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# AI Based Forest Fire Detection And Alert System

[1] Nandeesha S B, [2] Chetan G Arkachari, [3]Chethan B J,[4] Anil K S ,[5] Asst Prof.MD.Irshad Hussain B

[1234] Student,[5] Co-ordinator Department

of MCA

University BDT College Of Engineering Davangere-577004, Karnataka, India

***Abstract :***Every year, thousands of forest fire across the globe cause disasters beyond measure and description. There are a huge amount of very well studied solutions available for testing or even ready for use to resolve this problem. People are using sensors to detect the fire. But this case is not possible for large acres of forest. In this paper, we proposed a new approach for fire detection, in which modern technologies are used. In particular, we proposed a platform of Artificial Intelligence. The computer vision methods for recognition and detection of smoke and fire, based on the still images or the video input from the cameras. Deep learning method “convolution neural network” can be used for finding the amount of fire. This will enable the video surveillance systems on forest to handle more complex situations in real world. The accuracy is based on the algorithm which we are going to use and the datasets and splitting them into train set.

***IndexTerms-*** Fire detection, image classification, OpenCV, deep learning, and Convolutional Neural Network.

## I. INTRODUCTION

Forests are the protectors of earth’s ecological balance. Unfortunately, the forest fire is usually observed when it has already spread over a large area,making its control and stoppage arduous and is impossible at times. The result is devastating loss and irreparable damage to the environment and atmosphere (30% of carbon dioxide ($CO_2$) in the atmosphere comes from forest fires), in addition to irreparable damage to the ecology (huge amounts of smoke and carbon dioxide ($CO_2$) in the atmosphere). The conventional method is to prevent illegal logging. The goal of the system is to identify the possible dangers by continuously recording the noise in the forest, by processing segments of the recorded signals and decide upon the nature of each of these segments[1]. It is important to move adequate fire equipment and qualified operational manpower as fast as possible to the source of the fire. Furthermore an adequate logistical infrastructure for sufficient supply with extinguishing devices and maintenance is necessary as well as continuous monitoring of fire spread. An integrated approach for forest fire detection and suppression is based on a combination of different detection systems depending on wildfire risks, the size of the area and human presence, consisting of all necessary parts such as early detection, remote sensing techniques, logistics, and training by simulation, and firefighting vehicles. Nowadays, Wireless Sensor Networks (WSNs) are critical components of the increasingly typical Internet of Things (IoT) solutions. Such systems are widely applicable, and they can contribute new ideas to the field of environmental monitoring. The Raspberry Pi Model 3, analogue and digital sensors, and algorithms for signal processing form the basis of an intelligent system for monitoring the forest environment. Sensors monitor variables like temperature, gas concentrations, soil humidity, etc., while background noise is analyzed.[2] Forest fire automation uses functional circuit and sensor module building blocks that are put together as a whole to monitor three completely connected layers with a 1000- way softmaxn. We used the "dropout" regularization technique, a recently discovered regularization technique, to significantly reduce overfitting in the fully- connected layers.Regression, decision trees, and other machine learning approaches are compared in [6]. Adopting a comprehensive, diversified strategy that provides constant situational awareness and quick response is important to combat these calamities. In this study, we proposed a novel fire detection method that makes advantage of contemporary technologies. We specifically suggested an artificial intelligence platform. Using still photos or video data from the cameras, computer vision techniques are used to recognize and detect smoke and fire. The "convolution neural network" deep learning technique can be used to determine the fire's intensity.

## II.LITERATURE SURVEY

In conventional fire detection, much research has continuously focused on finding out the salient features of fire images. Chen [7] analyzed the changes of fire using an RGB and HSI color model based on the difference between consecutive frames and proposed a rule-based approach for fire decision. Celik and Demirel [5] proposed a generic rulebased circumstances of a particular forest. S J Chen [3] proposed WSN has biggest contributions since 33% researcher using WSN to tracking application, 41% use the WSN as a data exchange in their system, and 48% used WSN as data transmission between sensor nodes. Z.Tang[4] A robust AdaBoost (RAB) classifier is proposed to improve training and classification accuracy.[5]The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fullyconnected layers with a final 1000-way softmaxn. flame pixel classification using the YCbCr color model to separate chrominance components from luminance ones. Wang [8] extracted the candidate fire area in an image using an HSI color model and calculated the dispersion of the flame color to determine the fire area. However, color-based fire detection methods are generally vulnerable to a variety of environmental factors such as lighting and shadow. Borges and Izquierdo [9] adopted the Bayes classifier to detect fires based on additional features such as the area, surface, and boundary of the fire area to color. Mueller [10] proposed the neural network- based fire detection method using optical flow for the fire area. In the method, two optical flow models are combined to distinguish between fire and dynamically moving objects. In addition, Foggia [11] proposed a multi-expert system which combines the analysis results of a fire's color, shape, and motion characteristics. Although insufficient, the supplementary features to color, including texture, shape, and optical flow, can reduce the false detections. Nevertheless, these approaches require domain knowledge of fires in captured images essential to explore hand-crafted features and cannot reflect the information spatially and temporally involved in fire environments well. In addition, almost all methods using the conventional approach only use a still image or consecutive pairs of frames to detect fire. Therefore, they only consider the short-term dynamic behavior of fire, whereas a fire has a longer- term dynamic behavior.

### Deep learning-based approach

Deep learning has recently been successfully used in a variety of fields, including object detection and classification.in the processing of natural language, voice, and pictures. To enhance performance, researchers have carried out numerous studies on deep learning-based fire detection. The deep learning method differs from the traditional computer vision-based fire detection method in a number of ways. The first is that, after training with a huge amount of diverse training data, the characteristics are automatically captured in the network rather than being manually investigated by an expert. As a result, the focus is now on creating an appropriate network and getting the training data ready rather than trying to locate the right handmade characteristics. Another distinction is that the detector/classifier can be created by simultaneously training the neural network's features and detectors. as a result, the suitable algorithm Sebastien [12] proposed a fire detection network based on CNN where the features are simultaneously learned with a Multilayer Perceptron (MLP)-type neural net classifier by training. Zhang et al. [13] also proposed a CNN- based fire detection method which is operated in a cascaded fashion. In their method, the full image is first tested by the global image-level classifier, and if a fire is detected, then a fine-grained patch classifier is used for precisely localizing the fire patches. Muhammad et al.[14]proposed a fire surveillance system based on a fine-tuned CNN fire detector. This architecture is an efficient CNN architecture for fire detection, localization, and semantic understanding of the scene of the fire inspired by the Squeeze Net [15] architecture. A unit in CNN's deep layer has a broad receptive field, allowing its activation to be interpreted as a feature with a huge area of context data. This is also another benefit of using CNN's learnt features for fire detection. Even while CNN clearly outperformed conventional computer vision techniques in terms of classification, finding objects has been a different issue. In the suggested method, we use the object detection model to localise the SRoFs and non-fire objects. For the SRoFs, this includes the flame and smoke, and for the nonfire items, it includes other objects that are unrelated to the fire. Due to differences in shadows and brightness, things unrelated to the fire increase false alarms and frequently identify objects like red clothing.Therefore, special care must be taken to consider the decision based on long-term behavior with LSTM. Recently, Hu et al. [17] used LSTM for fire detection, where the CNN features are extracted from optical flows of consecutive frames, and temporally accumulated in an LSTM network. The final decision is made based on the fusion of successive temporal features. Their approach, however, computes the optical flow to prepare the input of CNN rather than directly using RGB frames.

## III. Proposed Methodology

### 3.SYSTEM DESIGN AND DEVELOPMENT

3.1. SYSTEM OVERVIEW

The general overview of the hardware module design and software implementation of fire detection system is shown in figure1. The hardware components of the fire detection unit, as shown in figure 2. A webcam is a video capture device that is connected to a computer or computer network, often using a USB port for video links, permitting computers to act as videophones or videoconferencing stations. Webcams can also be used with various computer video telecommunication programs which include the security surveillance and the recording of video files. At a high level, it comprises USB camera and communication with open CV module connected to a Arduino Uno that runs the Convolutional Neural Network (ConvNet/CNN), a Deep Learning algorithm for fire detection. The microcontroller polls the sensors at a regular interval and runs the inputs through the CNN application. If it concludes that a fire has been detected, a fire alert message is sent out through th the management information systems (MISs) to the occupants of the premises and the nearest fire station. If sending the message over the data connection is unsuccessful, then it sends the message out via short message service (SMS). The fire detection unit comprises the physical components, including the USb camera, the arduino microcontroller board, and the software that embodies the CNN fire detection algorithm and essentially drives the system. The software subsystem is that nonphysical part of the fire detection unit, which is concerned with reading inputs from the web camera, determining whether the readings are indicative of a fire or not, using Image processing with open CV and raising alerts in cases of fires. OpenCV (Open Source Computer Vision) is a library of programming functions mainly aimed at real-time computer vision and it is library used for Image Processing. It is mainly used to do all the operation related to Images. Machines are facilitated with seeing everything, convert the vision into numbers using pixels.

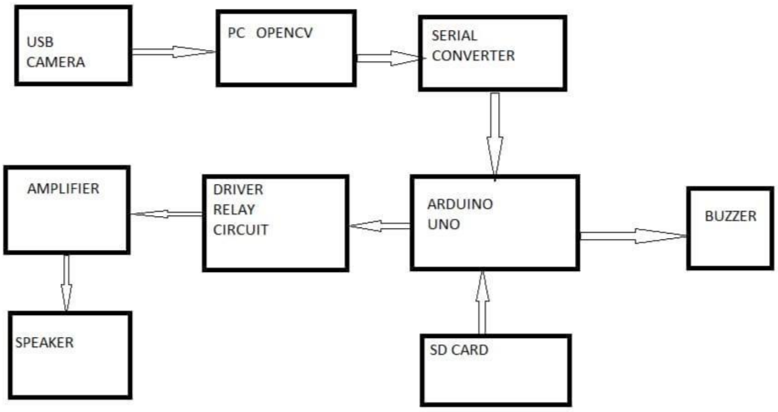


Figure1. Block Diagram of Fire detection system

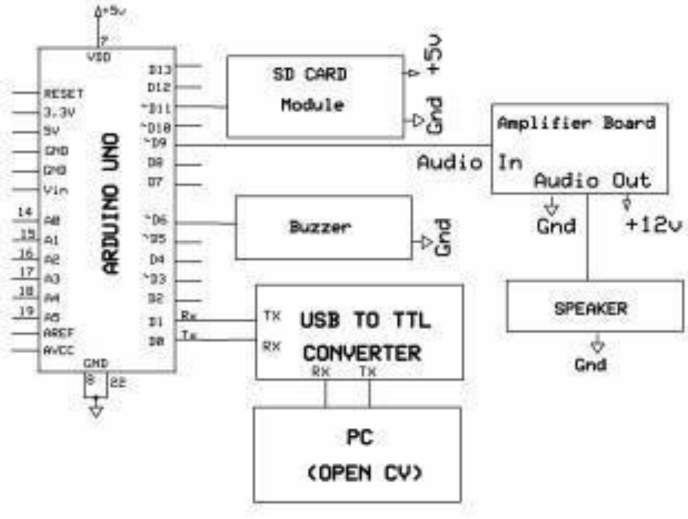


Figure 2. Circuit diagram of Hardware circuit

### 3.1.2.CONVOLUTIONAL NEURAL NETWORKS

Convolutional Neural Network (ConvNet/CNN) is a Deep Learning method that can take in an input image and assign importance (learnable weights and biases) to distinct aspects and objects in the image while being able to distinguish between them. Comparatively speaking, a ConvNet requires substantially less pre-processing than other classification techniques. CNN can learn these filters/characteristics with adequate training, but in primitive approaches filters are hand-engineered. Multiple three- dimensional planes make up the network's levels. Every 3-D plane has a number of neurons, which makes CNNs appropriate for handling picture data. Image data should be included in the input layer of CNN, which is represented by a three-dimensional matrix.

### 3.2 SYSTEM ARCHITECTURE SYSTEM IMPLEMENTATION AND TESTING

In convolution operation, several kernels of different sizes are applied on the input data to generate feature maps. These features maps are input to the next operation known as subsampling or pooling where maximum activations are selected from them within small neighborhood. These operations are important for reducing the dimension of feature vectors and achieving translation invariance up to certain degree. Another important layer of the CNN pipeline is fully connected layer, where high level abstractions are modeled from the input data. Among these three main operations, the convolution and fully connected layers contain neurons whose weights are learnt and adjusted for better representation of the input data during training process. The system architecture consists of both hardware and software components. hardware components comprise of the fire detection system, which will have the installation of the software components. For enhanced fire detection, a surveillance camera unit is incorporated as part of the hardware system implementation, which will continuously monitor the premises and send the video feed to a centralized server for fire incident detection and alert notification. A convolution procedure produces feature maps by applying a number of kernels of various sizes to the input data. These feature maps are used as input for the subsequent procedure, subsampling or pooling, which selects the highest activations from them within a local neighbourhood. These processes are crucial for bringing down the dimension of feature vectors and, to a certain extent, establishing translation invariance. Fully connected layer, where high-level abstractions are modelled from the input data, is another significant stage of the CNN process. The convolution and fully connected layers of these three major operations comprise neurons whose weights are learned and changed for better representation of the input data during the training phase. Hardware and software elements both make into the system architecture. hardware consists of the following.

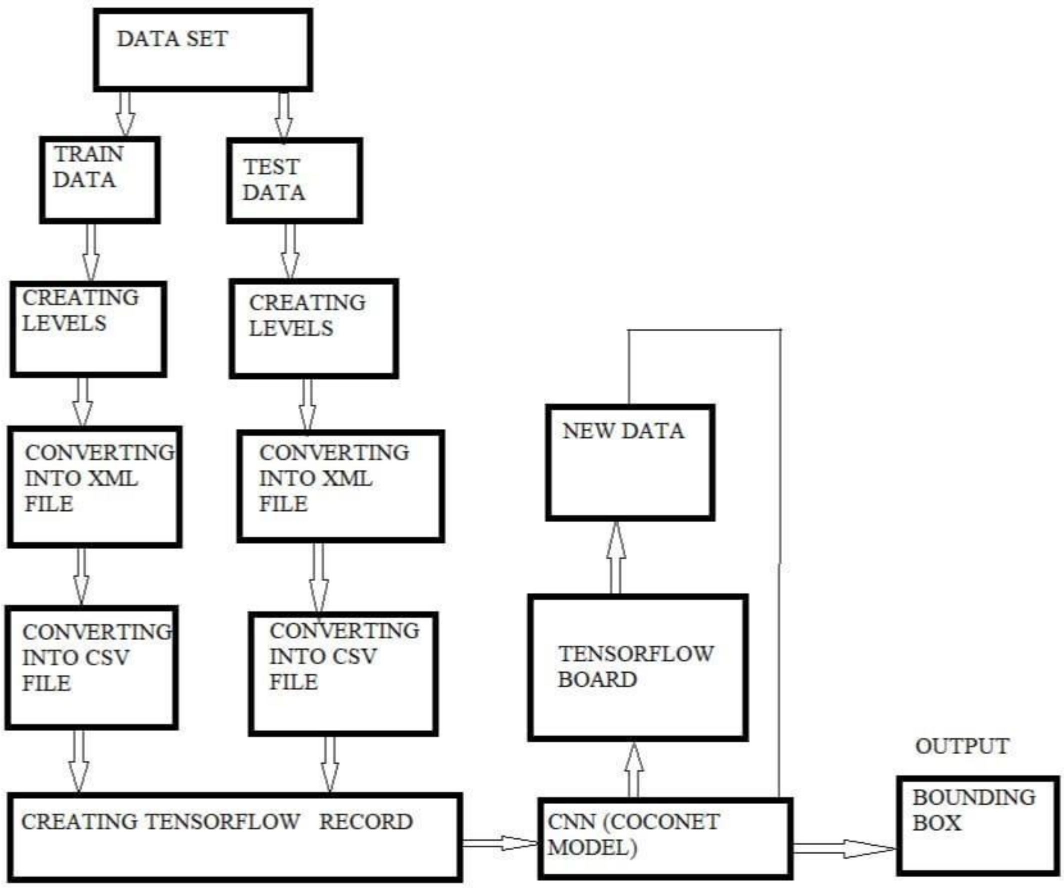


Figure 3: Flow diagram for fire detection software

The object detector is created to train a robust classifier. we need a lot of pictures which should differ a lot from each other. So they should have different backgrounds, random object, and varying lighting conditions. The different samples fire classes are as shown in figure.

Figure 4: Sample images for classes.

About 80% of the images must be transferred to the object_detection/images/train directory, while the remaining 20% must be moved to the object_detection/images/test directory. We require some sort of picture labelling software in order to classify our data. An excellent tool for labelling an image is labelling. The "Create RectBox" button can be used to define the bounding box. You must click save after generating the bounding box and adding annotations to the image. Repeat this procedure for every image in the training and testing folders. After the images have been labelled, we must produce TFRecords that can be used as training data for the object detector. We will use two scripts from Data Tran's raccoon detector to produce the TFRecords.

4. SYSTEM IMPLEMENTATION AND TESTING

In order to train the convolutional neural network, more than 1000 photos of both fire and non-fire conditions were used. The information was gathered from web resources for image data. Figure 5 displays some examples of the convolutional neural network images. The dataset was divided into training and testing sets according to a general rule for neural network training. Test video streams were sent into the system as input in order to get a conclusion from the model. Probabilities are produced by the classifier for the two classes of "fire" and "no fire." The classification algorithm's output is the class with the highest probability score. Google's Tensor Flow was used to construct the classifier module. Google offers the open-source software package Tensor Flow for numerical computation.

**IMPLEMENTATION**

Convolutional neural networks were trained to detect the forest fire, image data set has been collected form repository called kaggle, dataset has 2 caterogy of images in 2 folder labelled as fire and no fire. Following are the steps fallowed to implement the project. Step1: All necessary libraries are imported

Step2 : Datasets are read using python listdir() method

Step3: features of the images are extracted using image to array function

Step 4: Features and labels are split in 80:20 ration

Step 5: Model is trained using neural network

Step 6: Trained modelis exported to .h5 file

Step 7: Model is deployed to local system

Step 8: Test image is captured using webcam of system using cv2 library Step
9: Having done preprocessing of test image it is fed to model for prediction Step
10: having predicted the result user is alerted if fire is detected.

Fire

No Fire

## IV. Result And Discussion

The aim of this work is to present a method that can be smoothly deployed to an embedded device in order to finally build a complete fire detection unit. Therefore, it becomes inevitable to use a test dataset that includes images that are often encountered in real-world fire emergencies with an image quality that is commonly obtained with a camera attached to low- cost hardware like Arduino Uno, a microcontroller board based on the ATmega328P. The video classifier performed very well on the tests run on the classifier module. To avoid the instances of false alarms being triggered, a threshold for the classifier confidence was set. Hence, the alarm is only triggered when the confidence is greater or equal to the threshold. The aim is to detect a fire from the video stream with very high accuracy and trigger an alert as quickly as possible. To boost the speed of the classifier, TensorFlow's "optimize_for_inference" script was used to remove all unnecessary nodes in the module. The script also does a few other optimization processes like normalizing operations into the convolutional weights that help speed up the model.

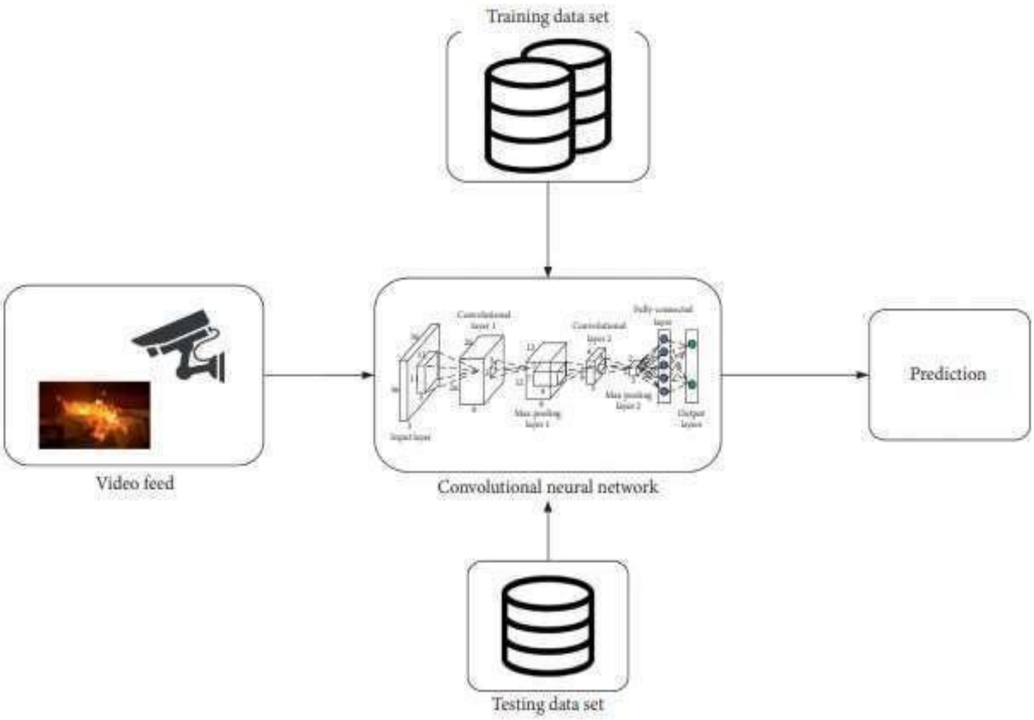


Figure 5: Video processing unit on a dedicated server.

## V. Conclusion

We describe a convolutional neural network that was created from scratch and trained on a hugely varied dataset in this work. The ultimate goal of the entire project is to create a fire detection device with internet of things (IoT) capabilities that can efficiently replace the current physical sensor-based fire detectors and lessen the issues with false and delayed triggering that come with such fire detectors. The newly developed neural network can operate smoothly at a frame rate of 24 frames per second on a low-cost embedded device like the Arduino Uno, a microcontroller board based on the ATmega328P. The model's performance on a regular fire dataset and a test dataset that it created itself (containing of difficult real-world fire and non-fire photos with image quality.

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