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Smart &Automated Fire& Smoke Detection, Monitoring and Alarm System

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Abstract
Fire and smoke are among the leading sources of the accidental casualties. Because fires seriously harm both human life and non-living property, fire detection is crucial. In this study, we offer a novel, energy-friendly, and computationally efficient CNN architecture for fire detection, localization, and semantic understanding of the fire scene, which is inspired by the Squeeze Net design. For monitoring the level of smoke in the surroundings, we have also created an Arduino smoke level detector utilising a MQ-135 sensor. To display data, we have simply connected an Arduino board to a MQ-135 gas sensor module. The MQ-135 sensor is the smoke sensor that we used. Both smoke detectors and the crucial safety factors are highly helpful in detecting smoke or fire in buildings.
Keywords:*fire detector, gas sensor, short message service (SMS), smoke detector*

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I. INTRODUCTION

The frequency of protracted fires, which have an impact on human health and security, has increased the use of fire detection as a tool. Heat and pressure sensors are typically used in this modern detection technique, which is based on electronic sensors. The fundamental problem in the earlier approach is that it only functions if a specific condition has been met. In the worst-case scenario, sensors that are damaged or improperly designed can result in significant casualties in the event of a real fire. Electronic security cameras should be installed to address this issue.They include a variety of wireless CCTV cameras that use computer vision to detect fire. Nonetheless, there are still situations when cameras have blind areas and fail to distinguish between smoke and fire. It may also be a little costly to have many cameras to cover all the blind spots in some particular places. Installing a smoke monitoring system is necessary to address this issue. The smoke detector circuit reads and displays the amount of smoke in the air in addition to detecting its presence. This circuit activates the buzzer when the smoke level exceeds the desired limit; the code's specified threshold value may be altered to meet the needs of the situation.

II. BACKGROUND STUDY

According to a review of the literature, computationally complex methods are more accurate, while simpler methods trade off accuracy for a higher proportion of false positives. Because present computationally expensive approaches do not work well for some application scenarios of practical interest, a better compromise between these metrics is required. We research deep features based on convolutional neural networks (CNNs) for early fire detection in surveillance networks to overcome the aforementioned problems. The following is a list of most significant original contributions.

- We examine deep learning architectures for early fire detection in closed-circuit television (CCTV) surveillance networks for both indoor and outdoor situations instead of the time-consuming efforts of traditional hand-crafted features for fire detection. In comparison to cutting-edge techniques, our suggested fire detection framework increases fire detection accuracy and decreases false alarms. As a result, our approach can be extremely useful in the early identification of fire to reduce damage.
- With the aid of a transfer learning approach, we train and improve AlexNet architecture for spotting fires. Compared to traditional hand-engineered feature-based fire detection techniques, our model performs better. The model is still rather large (238 MB), which makes it challenging to execute in equipment with limited resources.
- We fine-tune a model with a similar architecture to the SqueezeNet model for fire detection at the early stages to lower the size of the model. The 166 model's size was decreased from 238 MB to 3 MB, saving an additional 235 MB of space, lowering the cost and improving the feasibility of its use in surveillance networks. Also, the computational complexity of the suggested model is 0.72 GFLOPS/image as opposed to AlexNet's 2 GFLOPS/image. This increases the inference efficiency of our proposed model, enabling it to process various surveillance feeds.
- We create a feature map selection algorithm that is capable of selecting relevant feature maps from the trained CNN's convolutional layers that are sensitive to fire regions. Compared to other hand-made methods, these feature maps enable a more precise segmentation of fire. The segmentation data can be further analysed to determine the fire's key features, such as its growth rate. This method also allows for the determination of the fire's severity and/or degree of burning. Using a pretrained model trained on 1000 classes of objects in the ImageNet dataset, our system also has the unique ability to recognise the on-fire item. Our method can tell whether the fire is in a car because to this 188 a building, a forest, or anything else. Firefighters can prioritise their targets by concentrating largely on areas with the most intense flames utilising this semantic knowledge.
- After the GSM module is properly attached to the microcontroller and receives the initial signal from it, it responds by sending the microcontroller an acknowledgement signal. The gas sensor unit then uses a MQ-6sensor to determine if there is any gas leakage in the MO sphere. The microcontroller's ADC unit receives a signal from the sensor unit after it detects a gas leak, and it uses that signal to activate other externally connected devices including the buzzer, GSM module, and LCD display.

III. PROPOSED SYSTEM

Scenes with shifting lighting, shadows, and fire-like items make it extremely difficult to see a fire at an early stage; typical low-level feature-based approaches have a high rate of false alarms and poor detection accuracy. We research deep learning models for potential fire detection at an early stage while conducting surveillance in order to address these problems. In a variety of computer vision issues and applications, such as object identification and localization, image segmentation, super-resolution, classification, and indexing and retrieval, CNNs have demonstrated encouraging results. Three well-known processing layers make up the conventional CNN architecture, which has 221 of them.

A convolution layer- various feature maps are produced when different kernels are applied to the input data

- A pooling layer- to achieve translation invariance to some extent and dimensionality reduction.
- A fully connected layer -models high-level information from the input data and constructs its global representation.

This proposed system mainly has two units – (1) Live Camera Based Fire Detection and (2) Smoke Monitoring System based on Arduino UNO and MQ-135. In first unit, Live CCTV cameras will detect fire through convolution layer of trained CNN, which are sensitive to fire regions. These feature maps allow a more accurate segmentation of fire compared to other hand- 180 crafted methods. If cameras fail to detect any fire and the smoke is detected by the sensor, i.e., MQ-135 smoke sensor, then the system indicates it by turn on the Red LED and the Buzzer and the "Danger" message is print on the Display screen.

The main object of our proposed model is follows:

- To develop a fast and early responding fire alert system in cheap cost and also covers a large area.
- To design and develop a smoke monitoring & alert system using Arduino.

Overview of the System

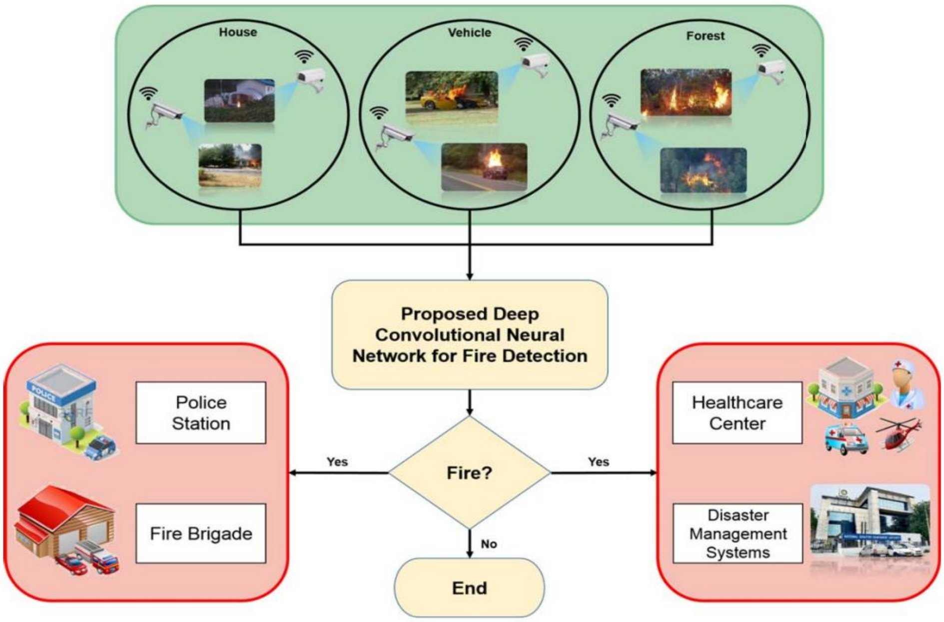


Figure 1: Overview of the System

Circuit Design of Fire localization using the deep CNN

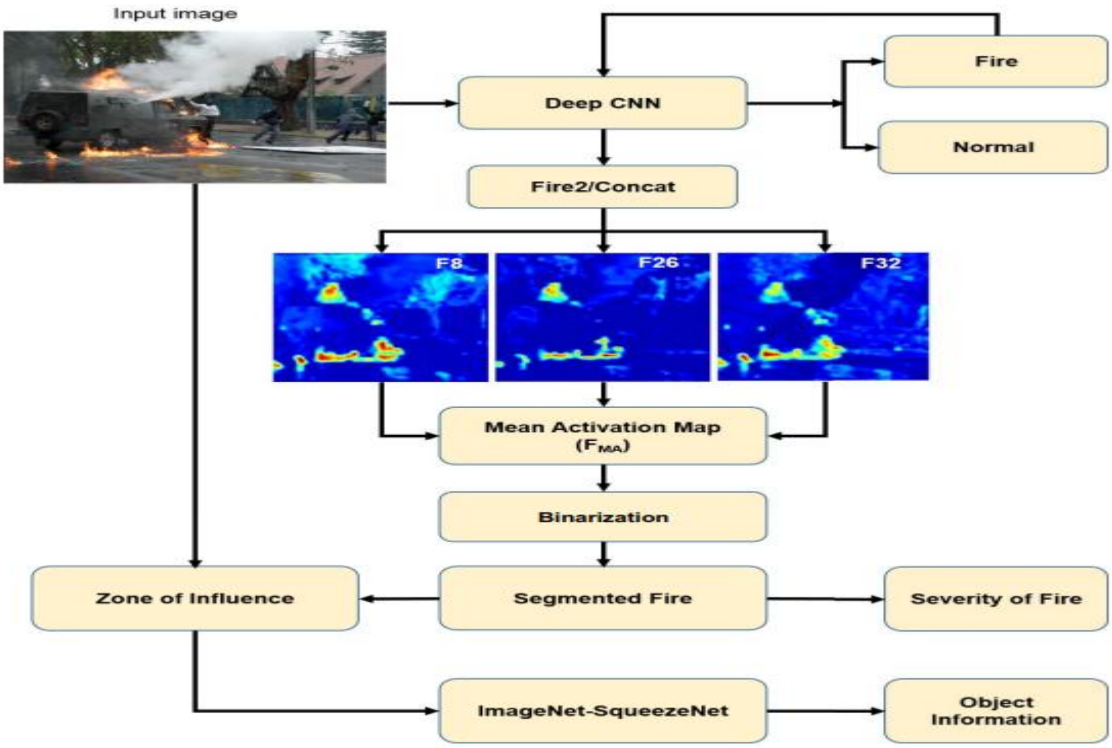


Figure2: Fire localization using the deep CNN

Circuit Design of Smoke Monitoring System

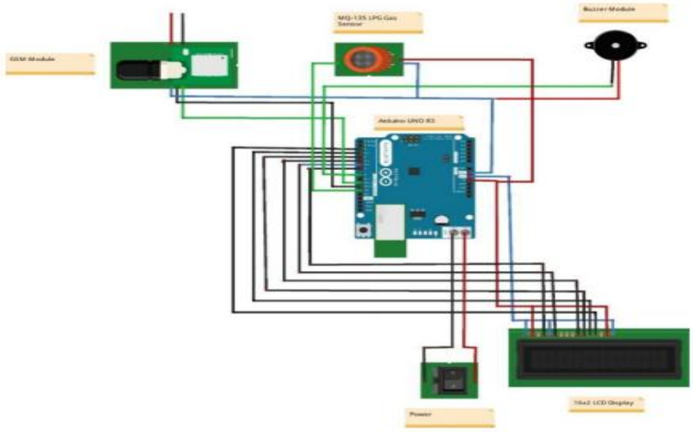


Figure3: Smoke Monitoring System

Algorithm Design for Live Camera Based Fire Detector

Algorithm used for fire detector:

1. Feature map section algorithm for Localization
2. Fire localization algorithm
3. HSV Color Model

Algorithm 1: Feature map section algorithm for Localization

Input: Training samples (TS), ground truth (GT), and the proposed deep CNN model (CNN-M)

1. Forward propagate TS through CNN-M
2. Select the feature maps FN from layer L of CNN-M
3. Resize GT and FN to 256×256 pixels
4. Compute mean activations map FMAi for FN
5. Binarize each feature map Fi as follows: F (x, y)bin(i) = 1, F(x, y)i> FMA(i) 0, Otherwise
6. Calculate the hamming distance HDi between GT and each feature map Fbin (i) as follows: HDi = Fbin(i) − GT This results in TS×FN hamming distances
7. Calculate the sum of all resultant hamming distances, and shortlist the minimum hamming distances using threshold T
8. Select appropriate feature maps according to the shortlisted hamming distances Output: Feature maps sensitive to fire

Algorithm 2: **Fire Localization algorithm**

Input:Image I of the video sequence and the proposed deep CNN model (CNN-M)

1. Select a frame from the video sequence and forward propagate it through CNN-M
2. IF predicted label = non-fire THEN

No action

ELSE

a) Extract feature maps 8, 26, and 32 (F8, F26, F32) from the "Fire2/Concat" layer of CNN-M b) Calculate mean activations map (FMA) for F8, F26, and F32

c) Apply binarization on FMA through threshold T as follows:

$F_{Localize}$ = { 1 , FMA > T ;

0 , Otherwise**}**

d) Segment fire regions from FMA

END

Output: Binary image with segmented fire $I_{localize}$

Algorithm 3: HSVColor Model

- Hue is the Absolute color
- Saturation is like mixture of white color
- Value is the illumination or brightness

Lower=[18,50,50]

Upper=[35,255,255]

Smoke Monitoring System

The MQ135 gas sensor begins to detect NH3, NOx, alcohol, benzene, smoke, CO2, and other dangerous gases as soon as the system's power source is turned on. It then outputs this information in the form of voltage levels. For the Arduino, this output voltage is used. The "MQ135.h" library, which is declared in the Arduino Code, is then used by the Arduino to transform this voltage into a PPM (parts per million) value. The PPM value will then appear on the OLED screen.

If there are no potentially hazardous substances in the neighbourhood, the sensor will give us a reading of 90 PPM. 350 PPM is normally considered a healthy threshold for air quality, and it shouldn't exceed 1000 PPM. Once the air quality level rises above 1000 PPM, symptoms including headaches, sleepiness, and stagnant, stale air begin to surface. An elevated heart rate is one of the many diseases that might occur when this level exceeds 2000 ppm. As a result, this system/device has indicators. When the air quality is less than 1000 ppm, the green LED goes on and the message "Fresh Air" displays on the display. When this value surpasses 1000 PPM, the system alerts you that the air is polluted by turning on the red LED and printing the phrase "Bad Air" on the display. If this value surpasses 2000 PPM, which denotes that the air is very contaminated, a "Danger! Air" message is printed on the display and the red Light goes on.

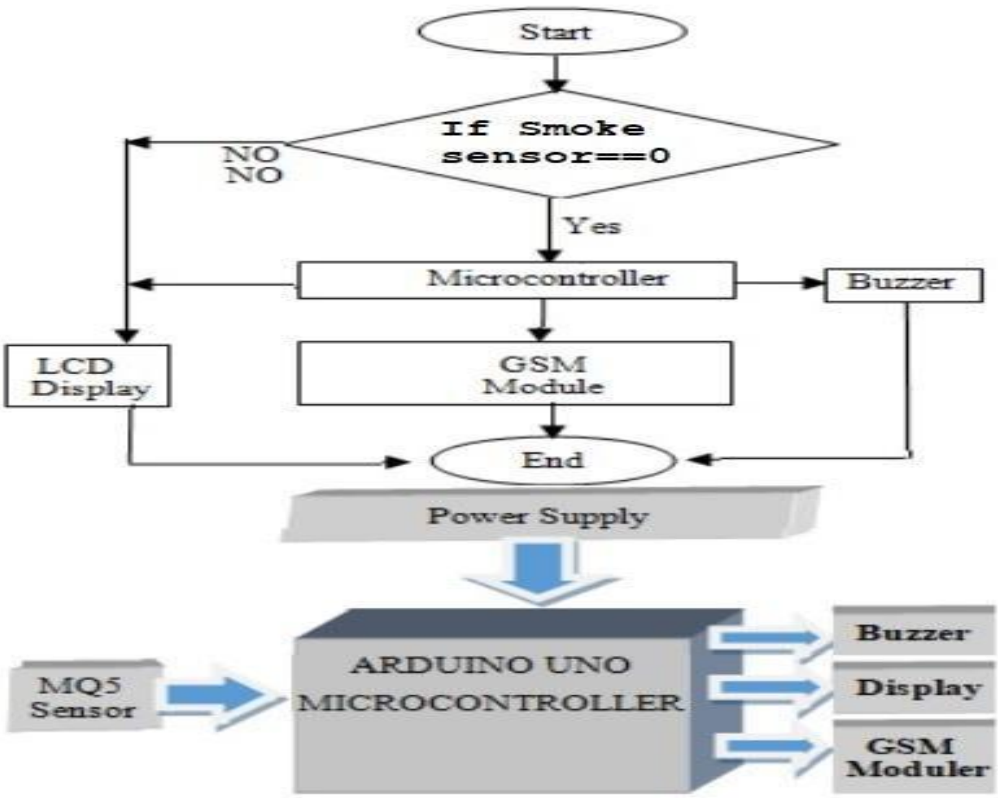
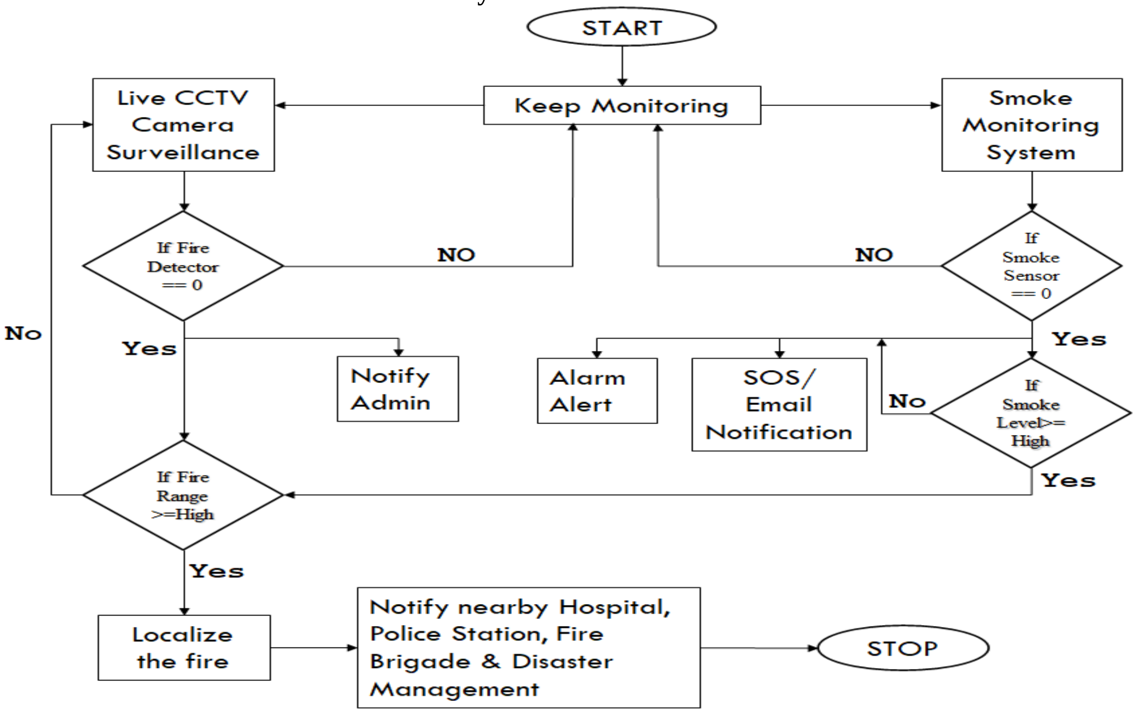


Figure 4: Block Diagram of Smoke Monitoring and Alert System using Arduino.

System Flow Chart



IV. RESULTS AND DISCUSSIONS

Based on our fire detection modulesin the generated report it is found that the accuracy levels has increased and it is also observed that somehow if the fire isn't detected by the python module then our Arduino is immediately catching the smoke and making the alarm. Accuracy is based on live camera generated reports and smoke sensor. We can let people in small scale and big scale industries as we have mentionedbefore.

Figure 5: Fire Detection

Figure 6: Fire Detection

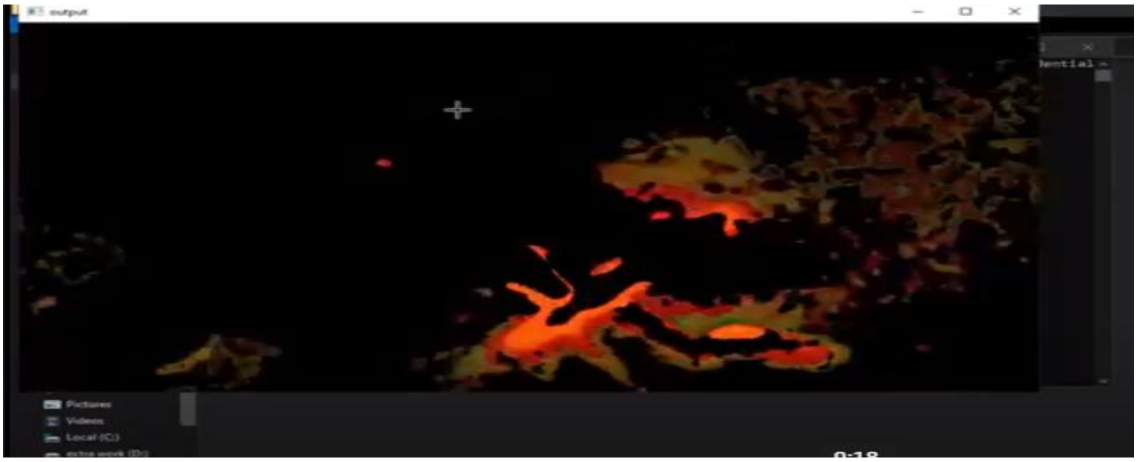


Figure 7: Fire Detection

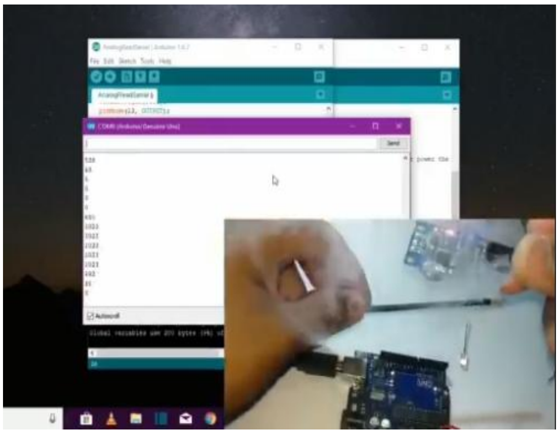


Figure 8: Smoke detection and Alarm

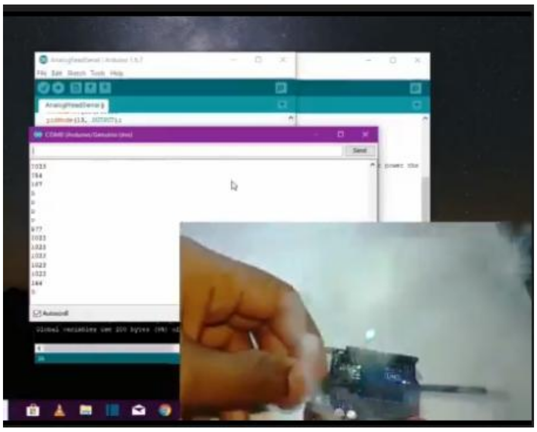


Figure 9: Smoke detection and Alarm

V. CONCLUSION

Our product is superior to others because it can be implemented on both small and large scales and is accurate and transparent. Two separate units that together make up the complete system do all the work.

With relatively little stress on comprehending the objects and scenes being observed, this paper primarily concentrates on the detection of fire and its localization. Making difficult and particular scene understanding datasets for fire detection methods and in-depth experiments may be the focus of future research. Additionally, fire detection systems can be combined with reasoning theories and information-hiding algorithms to intelligently watch and authenticate the video stream and start the necessary actions in an autonomous manner.

As this project's research continues, its potential application in areas like human action recognition or intrusion detection for security and monitoring purposes will grow significantly.

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