



Fire Detection: A Novel Approach for detecting fire using AI Techniques and evaluating its accuracy

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ABSTRACT

In today's world disaster's such as fire has become a very interesting topic in research and plays a very important role in the development of the smart environment. Disasters such as fire has caused many social and economic damages. We can prevent the damages by the early detection of the fire. The current advancement has permitted the detection of the fire using vision based. We have used various AI techniques such as CNN, RNN, ATT Squeeze net, HSV, YOLOV3 and compare the accuracy. To validate our system, dataset of approximately 3000 images is considered. Dataset consist of both fire and non-fire images. prove the validity of our method we will be using. We have trained the system using different AI Techniques and calculated the accuracy by detecting the fire in real time.

KEYWORDS: Fire Detection, Fire Prevention, Convolutional Neural networks, RNN, ATT squeeze net, Deep learning.

INTRODUCTION

Fire is one of the major part of disasters. threatening the human life and property. Reducing the damage caused by the fire has caused important theoretical and practical significance. Early methods of fire based on one or more of these features. Such models are based on the construction of the color models using static and dynamic features.

To overcome this, we have investigated it further. The features in the video sequences are extracted and used to determine whether the fire has occurred. We have used the background detection method to obtain the real time images of fire and smoke.

However, we have used the deep neural networks through automatic learning which can help to improve

the performance. CNN models face challenges in term of popularization that is basically due to high memory consumption. Moreover, high robustness of the deep learning models remains challenging.

The most important measure of the fire detector is to detect the fire situation correctly. Although smoke detectors are able to achieve acceptably low FNR. The reason for decreasing the smoke detectors is that they are weak to differentiate the smoke detectors such as cooking oil, cigarette smoke, smoke detectors which

NEURAL NETWORKS BACKGROUND KNOWLEDGE

This section contains some background knowledge about common terms used in neural networks and also throughout this research paper:

1) *Neural Network*: Neural networks are basically the behavior of the human brain, which allows computer programs to recognize patterns and try to solve common problems in the field of AI.

2) *Feed-Forward Neural Network*: The motion of this network is only forward, and moves to the point it reaches the output node. There is no feedback that can help to improve the nodes in different layers.

3) *Multilayer Perceptron*: We would like to move to neural networks having more than 2 layers, more than one hidden layer. In a Multilayer Perceptron, the main aim of using the method is when the data is not linearly separable.

4) *Convolutional Neural Network*: It is a filtering mechanism used in neural networks. When we repeat the filtering mechanism, it yields the location and strength of a detected feature. As a result of this ability, these networks are most widely used in image processing, natural language processing, recommender systems so as to yield effective results of the important feature detected.

5) *Recurrent Neural Network*: Through the name we get to that in this network something recurs. In this network the output of a particular layer is saved and is connected to the input again. Here the first layer will be a simple feed-forward neural network and each node will retain information in the next layers. On doing this, if the prediction is wrong the network will try to re-learn and learn it effectively to the right prediction. This is widely used in text-to-speech conversion.

2. RELATED WORK

There are numerous works that have been done related to fire detection.

Khan Muhammad^[1] The Hue, Saturation and Value of an object is the color space associated with an object where Hue is the color, Saturation is the greyness and Value is the brightness and it is used to solve the problems related to computer vision because of the better performance when compared to RGB, Blue and Green color space and the Hue range in HSV is [0,179], the Saturation range in HSV is [0,255] and the Value range in HSV is [0,255] which is used to perform object detection. Firstly, author will record the fire videos and then pass it to the HSV algorithm for the fire detection. The Zone of influence is calculated by subtracting the

segmented image from the original input image. However, in this work author have purposed to detect fire in house and vehicle.

Akmalbek Abdusalomov^[2] The convolutional layers which are included in the YOLOv3 architecture are used to produce a prediction related to fire. These features include the class label, coordinates, size of the bounding boxes. The prediction for the YOLO has in total 1×1 convolutions. The size of the prediction map is same as that of the feature map. In YOLOv3 the way this prediction map is interpreted in such a way that each cell predicts a fixed number of bounding boxes. The cell which contains the center of the ground truth box of object of interest is designated as the cell which will be finally responsible for predicting the fire.

A.Q. Nguyen^[3] The Single-Shot Multi Box Detector (SSD) algorithm is an advanced target detection algorithm. The SSD algorithm does the task of classifying and locating the target using only a fully convolutional neural network. With the Integration of fire detection and autonomous flight controller Flying drones could help to reduce the Human effort to find and detect fire. Whenever a drone detects a fire it will Send an urgent alarm including the Information of the drone localization (GPS) and the fire detected image will be sent to the monitoring center using wireless link using the telemetry module.

Anand Paul^[4] Ada boost i.e., Adaptive Boosting is a powerful machine learning algorithm. Commonly, it is used as a combination of many weak neural networks. It combines the output of other classifiers and weighted sum is calculated, and then it is used as the final output. It was mainly designed for feature classification and regression, but due to its great efficiency regarding classification, it has been used in many image processing applications. The AdaBoost algorithm is sensitive against noisy data and outliers. In authors' proposed work, Ada boost algorithm to boost the output of many MLP neural networks for better and efficient fire prediction is used.

Vinay Dubey^[5] The feedforward neural network is one of the most important types of artificial networks which has broad applications in IoT. Feedforward networks

consist of a series of layers. The first layer connection is from the network input. Each other layer has a connection with the previous layer. The final layer produces the network's output. For the prediction of fire, author is analyzing the data from the server have applied the feed forward neural network where there is no feedback obtained from the input Data analytics is performed at the server by applying fully connected neural network. The alert is sent to the user via Gmail or text message

Yuchun Zhang^[6] Dynamic features are extracted by detecting the motion and flicker features. Secondly the adaptive lightweight neural network is purposed to extract the deep static features of fire Region of interest acquisition is carried out based on the dynamic features. It involves background subtraction and flicker detection. Background subtraction helps to obtain the suspected region of interest and flicker detection is used for the region of interest. The images of interest are extracted and coordinates of the video frame are recorded. Adaptive light weight neural network whether each region of interest is in first phase. If so, alarm is generated and fire coordinates in video frame as output

Pengyu Wang^[7] Squeeze Net based asymmetric encoder-decoder U-shape architecture, Attention U-Net and Squeeze Net (ATT Squeeze U-Net), mainly functions as an extractor and a discriminator of forest fire. The segmentation of module extracting the shape features of forest fire. The classification module to check whether the detected fire area is true or not. In the first step input images from dataset are fed into the Att squeeze net Unet for training. The obtained segmentation would be trained by another data set for achieving feature maps. The feature maps would be selected to train classification module M4. Then a soft max classifier is used for testing the probability of fire existence

Tao Lu^[8] The complex content of images always has higher entropy. From this perspective, authors have purposed a feature entropy guided neural network for forest fire detection, which was used to balance the content complexity of different training samples in this paper first author described the purposed cross entropy

loss function. Then they have introduced a color attenuation neural network for the Fire color net. Fire color net is the backbone of fire detection algorithm. Neck is useful for the modified PA net. The neck performs the fusion of the extracted features from top to bottom and then goes from bottom to up to fuse the location and space information. The head part basically performs the classification and border regression

DiaaBadawi^[9] This system needs no special hardware to deploy and can implement a well-trained neural network A back propagation algorithm is used for training with need of small approximations. The author has trained the neural network by using wildfire images If the size of the video is huge (1080 p) we divide them into 180*180. The author has usually resized the video and then feed them into the network for fire detection

MertNakip^[10] Firstly, author has taken the weighted sum of change in the sensor reading from k-1 to k although the idea is usually depended on the Holtz winter double exponential smoothing. LP1 unit of the SDP 1 module predicts the module of reading of the sensor on the basis of the well-known exponential smoothing. Since LP 1 is recurrent neuron, the parameters are learnt during the training of rtpnn. The output layer of FP module uses one neuron for prediction of fire existence

3. PROPOSED SYSTEM ARCHITECTURE

This section presents details about system architecture of the Fire Detection model using AI techniques. Then we will be explaining the work flow of our overall model.

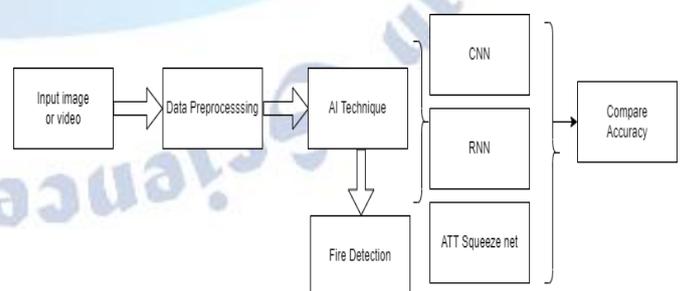


Fig 1-Proposed System Architecture

- We will be using fire and smoke images as an input in the form of the data set.

- Wherein data preprocessing will be performed with the help of slicing operation.
- With the help of slicing operation, we will try to divide the videos in segments
- Then We will apply AI techniques like CNN, RNN, Att squeeze net to do fire detection in real time and compare accuracy

3.1 Dataset: We will be using the data set which will be consisting of the mixture of fire and smoke images and non-fire and smoke

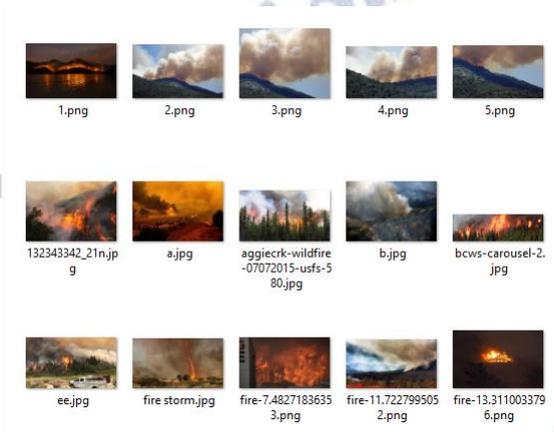


Fig 2- Fire Images



Fig3-Smoke Images

The following dataset contains 1000 fire images and 12000 smoke images. These images will be trained by our cnn model. In order to detect whether there is fire in real time.

3.2 AI Technique used:

3.2.1 CNN: A Convolutional Neural Network, also known as CNN or Conv Net, is a class of neural networks that specializes in processing data that has a grid-like topology, such as an image. A digital image is a generic representation of visual data

3.2.2 HSV: Unlike RGB and CMYK, which defined in relation to colors, HSV is defined in a way which is similar to how humans perceive color. It's based on

three values: hue, saturation, and value. The color space describes colors in terms of their shade and their brightness value

3.2.3 YOLO: YOLO is a class of deep learning models used for fast object Detection. There are three main types of YOLO, they are YOLOv1, YOLOv2, and YOLOv3.

3.2.4 RNN: RNN mainly works on the principle of using the output of a particular layer and then feeding them back to the input to predict the output of the layer.

3.2.5 Attsquezenet : SqueezeNet is a convolutional neural network that has basically 18 layers. It can load a pretrained version of the network which are trained on more than a million images from the ImageNet database. The pretrained network are used to classify images from 1000 object categories, such as keyboard, mouse, pencil, and many animals

4. IMPLEMENTATION AND RESULTS

4.1 HARDWARE AND SOFTWARE USED

HARDWARE REQUIREMENTS:

- DUAL-CORE 1.6 GHZ OR HIGHER
- 2 GB RAM
- 500 MB FREE DISK SPACE

SOFTWARE REQUIREMENTS:

- PYTHON 3.6+

4.2 ALGORITHM USED FOR FIRE DETECTION:

```
# Initializing CNN
cnn=tf.keras.models.Sequential()

# adding first Layer
cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3, padding='same', activation='relu', input_shape=[224, 224, 3]))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2))

# adding second Layer
cnn.add(tf.keras.layers.Conv2D(filters=64, kernel_size=3, padding='same', activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2))

# adding third Layer
cnn.add(tf.keras.layers.Conv2D(filters=256, kernel_size=3, padding='same', activation='relu'))
cnn.add(tf.keras.layers.MaxPool2D(pool_size=2))

# Flattening
cnn.add(tf.keras.layers.Flatten())

# Fully connected Layer
cnn.add(tf.keras.layers.Dense(units=128, activation='relu'))

# Output Layer
cnn.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))
```

Fig4 - CNN Algorithm

4.3 CNN Summary: It gives the overall summary of the layers being created

```

cnn.summary()

Model: "sequential"

Layer (type)                Output Shape                Param #
-----
conv2d (Conv2D)             (None, 256, 256, 32)      896
max_pooling2d (MaxPooling2D) (None, 128, 128, 32)      0
conv2d_1 (Conv2D)           (None, 128, 128, 64)     18496
max_pooling2d_1 (MaxPooling2 (None, 64, 64, 64)      0
conv2d_2 (Conv2D)           (None, 64, 64, 256)     147712
max_pooling2d_2 (MaxPooling2 (None, 32, 32, 256)      0
Flatten (Flatten)           (None, 262144)            0
dense (Dense)                (None, 128)               33554560
dense_1 (Dense)              (None, 1)                 129
-----
Total params: 33,721,793
Trainable params: 33,721,793
Non-trainable params: 0

```

Fig 5- CNN Summary

4.4. Accuracy Calculated: The accuracy calculated after training the CNN Model is 98%.

```

checkpoint=tf.keras.callbacks.ModelCheckpoint('D:\Datasets\Fire and Smoke\models\fire_and_smoke_model.h5',
                                              monitor='val_loss',mode='min',
                                              save_best_only=True)
callbacks=checkpoint

cnn.compile(optimizer='Adam',loss='binary_crossentropy',metrics=['accuracy'])
cnn.fit_generator(train_validation_data=validation,epochs=1,
                 steps_per_epoch=train.samples//batch_size,
                 validation_steps=validation.samples//batch_size,
                 callbacks=callbacks
                )

772/772 [=====] - 839s 1s/step - loss: 0.0704 - accuracy: 0.9852 - val_loss: 0.0270
<tensorflow.python.keras.callbacks.History at 0x2303b0cc088>

```

Fig6- Accuracy Calculated

4.5 CNN Result Analysis:

Fire can be detected through image and well as in real time video stream.



Fig7- Fire detected through Image

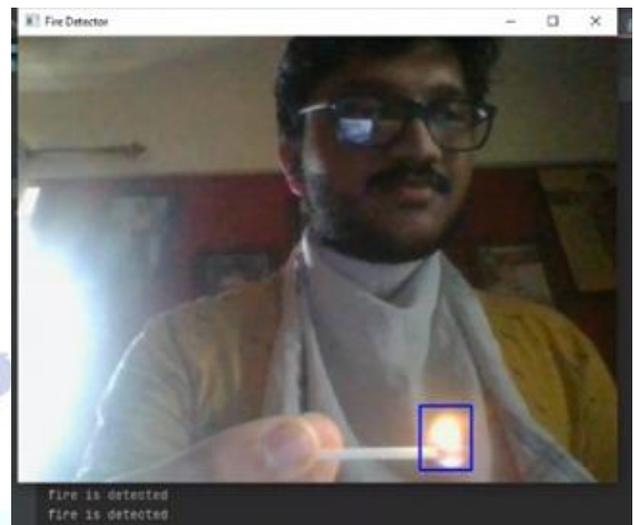


Fig 8- Fire detected Through real time video

4.6 Other Methods used:

4.6.1 HSV Algorithm: It is basically used for detecting fire in the video frame. It basically tries to take input as a video and divides it into the segments and tries to read one by one

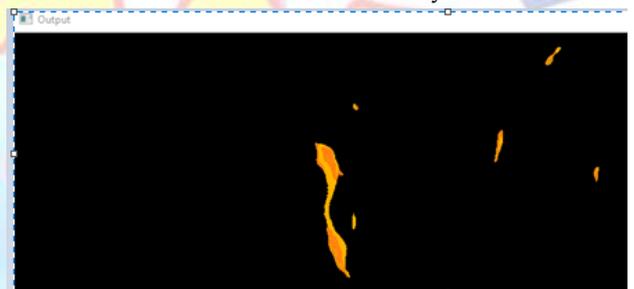


Fig 9- Fire Detected through HSV

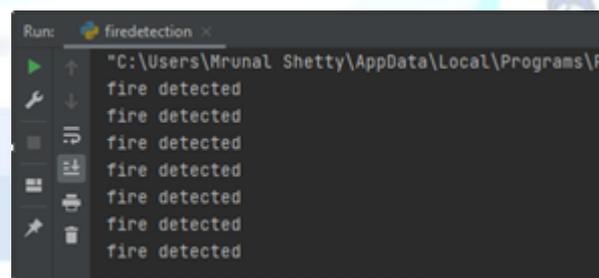


Fig 10- Output

Accuracy of HSV is 47%

4.6.2 Yolo Algorithm: YOLO is a Convolutional Neural Network (CNN) for performing object detection in real-time. CNNs belong to classifier-based systems that can process input images as structured arrays of data and identify patterns between them. YOLO has the advantage of being much faster than other networks and still maintains accuracy.



Fig11:Fire detected through Image



Fig 12- Fire detected Through Video

4.6.3 Accuracy Calculated:The accuracy calculated through YOLO is 52.46%.

```

detect_from_image()
# detect_from_video()

/usr/local/lib/python3.7/dist-packages/tensorflow/python/data/ops/dataset_ops.py:
"Even though the 'tf.config.experimental_run_functions_eagerly' "
fire : 52.46809124946594 : [228, 9, 616, 343]

```

Fig 13- Accuracy Calculated through Yolo

4.6.4 RNN Algorithm:Recurrent neural networks (RNN) is a state of the art algorithm for sequential data that are used by Apple's Siri and Google's voice search. It is one best algorithm that remembers its input, due to an internal memory, which can be perfectly suited for machine learning problems that mainly involve sequential data.In order to detect fire we need to go for the hardware approach.

4.6.5 Attsqueezenet Algorithm:In order to classify true fire, we make use of a fragment of the encoder in ATT Squeeze U-Net. The experimental results of modified SqueezeNet integrated Attention U-Net shows accuracy at 0.93 and average prediction time of 0.89 second per image are achieved for reliable real-time fire detection.We need to use fire module hardware for fire to be detected.

Accuracy Evaluation:

Sr No	Algorithms	Accuracy
1	HSV Algorithm	47
2	Yolo Algorithm	52.46
3	RNN Algorithm	96
4	Attsqueezenet	93
5	CNN Algorithm	98

Fig 14:Accuracy calculated

5. FUTURE SCOPE AND CONCLUSION

The results of my research have prompted more potential future studies in enhancing the issue of fire detection efficiency. As we have tried to detect fire in real time video as well as through image for my proposed solution is just moderately better, hence we need to strive for better results through IOT based methods. Companies can invest in future research to help with these issues.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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