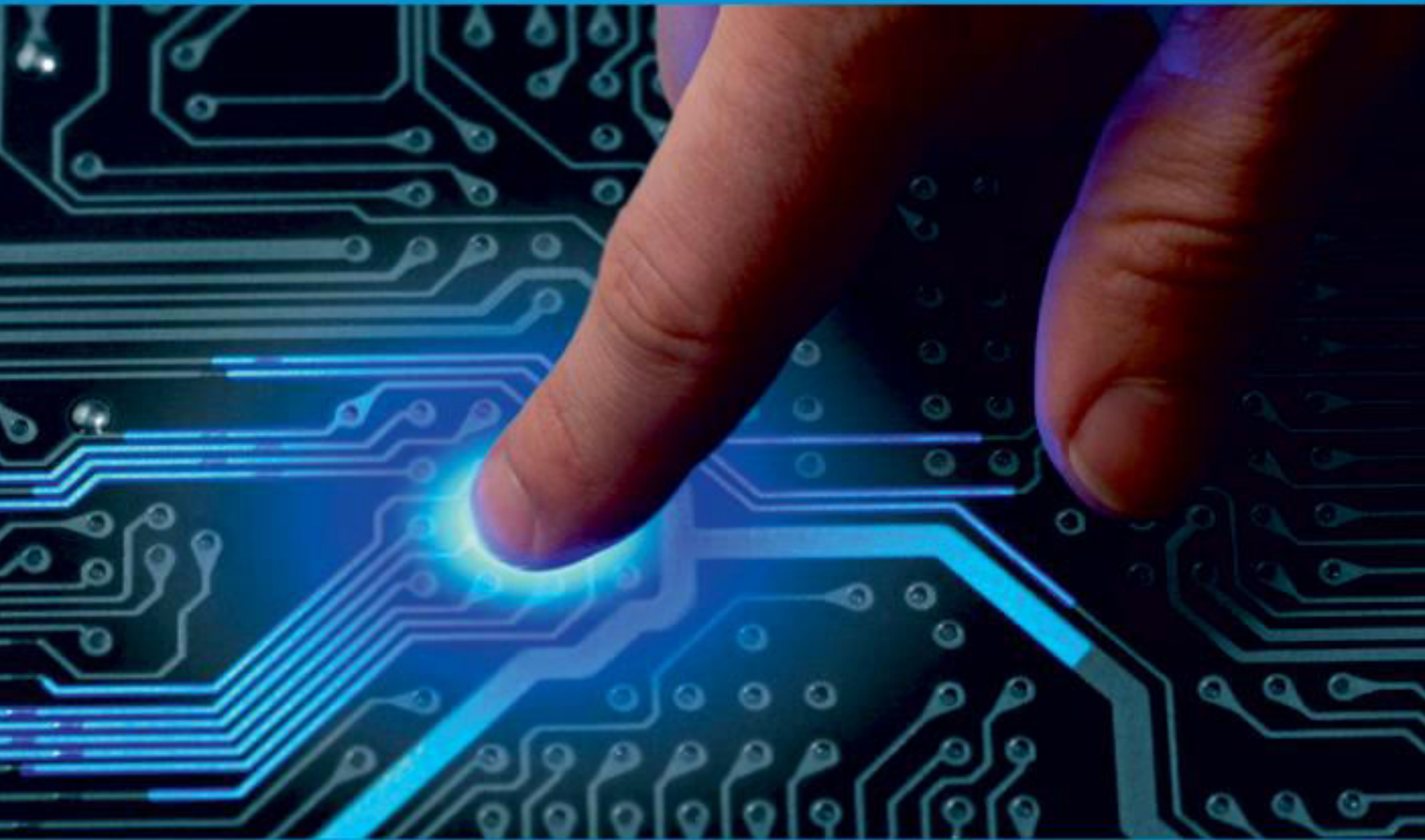

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Fire Detection Through Deep Convolutional Neural Network

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ABSTRACT: As fires inflict substantial damage to lives and property, video analysis for fire detection has become a hot topic. Traditional algorithms, on the other hand, use only rule-based models and feature vectors to determine whether or not a frame is a fire. These characteristics are difficult to define and are highly dependent on the type of fire observed. As a result, there is a low detection rate and a high rate of false alarms. Using a learning algorithm to extract useful features rather than an expert to design them is an alternative solution to this challenge. In this research, we propose a convolutional neural network (CNN) for detecting fire in videos. In the field of object categorization, convolutional neural networks have been found to perform exceptionally well.

KEYWORDS: Fire detection; Deep Learning; Convolution Neural Networks(CNN); Color Segmentation;Image Classification

I.INTRODUCTION

In India, fire incidents represent a severe threat to industries, crowded events, social gatherings, and highly populated places. These kinds of occurrences can harm property and the environment, as well as endanger human and animal life. According to the most recent National Risk Survey Report [1], fire ranked third, surpassing corruption, terrorism, and insurgency, posing a serious threat to our economy and population. By taking millions of lives and causing billions of dollars in damage, the recent forest fires in Australia reminded the world of fire's destructive power and the impending ecological disaster.

Traditional optoelectronic fire detection systems have several drawbacks, including the need for multiple, frequently redundant systems, fault-prone hardware, regular maintenance, false alarms, etc. It is also impossible to use sensors in hot, dusty industrial environments. As a result, detecting fires via surveillance video stream is one of the most feasible and cost-effective methods for replacing old systems without requiring massive infrastructure installations or investments.

The major goal of the Deep Learning-based classification model is to distinguish fires in images/video frames, ensuring early detection and reducing manual labor. In surveillance recordings, this model can be used to detect fires. Unlike other systems, this does not necessitate particular infrastructure for setup, such as hardware-based solutions, nor does it necessitate domain expertise or expensive computing for development.

II.LITERATURE SURVEY

Among the several computer-based ways to detect fire, we discovered that Artificial Neural Networks, Deep Learning, Transfer Learning, and Convolutional Neural Networks were the most popular. For a quick answer, the Levenberg Maraquardt training method is used in the Artificial Neural Network-based approaches shown in the paper [2]. The algorithm's accuracy fluctuated between 61% and 92 percent. The percentage of false positives ranged from 8% to 51%. This method produced good accuracy and a low false-positive rate, but it necessitates a lot of subject expertise.According to the author of this research [3], current hardware-based detection systems have low accuracy and a high rate of false alarms, making them more likely to misclassify actual fires. It's also ineffective in detecting fires in big regions like forests, warehouses, fields, buildings, or oil reservoirs. The authors employed a 12-layer simplified YOLO (You Only Look Once) model. Multiple samples of each image were created using image augmentation techniques such as rotation, contrast adjustment, zooming in/out, saturation, and aspect ratio, totaling 1720 samples. Its goal is to create a bounding box around the flame. When the color properties of the flames differed from those in the training set, it outperformed current models.Traditional feature extraction-based machine learning offered great accuracy and a low false-positive rate, but it required extensive domain knowledge, such as color model, color-space,

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patterns, and flame motion vectors. When an object's properties change, the models must be rebuilt to accommodate the new properties. The manual aspect of the traditional method to feature engineering [12] is evident. It entails iteratively handcrafting features using domain expertise, which is a difficult, time-consuming, and error-prone procedure. The model that emerges is problem-specific and may not function well with new data.Using a framework that can be applied to any situation, automated feature engineering ([3][5]) improves on this inefficient procedure by automatically collecting relevant and meaningful features from data. It not only reduces time spent but also produces interpretable characteristics and eliminates data loss. Instead of building a model from scratch, we may use transfer learning to start with a pre-trained model and fine-tune it as needed. Keras allows you to import these models directly. The use of pre-trained models reduces the amount of computing labor required, which would otherwise need the usage of high-end GPUs.

III.PROPOSED SYSTEM

We propose an effective RCNN-based system for detecting fire in surveillance films taken in uncertain settings. Our method employs lightweight deep neural networks with no dense fully connected layers, resulting in a low computational cost. The information will move through the firebase once a fire is detected. One type of database is Firebase. The firebase then sends an alert to the Android smartphone and also an Alert mail.

A.*Data set collection :*

- Data collection is a crucial part of the fire detection procedure.
- The learning of millions of parameters is common in deep learning approaches to picture recognition. Furthermore, this procedure necessitates the taking of a huge number of photographs. There are no publicly available data standards, including fire records, as far as we know. The dataset is made up of 31 videos from various circumstances. There are approximately 755 fire photos and 244 non-fire images in this collection.
- The dataset is challenging and huge, making it ideal for testing. Burning objects made datasets difficult with both color-based and motion-based fire detection technologies. One of the reasons for using this dataset for testing is because of this.

B. *Data Pre-processing :*

- Video scaling refers to the resizing of a digital video in computer graphics and digital imaging. Upscaling or resolution improvement are terms used in video technology to describe the amplification of digital material. When scaling a vector graphic Video, geometric transformations can be used to scale the graphic primitives that make up the video without losing quality.
- A new Video with a larger or lower number of pixels must be created when scaling a raster graphics Video. When the pixel number is reduced (scaling down), the quality of the image is frequently compromised. Scaling raster graphics is a two-dimensional example of sample rate conversion, which is the conversion of a discrete signal to a sampling rate, in terms of digital signal processing.

C. *Feature Extraction:*

- Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data.

D. *Classification Model:*

- Classification is a process of categorizing a given set of data into classes, It can be performed on both structured and unstructured data. The process starts with predicting the class of given data points. The classes are often referred to as target, label, or categories.
- The classification predictive modeling is the task of approximating the mapping function from input variables to discrete output variables. The main goal is to identify which class/category the new data will fall into.

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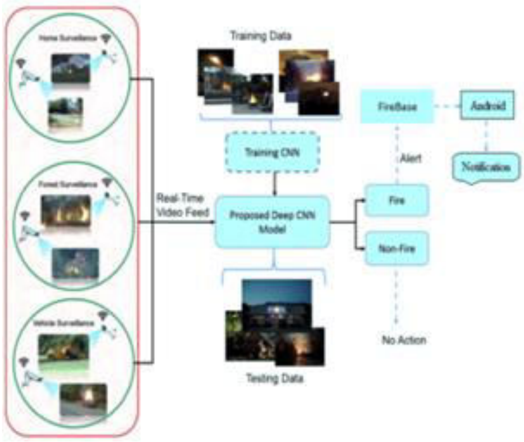
Classification Algorithms can be further divided into the Mainly two categories:

- Linear Models
  - Logistic Regression
- Non-Linear Model
  - Decision Tree Classification

E. *Block Diagram and Architecture Diagram of CNN*:



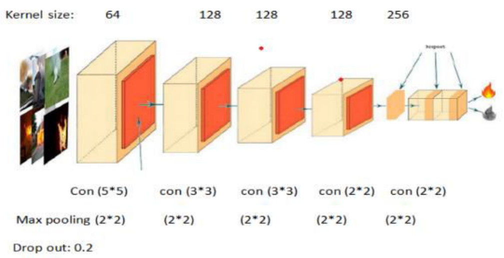


Figure a: Block Diagram

Figure b: CNN Architecture

V. RESULTS & DISCUSSION

The proposed enhanced deep learning method has been compared to existing techniques and proposed CNN techniques have been used to recognize the activity of video frame matching and proposed CNN techniques have been compared to existing detection of SVM and ANN classifier in terms of sensitivity, specificity, and the accuracy of the fire detection and giving the alarm to the notification to the android they have been calculated using the equations below.

Sensitivity, specificity, and accuracy are statistical parameters that can be considered.

- Specificity = $TNTN+FP*$ 100
- Sensitivity = $TPTP+FN*$ 100
- Accuracy =$TP+TNTP+FN+TN+FP$ * 100

Where TP stands for True Positive, FP stands for False Positive, TN stands for True Negative, and FN is for False Negative. The suggested CNN method is utilized to accurately identify fire alarms, as indicated in the experimental results in the table below, and the chart shows the contrast.

Parameters	CNN	SVM	ANN
Sensitivity	93%	73%	81.5%
Specificity	90%	78.8%	74.9.%
Accuracy	98.4%	63.4%	74%

Table 1: Performance analysis of proposed and existing machine learning algorithms. The comparison tables for the existing DL algorithms with our developed techniques are illustrated.

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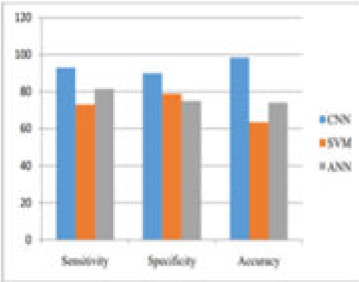
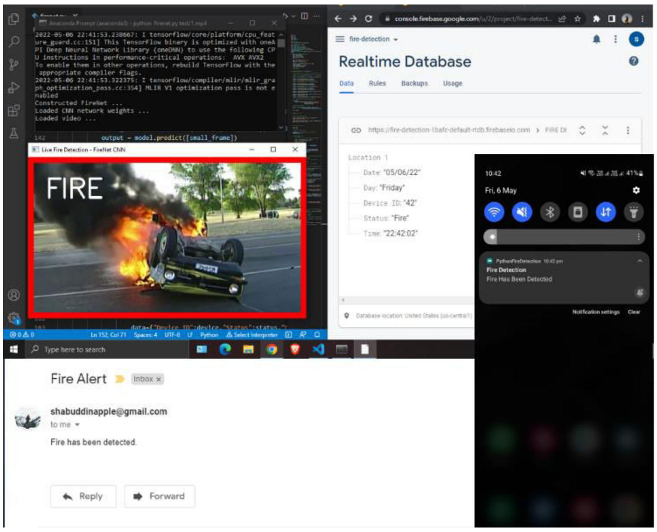
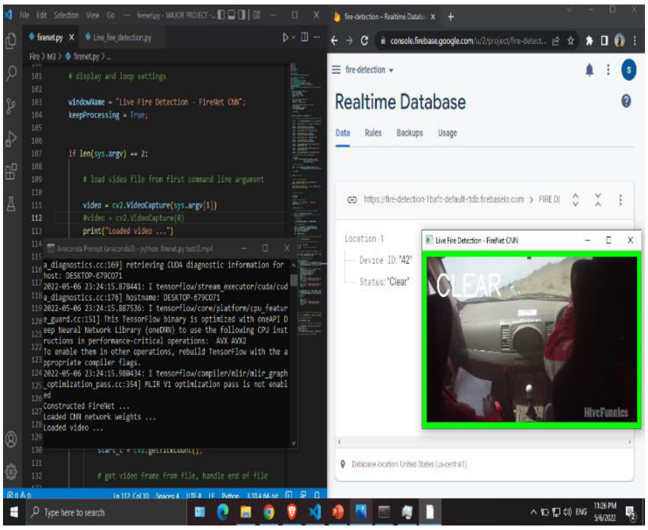
In comparison to existing approaches SVM and ANN classifier, the proposed method has a sensitivity level of 93 percent, a specificity level of 90 percent, and an accuracy level of 98.4 percent, as shown in the table above.



Similarly, the overall percentage of test data records that are accuratelyanalyzed by classifier algorithms represents the video activity recognition of the supplied test dataset. Specificity and Sensitivity are alternatives for the metric of exactness used to assess fire detection ability.

A. Sample Result when tested on pre-captured video:





Output 1: When the video contains fire

1. The database is Update
2. Mobile Notification is received
3. Alert Mail is generated

Output 2: When the video does not contain the fire

1. The database is Updated

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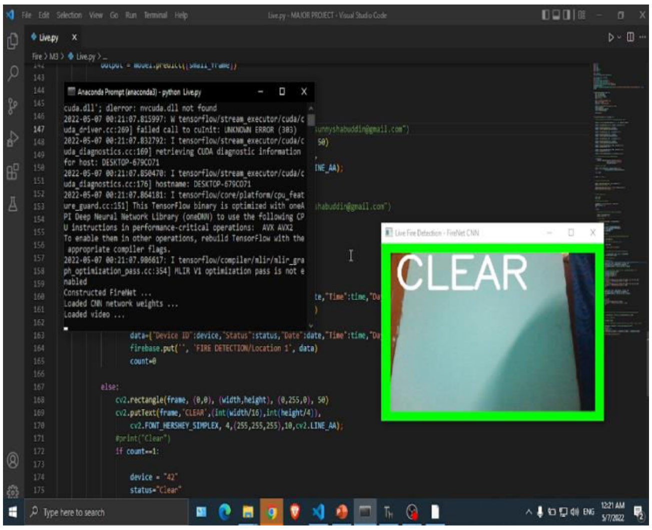
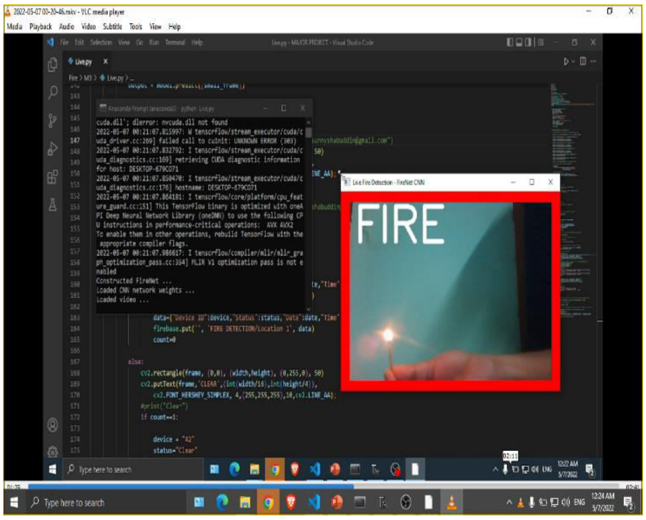
B. Sample Result when tested throughLive Surveillance:



Output 3:During the Live Surveillance if the video frames doesn't contain fire the clear status is maintained.



Output 4: During the Live Surveillance if the video frames contain fire the FIRE status is maintained along with that

1. The database is Updated

2. Mobile Notification is received

3. Alert Mail is generated

VI.CONCLUSION AND FUTURE WORK

Fire is the most dangerous abnormal event because it can cause massive disasters, resulting in human, ecological, and economic losses, if it is not controlled quickly. Accidents involving fire can be discovered utilizing the cameras. As a result, we presented a CNN approach for camera-based fire detection. Under the supervision of cameras, our method can detect fire. Furthermore, by fine-tuning datasets, our suggested approach balances the accuracy of fire detection with the size of the model. We were able to get a 98.4 percent accuracy. The F-measure value is also 0.95. These figures indicate that the model provides a more accurate prediction. We conducted trials with datasets gathered from fire recordings and compared them to our suggested method.Because of the CNN model's reasonable fire detection accuracy, size, and rate of false alarms, the system can assist disaster management teams in quickly controlling fire disasters. As a result, substantial losses are avoided. This project is primarily concerned with the detection of fire scenarios that are being observed. Future research could concentrate on putting the model on a Raspberry Pi and employing the appropriate support packages to identify real-time fires by creating challenging and particular scene understanding datasets for fire detection methods and extensive trials.

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BIOGRAPHY

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