International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-11, September 2020

Innovating Fire Detection System Fire using Artificial Intelligence by Image Processing

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***Abstract:** with fires spreading increasingly around the world due to increasing global warming, it has become imperative to develop an intelligent system that detects fires early, using modern technology. Therefore, we used one of the artificial intelligence techniques, which is deep learning, which is one of the popular methods now. Professionals have done a lot of research, experiments, and coding software to detect fires using deep learning. Through this paper, we review current methods that are reached by industry professionals, as well as data sets and fire detection accuracy for each method.*

***Keywords:** fire; artificial intelligence; deep learning; Kagle; CNN; Image Processing; Kiras; Quality; Tensorflow; Sensitivity; Machine Learning.*

I. INTRODUCTION

Fires are one of the biggest challenges in the world right now, due to the global warming that the planet is currently suffering from. We all know what fires are and what they are capable of causing great damage, whether to humans, animals, or other forms of life[3]. The authorities in all countries of the world work to reduce or identify fires early so that they are brought under control.

Where there are many reasons for their occurrence; among these reasons: poor training of workers in places at risk, the development of the industry, as it became heavily dependent on high-risk, high explosive parts, and poor storage of hazardous raw materials[4].

The most prominent example of this being the destruction of Beirut on August 4, 2020, following the explosion of high-risk materials in the port of Beirut.

Of course, one of the causes of the spread of fires is not identifying them early, so it has become an urgent necessity in the world to recognize fires early and not to rely directly on humans and rely heavily on the machine in this regard, using the latest technologies.

II. FIRES ACCIDENTS

Not a day goes by without you hearing about a huge fire or several fires in different parts of the world, the fire may be in a factory or a house and may lead to injuries or deaths among citizens, as well as the tremendous losses that result from the occurrence of the fire, and among the things that may cause The fire.

Revised Manuscript Received on September 30, 2020.
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First: Human causes, the human element may have a part in them, such as[4]:

1- Leave inflammable garbage and waste in the manufacturing area, which self-ignite in the presence of heat.
2- Forgetting the gas oven and what is on it.
3- Accidents: such as car or plane accidents.
4- Poor and dangerous storage of inflammable or explosive materials.
5- Sparks or unusual rise in temperature due to friction in mechanical parts.
6- Indifference and negligence: such as throwing a burning matchstick or the stump of a cigarette at a combustible object.
7- Electrical faults or the presence of easily flammable materials near electrical appliances used for heating purposes
8- The presence of liquid waste and inflammable oils in the workplace.
9- Messing around and setting fire on too dangerous places, or throwing cigarette remains.
10- Ignorance: like the misuse of fire.

There are also other causes that humans have no hand in, such as thunderbolts, earthquakes, and high air temperatures.

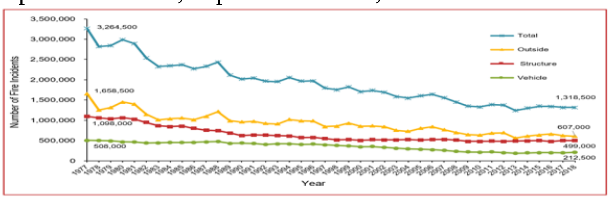
III. TYPE OF LOSSES DUE TO FIRES ACCIDENTS

Fire damages vary and these damages depend greatly on the cause of the fire, but no matter how many and different causes, the damage may be devastating on a large scale and difficult to predict, and in general, fire losses are divided into loss of lives and loss of Money[4].

Money losses are divided into two types:

1- Natural: property damage due to heat and ignition, or damage because of smoke or falling walls and ceilings.

2- Inevitability as a result of attempts to extinguish the fire and try to reduce it: losses of firefighting water and chemicals used in extinguishing, losses arising from the attempts of firefighters to try to reach the place of the fire and try to limit its spread and demolish the walls, evaporation losses, explosions losses, theft.



[5]Figure1, NFPA. orgfire Loss report in the United States2019

IV. FIRES ACCIDENTS IN SULTANATE OF OMAN

The Omani family is very important for the Omani government. From which the individual acquires his habits, behaviors, and culture, and in order to preserve this entity, a family environment free of risks must be created. Moreover, this will only be achieved through raising awareness of the preventive measures that must be available and followed. Moreover, the need for the head of the family to raise its members on the importance of paying attention to preventive aspects and informing them of the risks Surrounding them and following them continuously. Especially in this great development in contemporary life, which increases the risks and makes family members' awareness of the importance of safety inevitable. Whether it is in the home or the surrounding environment such as work, factory, school, or during trips or other things[6]. There is no doubt that fires have increased in the Sultanate in the recent period in various governorates and states, according to a report presented by the Royal Oman Police. As mentioned in the report that fires in residential facilities are among the most reported reports that the Public Authority for Civil Defense and Ambulance centers have dealt with. As their number reached 1,335 fires during the year 2018, which requires concerted efforts of all governmental and private institutions to work to limit their increase and reduce their losses, especially in lives. In addition to other damages such as property, health and psychological problems, and other indirect consequences[3]. The statistics of the General Administration of Civil Defense also revealed an increase in the rate of factory fires since the beginning of this year over the same period last year. There has been a fire in (23) factories since the beginning of the current year 2020, while the number of factory fires last year did not exceed (19) A fire. Statistics identified various causes for the outbreak of fires, on top of which was the poor storage of raw and manufactured materials in many factories and warehouses, the development of machines whose components constitute sources of danger, and human errors because of not training factory workers on how to extinguish fires the moment they ignite.

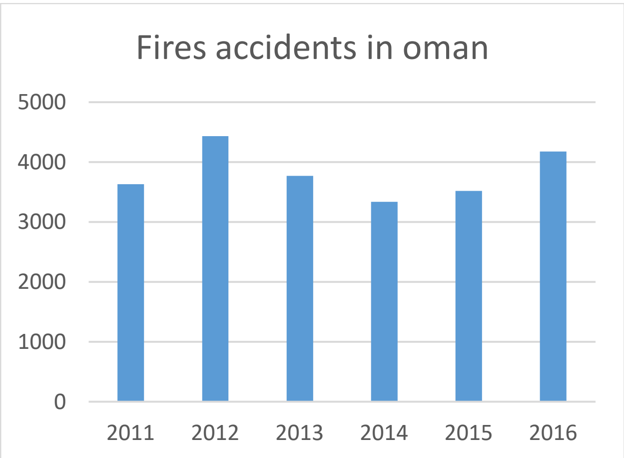


Figure2, Fires Accidents in Oman

V. ARTIFICIAL INTELLIGENCE

Artificial Intelligence is one of the modern technologies that will be useful in helping to detect fires. It is generally the intelligence shown by machines, which enables them to look at the environment and surrounding conditions and then take appropriate action. Therefore, the deep integration between artificial intelligence and fire recognition techniques increases the chance of the machine in successfully achieving the desired goal, which is to recognize fires, by studying smart factors and simulating the cognitive functions performed by humans using the human mind, such as learning and problem solving. In addition, the goal of artificial intelligence is to enable machines to be able to think, plan, and perceive the ability to move objects, the ability to process natural language and other human abilities that would help identify fires[7]. In addition, Artificial Intelligence research takes two different approaches, the symbolic approach, or the so-called "top-down," which analyzes perception independently of the biological makeup of the brain through symbol processing. In addition, the so-called "bottom-up" communication approach, which is based on creating artificial neural networks to mimic the structure of the brain.

VI. DEEP LEARNING

Deep learning is a branch of machine learning that depends entirely on neural networks, as the neural network will simulate the human brain, so deep learning is also a kind of simulation of the human mind. This method has many important applications in identifying fire, faces, and so on[7]. Deep learning saves us from wasting a lot of time and writing a lot of code[2].

The great development in deep learning has a major role in reducing the cost and using computers with relatively few capabilities than they were in the past, which will have the greatest impact on the ease of application of our fire detecting system and on the prosperity of deep learning worldwide.

Where one of the most important advantages of deep learning is image recognition, as it recognizes people and objects in images and identifies them with ease and great accuracy. To achieve an acceptable level of accuracy, deep learning programs require access to massive amounts of training data and processing power, neither of which was readily available to programmers until the era of big data and cloud computing.

In addition, because deep learning programming is able to generate complex statistical models directly from its own iterative output, it is able to generate accurate predictive models from large amounts of ungrouped and unstructured data. Because it processes information in ways similar to the human brain, these models can be applied to many tasks that people do.

Deep learning is currently used in most common image recognition tools, NLP protocol processing and speech recognition software, and these tools have also begun to appear in applications. As varied as self-driving cars and language translation services[9].

VII. DL MODELS

Because this process simulates a system of human neurons, this form of learning is sometimes referred to as deep neural learning or deep neural networks and contains the following network structures:

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A. Restricted Boltzmann Machine (RBM)

The Boltzmann machines are a kind of neural network model made up of random elements. Since it was proposed more than twenty years ago, it has been shown to be able to solve various problems such as optimization problems, fix degraded images, and learn the interdependence of random variables. For optimization problems, convergence is ensured to a global optimum, provided the system is solid at a sufficiently slow rate.

B. Convolutional Neural Networks (CNN)

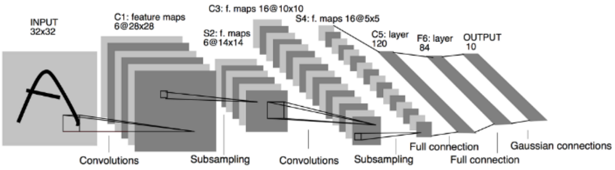

Figure3, The convolutional neural network[9].

A convolutional neural network, a type of deep learning, is analogous to a multilayer perceptron network. However, the difference lies in what the network learns, how it is built, and what the intended goal is. CNNs are commonly used in computer vision and visual field analysis; it is characterized by the presence of one or more hidden layers, which can extract the features found in images or videos, and a fully linked layer to produce the desired output[9]. The detection of fire in the live video feed is alerted to the user through e-mail. The overview of the proposed system is depicted in the figure next.

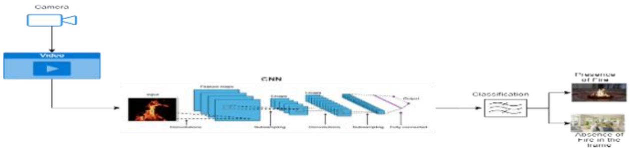

Figure 2: Proposed system Overview[9]

C. Recurrent Neural Networks (RNN)

It is a type of neural network where these deep learning algorithms save the output of processing nodes and input the result into the model; this is how the model is said to learn[9]. It includes loops within the network; this gives it a memory effect, but training these recurring neural networks in particular is very expensive.

VIII. MACHINE LEARNING

Machine learning is one of the most popular branches of artificial intelligence that emerged in the 1980s and supports modern society in many ways. It has developed in an amazing way, and it is called machine learning because it depends on the machine as it allows computers to have the feature of "learning".

Every method allows us to create a real model from existing information, whether we refine an existing model or create it anew. In general, there are two levels of learning: inductive and deductive. Inductive inferred general rules and judgments from big data. While deductive is the opposite, it starts from general provisions and applies them in specific examples.

Examples of learning methods include the rule-based system, artificial neural networks, decision tree, probability theory in decision-making, and classification method. As for the fields of using machine learning, they are many and varied, and we can mention some of their most important uses, such as improving the performance of the voice recognition program, in the field of robotics, and chess games.

IX. IMAGE PREPROCESSING

Image processing is one of the branches of deep learning, which is concerned with performing operations on images with the aim of improving them according to specific standards or extracting some information from them. Image processing systems are used in many applications, especially those of automatic control, and the recognition of patterns or objects within the image. For example, identifying the location of a fiery flame in an image or feeling the presence of an object in the image. In order to determine the flame, it is possible to study the interface of the moving flame and its properties, and then determine the flame or isolate its area. Therefore, a method must be used to determine the identity of the flame, its origin, knowledge or its location, and this is through the continuous change in its shape within the moving pictures, and the difference in its boundaries. In addition to that, it has one of the most important characteristics, which is the light emitted from the flame, i.e. the intensity of the illumination, and this helps to determine and track the flame. The digital images are entered into the computer, using the necessary software, then the extension of the input digital image is converted into a file with the BMB extension, then the image resolution is known by determining the number of colors that the image depends on, and then determining the dimensions of the images (height and width). After that, the image is analyzed into three separate images, which are an image with blue gradations, an image with red gradients, and an image with green gradients, and the light point's values of the resulting three images are between 0.255. Then, to improve the work performance, the image data is converted from integer numbers to real numbers so that the image data is within the range (0, 1). Then, work on improving the images by adjusting the contrast, so that this process increases the contrast ratio of the three-color levels, which results in an increase in the contrast of the image with slight contrast that may result from poor lighting during photography.

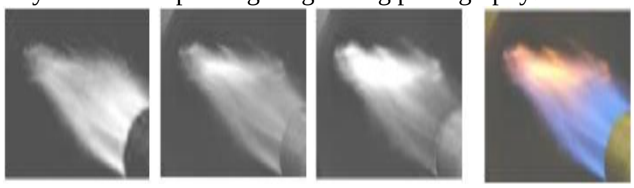

Figure4, Analyze the color image into three colors (red slide, green slide, and blue slide)

X. DATASETS

Datasets is a collection of data, usually represented in the form of a table. Each column in the table represents a specific variable, and each row refers to an element of the data set. This table defines values for each variable for this element. For example, it can specify the height and width of a specific object. A data set can contain one or more items, depending on the number of rows.

Kaggle Dataset:
Since the platform contains data analysis and machine learning competitions in various fields, there are many valuable data sets available for download. Indeed, it has many datasets that help us identify fires with deep learning.The data set used to train our deep learning model contains 1,213 images, of which 671 images with fire appear in different parts of the frame, and 542 random images do not have fire in the frame. The data set has not been modified. The number of images I plan to use I got it from websites, mostly from Google, kaggle., and GitHub,

(https://github.com/VISWESWARAN1998/FireDetection-Dataset), (https://github.com/breed2137/fire_dataset) and (www.google.com)

dataset Images of without fire and fire [11]

The images present in the left side of figure 1 is the images of fire and the images present in the right side of the figure 1 is the images which does not consists fire. DL approaches. Additionally, a large number of images need to be obtained in this process. There is no public data standard accessible to the best of our understanding and consists of photographs of smoke and flames. We therefore generated a dataset of these pictures. The more images the number of the more accurate the number of fire detection increased, but the delay to obtain the result, also when training in the training data set to an XML file for the Cascade Classifier more two hours.The proposed work uses a convolutional neural network (CNN) in a deep learning model to automatically detect fires within the range of the video captured using a camera. Technologies such as Tensor Flow, Keras, Python, Open CV and CNN make the feasibility of the fire detection model possible. The main idea of the system is to generate alerts via email or SMS (Short Message Service). The video from the camera is used as the input to the CNN. The purpose of this project is to use a convolutional neural network to detect whether there is a fire in a given frame. With the emergence of deep learning models based on neural networks, many studies on using deep learning models based on image processing technology for fire detection are ongoing.

XI. ALGORITHMS

The fire system detection makes used of the convolution neural network (CNN) that detect fire automatically. CNNmethod is one of the neural networks that mostly applied for image recognition and classification. The following points represent the basic steps of this system:

- The first step is to train the classifier to determine accuracy. And use only a small number of images, which is approximately 1213
- In the second step, convert the frame captured by the webcam directly to grayscale.
- The third step is to convert the image to grayscale, and there is only one channel, either black or white, to facilitate its processing.
- The fourth step in which we use the gradient factor is to create a scale pyramid, directly the image is trained, and this will allow the scale operator to shrink the frame to the fire detection this result

The algorithm I used was how much training and testing accuracy I got is inaccurate. But after modifying the codes and rewriting them and deepening the search for references, my result of the algorithm was the amount of accuracy of training and testing completely different and the number of images used were very accurate results.

No result	result existing algorithms	I got a better result with the existing algorithms
No fire	Inaccurate	very accurate results
		

Testing the system

XII. FLOWCHART

In the following figure is a flowchart that represents how the system will operate

- First, the image or video is captured by the webcam
- Secondly, processing is done.
- Third, check the image
- fourth, if a fire is detected, send directly to the email the responsible person within the institution

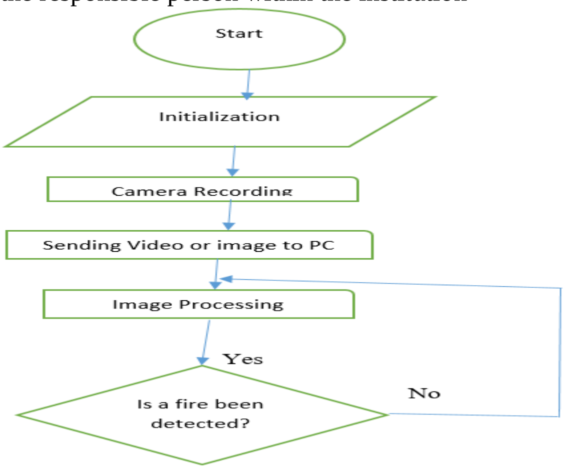

Figure: Flowchart

XIII. THE LIBRARIES I NEEDED AT THE PROJECT AND IT'S IMPORTANT

Python is becoming popular day by day, and is starting to replace many languages that are popular in this industry. The main reason behind the popularity of Python is because:

- Python is popular for beginners because of its simplicity.
- Python helps developers be more productive from development to deployment and maintenance.
- Python syntax is very simple and high-level as compared to Java, C, and C++.Hence, applications can be built with fewer lines.
- Python has a large collection of libraries.

Python's simplicity has attracted many developers to build libraries for machine learning and data science, and because of all of these libraries, Python is very popular. In addition, some of the best machine learning libraries for Python are:

a. TensorFlow

Developed at Google by Brain Team. Almost all Google apps use Tensorflow for machine learning. If you use Google Images or Google Voice Search, then you are indirectly using the forms built with Tensorflow[12].
Tensorflow is just a computational framework for expressing algorithms that include a large number of tensor operations, where neural networks can be expressed as mathematical graphs that can be executed. Tensors are the N-dimensional matrices that represent our data.

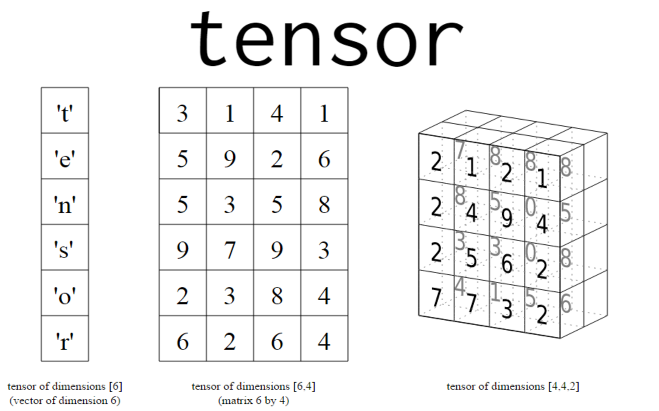

Figure5, Tensor of dimensions

The main feature of Tensorflow is Parallelism, it means your mathematical graphs are executed in parallel you have full control over the execution, and you can schedule different operations on different processors like CPU, GPU, etc. Tensorflow is primarily written in C and C++ but has a sophisticated front-end for Python. Your Python code will be compiled and then run on Tensorflow distributed execution engine developed with C and C++[13]. Tensorflow optimized for speed; it can take advantage of techniques like XLA for faster linear algebra operations.

b. Keras

Keras provides an easier way to express neural networks. It also provides some utilities for manipulating data sets, aggregation models, evaluating results, visualizing graphs, and many more[14].
Keras internally uses either Tensorflow or Theano as background. Some popular neural network frameworks such as CNTK can also be used. Keras is slow compared to other libraries because it creates a math graph with the backend infrastructure and then uses it to perform operations. Keras models are portable (HDF5 models) and Keras provide several pre-prepared datasets and pre-processing models like Inception, SqueezeNet, VGG, ResNet, and others.

c. Open CV

The OpenCV library is used for all types of image and video processing which include face recognition and detection, traffic sign reading, image editing, optical character recognition, and more[10]. The latest releases of OpenCV now support the Python language. The OpenCV library was developed in C++ (the first version was built using C). In terms of execution speed, C and C++ are faster than Python, so rebuilding the OpenCV library in Python would be unhelpful work in the field of image and video processing that requires fast execution. OpenCV library offers the so-called Python Wrappers, which enables you to use the library within the Python language code in the form of packages and Python functions. These Wrappers are interfaces that call the library functions built in C and C++ languages, which means building the application in the Python language (the element of ease and little code) and the implementation in the language of the library Native (speed component).

XIV. SOME RELATED WORK TO THE PROJECT

Recently, deep learning has been applied effectively to numerous fields such as image detection / classification of objects, voice recognition and natural language processing. Researchers have performed numerous fire detection experiments to enhance efficiency, focused on deep learning[15].
The deep learning methodology has many variations from traditional vision-based fire detection on computers. The features are not tested by a specialist but are then collected dynamically in the network after practicing with a vast volume of different testing data.
The initiative to find the right handcrafted features is then moved to the creation of a proper network and the preparation of the training details.
Thus with an effective training algorithm, the correct network configuration becomes more essential. Sebastien suggested a CNN-based fire detector network where the features are trained simultaneously by practicing with a neural net classifier of the Multilayer Perceptron (MLP) type[15]. Zhang et al. have suggested a fire detection system focused on CNN that would be run in cascaded format. The global image level classifier first checks the entire picture in their process, and if a fire is found then a fine-grained patch classifier is used to specifically identify the fire patches[16]. Muhammad et al. suggested a fire detection device that would be based on a fine-tuned CNN fire detector. This software is an effective CNN framework influenced by the Squeeze Net system for fire prevention, translation, and procedural interpretation of the fire scene[17]. Hu et al. used LSTM for fire detection, where the CNN features are derived from consecutive frame optical flows and briefly stored in an LSTM network.

The definitive judgment is taken based on the combination of successive temporal traits.
However, their approach calculates the optical flow to prepare the CNN input, rather than using RGB frames directly[16]. Chen et al. found out that in the RGB model the gray values of smoke color on the three channels are similar, spread primarily within the range of 80–220[18]. Although the approaches based on CNN provide excellent performance, it is difficult to capture the dynamic behavior of fire, which can be obtained through neural networks (RNN) of recursive type. LSTM proposed by Hochreiter and Schmidhuber is an RNN model, which solves the RNN question of the vanishing gradients.LSTM will collect the temporal decision-making features via the memory cells that retain the internal states and the repetitive actions. Nonetheless, the amount of recursions is typically small, which renders it impossible to catch the long-term complex behavior required to make a judgment. Thus, the judgment centered on long-term actions for LSTM must be treated with great caution[19]. Considering the above methods of fire detection, it can be found that some of them are too naïve; their time of execution is quick but these methods compromise on precision, generating a significant number of false alarms.In comparison, certain methods have achieved strong fire detection accuracies but their implementation time is too large, so they cannot be implemented in real-world settings, especially in sensitive areas where a small delay may lead to a huge catastrophe.Thus, in order to diagnose fire more reliably and early, we need a reliable framework that can identify fire in various circumstances and can automatically transmit critical key frames to emergency response networks and warn them.

XV. USE DEEP LEARNING TO IMPROVE FIRE DETECTION SYSTEM PERFORMANCE

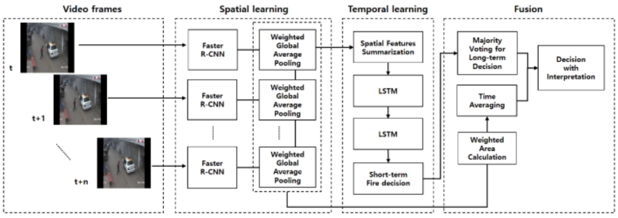

Figure6, The proposed network architecture

Current machine vision-based fire detection systems have commonly utilized the static features or transient short-term actions such as colors and flame and smoke movements. Nevertheless, because fires have a variable temporal presence, the precision of identification of these methods is restricted, based on the static and short-term temporal actions.We suggest a system of deep learning-based fire detection, which imitates the human cycle, called DTA for decision on fire. We believe this DTA method will significantly minimize mistaken decisions regarding flames. The conceptual layout of the network is split into three parts[20]. In the first segment, we use a deep object detection pattern, Faster R-CNN, which consists of CNN attribute extractors and a bounding box localizer with a classifier to identify SRoFs or non-fire artifacts inside the video frames.The boundary boxes place three distinct types here: flame, smoke, and non-fire. Normally, in a burn, flame and smoke cannot be completely differentiated, such that the gas-only entity in a boundary box is marked as gas[9]. The whole area of the fire is often viewed as one bounding enclosure.A non-fire entity means a still picture that has no fire-related artifacts or a grouping of items that are hard to discern from a burn, such as a chimney evening light, haze, and fog.The non-fire artifacts have boundary boxes of their own. In the last layer of CNN of Faster R-CNN, the bounding frames, including SRoFs and non-fire artifacts, are then mapped onto the studied function maps to retrieve the related spatial features[17]. Within the second portion, the condensed and concatenated CNN features are briefly compiled to catch the fire's complex activities, and the short-term fire decision is taken in the LSTM network of two levels. There in the segment, we do not distinguish flame from smoke, so that the LSTM accumulates all flame and smoke characteristics in order to determine whether fire or non-fire. In the third portion, the short-term decisions for a long-term fire decision are merged in the last majority vote point. The last section often incorporates the knowledge to describe the complex fire behaviors to assess whether or not the region of SRoFs, like flame and smoke observed at Faster R-CNN stages by bounding boxes, is through over the long term.

XVI. CHALLENGES AND RECOMMENDATIONS

As any computer program, fire detection algorithms involve certain drawbacks even in strong DL versions. The processing of images from specific equipment or from separate databases that are not present on the training stage can sometimes contribute to reduced accuracy. However, this challenge can be overcome by training the models on broader datasets or by fine-tuning the model on the new information. The models could not be equipped using a dataset of larger-size images. The system would be able to operate with a bigger pixel in dataset to detect the problem more accurately if the graphics card's memory size is increased. One of AI-based technology's most critical problems is that the fire photos are relatively similar to the colors seen in existence in general, such as the sun, lighting systems, and others. Many experiments used a dataset for training models and was available to the public. This problem may also be overcome by diversifying the data collection to be used during the training process. In future research, we expect to investigate CNNs that are lightweight to minimize model size whilst preserving a compromise between accuracy and false alarms[21]. In fact, the suggested structure disseminates essential frames at the emergency response network without any verification method.In this context, data hiding strategies such as steganography and watermarking can be used to hide any details for authentication purposes within key frames, as stated in recent social networking plays[22].

XVII. CONCLUSION

CCTV systems are able to conduct different processing styles, such as target recognition and motion monitoring, due to recent developments.With such computational capacities, fire may be observed through monitoring at the early level, and can be beneficial to emergency relief programs, preventing massive ecological and economic casualties, as well as protecting a significant amount of human lives[3]. With that motivation, during CCTV surveillance, we proposed an early fire detection method based on fine-tuned CNNs. Incorporating deep features in our system, we demonstrated that fire can be identified with higher precision in various indoor and outdoor settings at early stages, thus reducing false fire alarms.Another important feature of crisis management is autonomous reaction and efficient connectivity, for which we have suggested a system of prioritization that will change the importance of camera nodes depending on the relevance of the information it perceives[23].A complex channel allocation scheme using intelligent radio networks guarantees the precision of the critical frames and early reaction to the emergency management program.Via tests on videos involving fire-like moving items and a real fire in indoor and outdoor environments, we have established that our system can identify fire at an early stage with reasonable precision and minimal false fire alarms, as well as ensuring autonomous reaction and accurate transmission of representative contents under surveillance.That can greatly facilitate systems for managing disasters. The proposed design increased the precision of fire detection with limited false alarms but the scale of the device is comparatively high.

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