Computer Communications 150 (2020) 818–827

Contents lists available at ScienceDirect

Computer Communications

journal homepage: www.elsevier.com/locate/comcom

Deployment and integration of smart sensors with IoT devices detecting fire disasters in huge forest environment

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ARTICLE INFO

Keywords:
Disaster management
Deep learning
Convolution Neural Network
Forest monitoring
Abnormal identification
Feature extraction
Classification

ABSTRACT

Surveillance system applications are drastically growing from small buildings to a wide area of forest monitoring. Forests provide various important things to our daily lives like oxygen, honey. Living things like animals and birds are living in forests. Thus, it is essential to monitor and protect the forests and their assets. To do that, smart sensors have been deployed in the forest to monitor and record the environmental impacts. The abnormal events are identified and detected using the appropriate IoT devices to reduce the risk. Also, to improve the accuracy, the sensed data is analyzed, processed using a software module. Various existing approaches used for learning the data and object detection was good, but slow in the process, which fails in reducing risks. To overcome these issues, this paper utilizes one of the Deep Learning Algorithms such as the Convolution Neural Network (CNN) for Forest Monitoring and identifying the abnormality. The deep CNN has experimented with MATLAB software and the results are verified. The performance of deep CNN is evaluated by comparing the obtained results with the existing approaches and found that deep CNN outperforms the others.

1. Surveillance monitoring

Active or passive observation of places, things and persons or tasks systematically, continuously is called monitoring. Whereas Surveillance Monitoring (SM) is the process which monitors a target, certain activities, and any specific evidence of a process. SM generally used for monitoring buildings, properties like vehicles, and individuals. But in real-time applications, it is mainly focused on monitoring and detecting credible information which are connected in the activity. The operations of the surveillance being done by static or mobility-based monitoring technologies where it records and transmits the natural data captured from the surveillance environment. It records the activities, timestamp, day/date, behavior of certain objects and patterns of the behavior. In recent days the surveillance devices record even telephonic communication among people, email correspondence and messages transmitted between people. Surveillance is generally applied in covert methods including legal authorities.

Artificial intelligence provides a way for machines to behave like a human. Machine learning is an important subset of artificial intelligence. Whereas it adds training and learning components to classify the given dataset. But when the dataset increases in terms of volume and variety of machine learning cannot perform well. Hence recent days data analytical research works focused on using deep learning methods, where it learns and classifies the large volume of data automatically and effectively. Among the various architectures in deep learning, commonly used models for surveillance analysis are CNN, auto-encoders and their combination, because of their efficiency. From small buildings to large size industries, surveillance monitoring is more essential to provide security. To make faster and easy communication Internet of Things is used nowadays. Since most of the industries used the internet for storing and transmitting their data. Also, IoT devices used in the surveillance applications the amount of data generated is voluminous. Raspberry Pi, CCTV camera, mobile devices, and other sensors are used in the IoT circuit. Thus, this paper utilizes IoT circuits with the CNN algorithm for disaster management through surveillance monitoring applications.

The monitoring process involves recoding the activities to watch the abnormal activities troubling people. Public places like shopping malls, airports and other places where a large number of people meet are monitored, helps to secure the public. People doing wrong things are monitored is called targeted monitoring. Some of the existing monitoring tools are “smoke-detectors”, “turnstile-counters” and counting the subway passengers. In certain places, the surveillance monitoring is used electronic cameras, electronic listening devices, and building access cards to avoid misbehavior and improper use of places. Also, various recent applications are using a surveillance monitoring system. Some of them are:

- Hospital Monitoring System
- Airport Monitoring System
- Building and Industries System

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https://doi.org/10.1016/j.comcom.2019.11.051
Received 8 October 2019; Received in revised form 22 November 2019; Accepted 29 November 2019
Available online 10 December 2019

- Healthcare Monitoring System
- Forest Monitoring System

1.1. Sensor-based surveillance monitoring system

The sensors used in the surveillance monitoring system are very tiny, high-powered battery, and a greater number of inbuilt functionalities of monitoring various environmental parameters. Sensed data is transmitted to the major data collection unit like cluster head or sink for data-processing [1,2]. This paper discussing fire detection using WSN with similar functional properties. Sensors are defined and deployed to sense heat, gas, smoke and other atmospheric parameters that cause fire accidents in the network. Once it detects the abnormal conditions occur in the atmospheric parameter values, then it alerts the nearest or linked other administrative devices in the network. For fast intimation, the alert message transmitted to the web services and spread to all the devices connected with the surveillance network. Then the collected data from various sensors are fed as input into the CNN model for further analyzation. Based on the results obtained from the sensors and CNN the alarm is generated. The duration of playing alarms defines the severity. Short alarm says abnormality with high risk and long alarms alarm says it is very dangerous. Several methods have been proposed for fire detection using WSN. Some of the methods are stand-alone and some are using hybrid methodologies. Few of the event detection methods have been used for fire detection by identifying gas, heat, and smoke.

1.2. Forest monitoring using sensor devices

Emergencies like fire make huge losses on materials and personal. Opposite action to natural events and atmospheric pollution created by human activities make disasters when the limit of the normality increases and make damages in the ecosystems and various diseases for the people. The severity of the events can be controlled by amplifying the resources like security, control methods, emergency plan, and intimation methods. Also, the presence and combination of abnormal atmospheric conditions with an unusual presence of pollutant gases can create natural disasters.

Generally, this type of event results in critical emergencies and it requires the mobilization of various emergency management services from public and private sectors. Hence the "Rule of 30" [1]: "the temperature increased than **30** °C, humidity decreased lesser than **30%** and the speed of the **wind** > **30 km/h**" in the forest, is verified for fire detection. This rule helps to prevent fire accidents, determine the high risk of fire occurrence in the remote forests and by deploying the IoT devices at predefined locations in the surveillance network.

There are two interrelated modules are used in this paper (see Fig. 1). One is IoT circuit-based surveillance monitoring and another one is CNN based data analysis. The devices like sensors, IoT devices, and cameras connected hardware size of the application monitors, record, gather and transmit the data to the appropriate storage medium. The sensors connected in the application are more sensible devices which can make an alert message immediately when it detects abnormal data. Data generated from the IoT devices are analyzed by the proposed CNN architecture. CNN analyzes and detects the abnormal data by learning the entire data with the help of more than two numbers of convolution layers, the pooling layer, and the fully connected layer. The final classified output is generated at a fully connected layer.

This paper presents a technically sound approach which has two modules as hardware and software. One is the IoT platform where it has various devices like sensors, cameras for recording and sensing the abnormal data. The second one is analyzing the recorded data using the convolution neural network (CNN) model. CNN has trained with 60% of the data and used for evaluation. The proposed approach is essential to identify the abnormal event occur in the forest environment. Data is transmitted to the admin or server in the cloud. Webserver, data baser server, socket server, IoT devices, and CNN model are interconnected in the surveillance network. The IoT devices are connected with the servers through various internet technologies like WiFi, broadband, and 4G/5G, etc. Also, IoT devices are connected through Raspberry Pi, Arduino pin through USB ports. The monitored data is analyzed finally using CNN architecture. The CNN analyze the input images layer by layer and extract the features as much as possible for classifying the data.

2. Related works

Nowadays fire detection is one of the major issues where largely damages the environment and affects human life. Most of the time the fire accidents are more critical and destroy the surroundings also. Identifying and detecting the high-risk factors and the early stage of the fire accident can avoid more danger and save human lives. To escape from the fiery place and to douse the fire source it should be intimated to the respective caring unit and the closest people nearer to the place. It can be done by installing an alarm system which is a fast and convenient method to intimate the people. Various devices involved in the alarm circuit performs the identification, detection and classifying the fire object in the image and enable the audio application. This paper makes alarm using sensor devices and CNN applications for intimating respective people available at long distances and short distances respectively. The alarm is activated by bells, horns and mountable sounders. Different methods used the technologies belongs to WSN, because it has more popularity in terms of usage in various applications like localization [3,4], smart transpiration, target tracking [4,5], healthcare [1,6,7], industrial automation and environment [7]. WSN is used for surveillance monitoring with the help of users and autonomously [8,9]. WSN based applications also help animal monitoring, human monitoring [10,11], and industrial monitoring (underground applications).

In recent days, fire detection applications used sensor and sensor-based circuits for fire detection [12–17]. The author in [12] proposed a novel method for fire detection in mines, using a sensor network named as WMSS. Gas sensors are used for fire detection in mines, by analyzing the gas level. The author in [13] proposed a Zigbee-based WSN for fire detection in remote areas of forests. Temperature sensors are used to check the temperature for examining the intensity of the fire occurred in the forest. To do this CC2430 chip is used in the hardware portion of the sensor network. The author in [14] proposed a framework for fire detection in the forest. The author [15] applied various clustering methods and various communication protocols for fire detection.

In the experiment, the author verifies and validates the efficiency through the simulation. The author in [16] implemented a novel method for fire detection using multi-sensor and cameras connected in wireless IP to avoid false alarms. The data transmission, uploading and downloading is carried out using a gateway in the cloud environment. A ZigBee based fire detection method is proposed in [16], and it has been implemented, tested and results verified in a china-based sensor network. In addition to the above methods, authors from [17–20] proposed a fire detection method based on a surveillance monitoring system. They all followed a 3-tier format which comprises of WSN, middleware and user front applications.

The author in [20,21] proposed a new system which integrates IoT devices and sensors that can perform real-time control of different atmospheric variables and polluting gases, in order to activate alerts when pollution levels increase excessively or when detecting certain conditions that are considered to be possible factors for causing adverse climatic events. These events can favor the occurrence of fires and other emergency situations. Particular attention has been paid to communication security among IoT devices, Web service, and mobile devices. Moreover, a secure data transmission protocol, a block cipher algorithm and a secure authentication scheme have been implemented. The author in [21,22] proposed an analyzation method for rescue

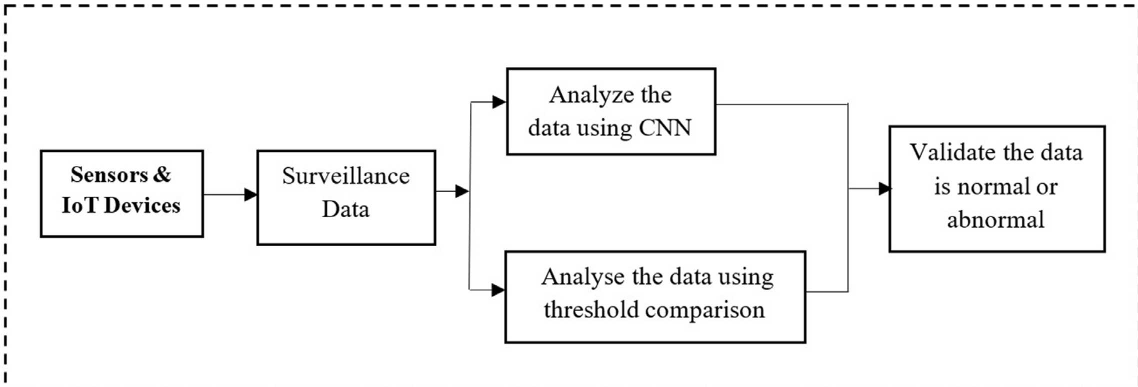

Fig. 1. Overall architecture of the proposed system.

operation for such natural disasters and proposes an IoT based solution to cater to the identified requirements. The proposed solution is further validated using the task-technology fit (TTF) approach for analyzing the significance of the adoption of IoT technology for disaster management. Results from the exploratory study established the core dimensions of the task requirements and the TTF constructs [22–25]. Results from the confirmatory factor analysis using PLS path modeling, further, suggest that both task requirements and IoT technology have a significant impact on the IoT TTF in the disaster management scenario. This paper makes significant contributions to the development of appropriate constructs for modeling TTF for IoT Technology in the context of disaster management. Yann LeCun developed LeNet5 in 1998 using CNN [23]. This technique has an effect on number recognition.

The earlier applications significantly depend on the data collected by sensors deployed in the network distributedly. Including the sensors, various IoT devices are integrated into the surveillance network for enabling potential technologies. Monitoring the disasters using satellite communication and GIS, early warning system, emergency response, and disaster recovery are some of the major applications where IoT devices are used. From the above discussion, it is noticed that the earlier methods have proposed various methods for fire detection, but the efficiency in terms of prevention is less. Also, few of them used only sensors and others used only simulation-based fire detection. The earlier approaches did not provide a complete evaluation process on the surveillance data. This paper motivated to integrate both sensor-based alarm generation and CNN based implementation for fire detection.

Learning accuracy obtained from the earlier research works is less. Two separate algorithms are used for learning and classifying the data. Thus, earlier approaches are not efficient in terms of time and cost. Prevention methods are very few, and the prevention accuracy is also less.

2.1. Problem statement and contribution of the paper

Today surveillance monitoring system requires a fully automatic disaster detection system. Fire accident is frequently happening in wide forests, needs to save the forest. Earlier approaches are efficient in terms of time, cost, prevention, and detection accuracy. This problem needs a better solution to save the forest and assets in the forest. To manage the forest, this paper motivated to design and implement a two-stage method using IoT. In the first stage, it used sensor-based risk identification and the second stage process the surveillance data to identify the severity of the fire event. Considering the issues and challenges discussed in the literature survey, this paper proposed an efficient method for fire detection in the forest using IoT devices and technologies. The data gathered from the environment is treated and it is focused on the identification, detection, and activating alarms for immediate action to avoid fire extension and other related problems. A two-stage system with secured communication is implemented for manipulating various environmental variables, processing and visualizing the information gathered from the real-time environment promising access for all the users through various platforms. The proposed approach utilizes an IoT based network solution for the design and implements an efficient surveillance monitoring system for detecting disasters that occur in the remote area. There are two different stages are carried out in the proposed work. The first stage is the tasks applied in the surveillance network and the second stage is CNN based data processing. Data gathering and transmission are the two initial tasks are carried out in the first stage, and the data processing is the main task applied in the second stage of the proposed work.

- Data Gathering
- Data Transmission
- Data Processing using CNN

3. Proposed system

The entire system performs based on a set of sensor nodes distributed, interconnected with one another and with the server. Sensors able to sense the humidity, temperature and other natural factors. The entire architecture of the proposed system comprises three different components such as IoT devices, user applications, and web interfaces or services.

The IoT devices connected in the surveillance network senses and observe the data from the environment and processed in real-time. The main motto is to inform the emergency (natural disasters such as a fire) occurred because of a fire accident. In two different ways, the information is passed. One is by the sensor devices and the other is by data processing. The sensor devices sense the data of atmospheric and magnitudes which determines the meteorological constraints and the availability of pollutants, gases in the air zones, are transmitted as useful information can be visualized using interfacing elements. Graphs, pictorial representation, and statistical reports are the visualization models, shown in Fig. 2.

Monitoring and controlling pollutant gases can help to prevent the forest from fire accidents. It helps to determine the risk areas of the forest and prevent them by reducing the risk. For example, first, the temperature increased than 30 °C and humidity decreased lesser than 30% in the forest area defined as a danger zone. This condition is informed through an alert message to the management. The reason is the presence of meteorological conditions are favorable to the fire generation in the forest. Second, the pressure is another factor that determines the period of storms/anticyclones where it aggravates the weather conditions, for example, fire. Then, the excessive amount of CO_2 and CO concentration, increase in temperature, and less humidity are the evidence of biomass fire. This way, the sensor devices can determine the risky situation will make fire accidents and generate an alarm to the nearest nodes and routers. It helps to identify and detect the fire in the forest and the location of the remote environment.

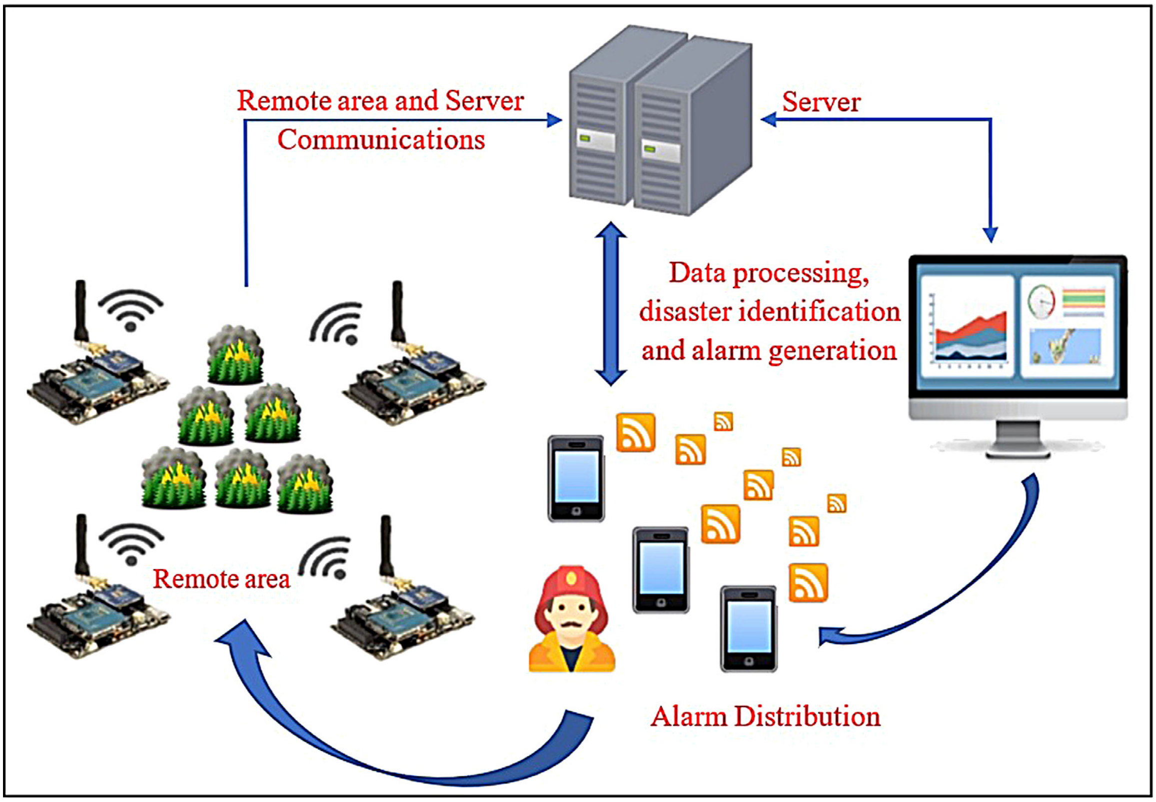

Fig. 2. IoT based fire detection in remote area.

3.1. IoT devices

Each IoT device connected in the surveillance network is communicating with one another using 4G internet and web-interfaces are responsible for persisting and processing the gathered data. Various types of sensors are used in the network as monitoring devices and the variables like temperature, atmospheric pressure, humidity and pollutant gases as CO and CO2. The entire devices including sensors are interconnected with Arduino composed into a motherboard, having 4G sensing capabilities to sense the data. Also, the set of all essential hardware elements are integrated with the sensors for recording the atmospheric variables. The 4G module is used to fetch the location of the sensors distributed in the environment, and it helps to identify where the risk is high. Once the IoT devices are deployed and activated in the surveillance network, it starts sensing the atmospheric variables, pollutant gases cross the condition in a particular location.

In addition to these, the IoT performance parameters such as latitude, longitude, battery level and international mobile station equipment identity for identifying the devices. Hence the first stage determines the risk level of the fire accident obtained from the sensed data. The range of the atmospheric parameters is given in Table 2. Based on the values the IoT system enables the alarm as the alert message. Alert information is generated based on the atmospheric values such as Temperature, Humidity, CO2, and CO. Three different threshold values are assigned for the atmospheric values. If the value of the atmospheric variables reaches the first threshold value, then it generates the first alert, if it reaches the second threshold value then the second alert message is generated, finally, the third alert message is generated when it reaches the third threshold value. For example, the three-threshold value of temperatures is 30 °C, 37 °C and 40 °C. The threshold values for four different atmospheric variables are given in Table 1.

Considering the variable temperature, if it is higher than the 30 C it will make the first level alarm, higher than 37 C enables the second level alarm, and higher than 40 C enables the third level alarm. Considering the humidity value below 30% enables the first level alarm, below 20% enables the second level alarm and below 10% enables the third level alarm. Similarly, the level of alarm due to the value of CO2 and CO is given in Table 1. Every parameter value is analyzed and the range of values is verified for deciding about the level of severity and the alarm is enabled. According to the level, the duration of playing the alarm has been assigned. The long duration-based alarm indicates, the fire accident is severe and needs to take immediate response to save the forest and the public.

Table 1
Values of the atmospheric parameters.

Atmospheric variables	Alert-1	Alert-2	Alert-3
Temperature	$\geq$30 °C	$\geq$37 °C	$\geq$40 °C
Humidity	$\leq$30%	$\leq$20%	$\leq$10%
CO2	$\geq$350 ppm	$\geq$2000 ppm	$\geq$5000 ppm
CO	$\geq$10 ppm	$\geq$25 ppm	$\geq$50 ppm

3.2. CNN based abnormality identification

Convolution Neural Network (CNN) is one of the popular algorithms of deep learning. CNN is highly flexible, where the developer can configure its architecture in accordance with their requirement. Any number of layers can be included in the architecture, where each layer has its own defined functionalities. The major advantages of CNN are fully automatic and capable to learn the huge size of bigdata.

In the second stage of the paper, the gathered data is analyzed and processed using the CNN model illustrated in Fig. 3. It is assumed that some of the IoT devices like digital monitoring cameras monitor and record the data in video format. The video is transmitted directly to the CNN model implemented in MATLAB software and abnormal activities are obtained. Video is divided into frames (as digital images) and feed into CNN, where it learns and recognizes the color objects present in the images automatically. In the training phase, the learned images are labeled for improving the accuracy of the testing process. While analyzing the images, the set of all features such as color, appearance, pixel intensity, and location are learned thoroughly. The CNN model has different layers such as input, convolution, pooling, and fully connected layers. Each layer delivers its processed data as input to the next layer. Hence the CNN learns the data directly and automatically like other neural network layers but all the layers involved in learning and extracting as much as possible features automatically. The convolution, pooling, and rectified layers are involved in the learning phase. Convolution layers applied convolutional filters on each input image to activate certain types of features on the images. The pooling layer reduces the number of parameters using a non-linear down-sampling method. A rectified linear unit increases the speed of the training phase using the mapping method, which eliminates 0s and negative values for maintaining only positive values. These three functions repeated until all the layers learn and obtain various features. After successful feature detection, CNN transfers to classifying them at the SoftMax layer.

In this paper, the UNet of CNN is used for improving the efficiency of segmenting objects and identifying the fire in the video frames. U-Net, [24–26] architecture is the fully convolutional network and a subset of CNN. U-Net is CNN is purely used for image segmentation. It predicts the pixels' class and groups them for segmentation. U-Net is completely created using the fully convolutional network and modified in accordance to improve the segmentation quality. To do this, it creates a down-sampling, up-sampling and concatenation operations for segmentation over the data. Both sampling processes map the extracted features with the classes. Hence, the greater number of features mapped into classes reduces the size of the data. U-Net uses the layers from C1 to C9 for the convolution process with the kernel size is 3 × 3, and the pooling process with a kernel size of 2 × 2 and the last layer uses the kernel size 1 × 1. The numbers given in the boxes indicate the width(W), height(H) and depth(D) of the feature map. The Fully Connected (FC) layer is the previous layer to the last layer. FC layer predicts n number of classes, output as an N-dimensional vector. The output vector comprises the probability value of each class of the input image, to be classified. Finally, the last layer in the CNN architecture provides the classified output using a "**softmax**" function. There is no mathematical formula for choosing the layers in the DNN.

3.3. Abnormal parameter estimation using CNN

The proposed method calls CNN, [24,26] in deep learning is used for estimating various parameter helps to identify the condition of the color of the natural image based on the bright-region of the input image. The image segmentation is obtained semantically to get the initial value of pixel intensity. For the initial estimation of the CNN, the labeled trained data is collected as

$$\left\{\left(x_k, y_k\right) | k = 1, 2, \ldots, N\right\} \tag{1}$$

over video images. From the above equation, x_k denotes the center patches of the target pixel size of 128 × 128, and $y_k = \left(y_{k1}, \ldots, y_{k4}\right) \in \mathbb{R}^4$ denotes the label of the target pixels. If the label $y_k = 1$ then, x_k belongs to the ith class, else $y_k = 0$. The main goal of the initial estimation of CNN is represented as a function f^* then it is considered that the patch X has four labels and the function for training data as,

$$f^* = \underset{f}{\operatorname{argmin}} \sum_{k=1}^{N} \left\| f\left(X_k\right) - y_k \right\| \tag{2}$$

Based on the CNN architecture, the function f is written as

$$f(X) = f^{(1)}\left(f^{(0)} \ldots \left(f^{(0)}(X)\right)\right) \tag{3}$$

where $f^{(j)}$ represents the jth layer on CNN. Also, $f^{(j)}$ maybe any of the layers such as convolutional, pooling, or fully connected. In case, if we are using the bias and weight in $f^{(j)}$, then the function f is determined by the parameters θ as,

$$\theta = \left(W_1, b_1, \ldots\right). \tag{4}$$

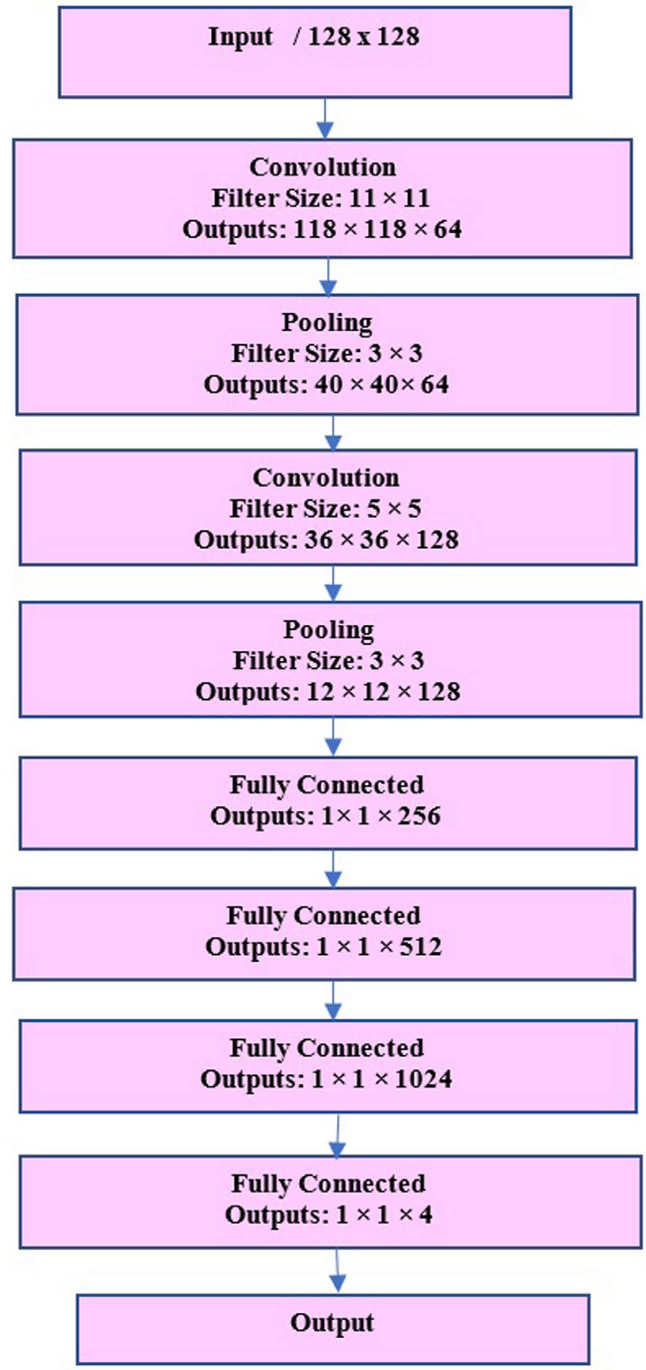

Fig. 3. Proposed CNN.

From Eq. (4), Eq. (3) can be written as,

$$\theta^* = argmin_{\theta} \frac{1}{N} \sum_{k=1}^{N} L\left(X_k, y_k;\ \theta\right) \tag{5}$$

where, Eq. (5) describes, instead of determining f^*, the set of parameters θ^* can be calculated. L shows the loss function for cross-entropy used to estimate the error occurred between the label y and output $p_i(x, \theta)$ obtained from each label (class) as

$$L\left(x_k, y_k;\ \theta\right) = -\sum_{i=1}^{4} y_{ki} \log p_i\left(x_k;\ \theta\right) \tag{6}$$

It gives the minimized error for all the trained patches, referred from [24,27]. To segment the various regions, U-Net is adopted. Now one of the parameter **highest intensity** can be calculated from the dark region segmented semantically, whereas it can be transformed into the original testing image by mapping the coordinate values of the natural images. To perform the intensity calculation, the Hough-Transform [15,27] method is applied on the pixels available on the edges of the **texture** from the changed/transformed image where it identifies and detects the fire objects are computed iteratively for selecting the boundaries like the maximum edge pixels. The pixels of the initial estimation is feed into CNN again to locate the highest intensity. To do that, a stretched patch with a size of 256 × 128, lengthy, propagation direction is feed as input to calculate the mid-point in the upper side of the square around the bright portions. The square boundary of a larger area around the target pixel to find out the **fire** location. To locate the fire, the boundary is extended based on the bright regions from the center location of the images.

3.4. Experimental results — Stage-1

To examine the efficiency of the proposed work, it is implemented in MATLAB software and the results are verified. The MATLAB software is installed in Intel Core i7-7th Gen CPU @ 3.40 GHz, 64 GB RAM machine. The data is collected and produced in matrix form, obtained during the fire and normal situations, to evaluate the efficiency. During the performance evaluation, the system took the initial values of the sensors with additional parameters. A threshold value is assigned to each sensor and the GSM module to circumvent false alarms.

Whenever the sensor-generated values exceed the threshold value then it generates a fire confirmation alert message. The system has been tested by experimenting a greater number of times and the results are verified and the false alarm is eliminated. Finally, the obtained results are compared with one another and with the existing methods to evaluate the performance. From the comparison, it is found that the proposed system is efficient. The simulation results are presented and discussed below.

Two different simulations are obtained here for evaluating the performance of fire detection by eliminating the false alarm. One is sensor-based fire detection and alarm generation. During the simulation, the behavior of the sensors is analyzed and the issues faced by the existing methods have been reduced. To do that, single and multiple sensors are deployed in the network and the atmospheric parameters are evaluated. For example, the temperature sensors are executed and the obtained values are verified. Initially, the data generated by the temperature sensors are recorded and the data are evaluated. From the values, the sensors' behavior is verified and the result is given in Fig. 4. From the results, it is found that the temperature sensors outperform and record the real data according to nature. When the gas, smoke and temperature values increased than the threshold values, then the sensors start sending the alarm to the sink. The results obtained from the simulation using GSM communication are shown in Tables 2 and 3. The results are verified by repeating the experiment five times to evaluate the performance. From the experiment, it is obtained that the proposed method is highly efficient than the others, and it is also proved in through Table 3.

Time consumption is one of the major factors determines the performance of the algorithm. Based on the time, various performance factors are calculated and verified for performance evaluation. In this paper time-based temperature, sensed by the sensor devices are calculated and given in Fig. 4. Temperature determines the normality and abnormality of the natural conditions of the environment. Increasing temperature leads to dangerous natural disasters. The obtained result shows that temperature increases only in the mid-day time.

To compare the efficiency the % false alarm generation is calculated and compared with the existing methods. For every year, the false alarm generation is obtained from the experimental results and given in Fig. 5. False alarm generation means, wrongly identifying the activities, that is "false positive" rate is high. It highly degrades the performance of the algorithm or approach. From the result, it is identified that the false alarm generation rate is high using existing methods and less using the proposed method.

Table 2
Results obtained from different experiments.

Experiment No.	Temperature sensor	Smoke sensor	Gas sensor	Decision
1	Fire	Normal	Fire	Fire
2	Fire	Fire	Fire	Fire
3	Normal	Normal	Fire	Fire
4	Fire	Fire	Normal	Fire
5	Fire	Normal	Normal	Normal

Table 3
Performance comparison.

Features	Tan et al. [15,28]	Yunus et al. [28,29]	Son B et al. [29,30]	Proposed method
Multiple sensors	No	No	No	Yes
False alarm	Yes	Yes	Yes	NO

Fig. 5 depicts the fire cause every year. The fire loss due to various reasons such as fire damage by a false alarm, no human response, and undetermined reason. It shows the losses because of a false alarm. Most of the time the sensors are not able to detect the fire event because of the sensor's failure. Hence, a greater number of sensors are deployed for monitoring the entire forest and detect the fire accurately and in-time. The false alarm generation is calculated and compared with the existing system. It is given in Fig. 5.

The experiment is carried out several times and the abnormality identification using sensors is calculated. Four different sensors such as temperature, smoke, and gas sensors are used in the experiment. All the sensors together function and sense various atmospheric factors to determine the conditions of nature. From the obtained variable values, each sensor provides its own decision, which is given in the decision column (in Tables 2 and 3).

The performance regarding sensor behaviors is calculated and compared with the existing approaches (Tan et al. [15,28]), Yunus et al. [28,29], and Son B et al. [15,29]) [1–23,25–31]. From the comparison, the false alarm rate is high with the existing approaches and very less using the proposed approach, given in Tables 3 and 4. Also, it is identified that existing methods have not used multiple sensors for the monitoring process.

3.5. Experimental results —Stage-2

In the second stage of the work, the recorded data (in the form of video) is transmitted to the CNN server, learned, analyzed, and detect the fire event, location, and severity of the event. The video frames recorded from the forest environment is given in Fig. 6. The video frames are obtained continuously from the video to check the difference and similarity of the events.

Moreover, a different strategy that is projected by various earlier works is contrasted with the presentation of this strategy and the resulted outcome is evaluated. Each frame is divided into four segments in our present research work, and it could be modified easily. The entropy is computed for every segment also the median rate for the first 500 frames is calculated. Concerning this research and analyze, to categorize the abnormal happenings for the threshold median entropy it is positioned to 3 times than the median rate. If there are any unusual happenings in any of the segments, in such cases an unusual indicator raises for the entire structure. Fig. 6 represents the set of all frames extracted from a video short. The duration of the video short is 1 min.

Different videos are collected (from different sensor cameras) and experimented to verify the fire detection accuracy. The obtained results

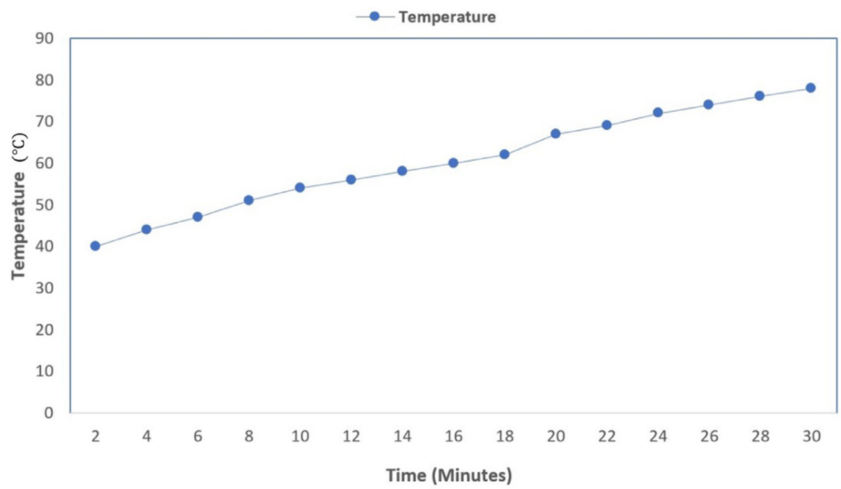

Fig. 4. The temperature in terms of time.

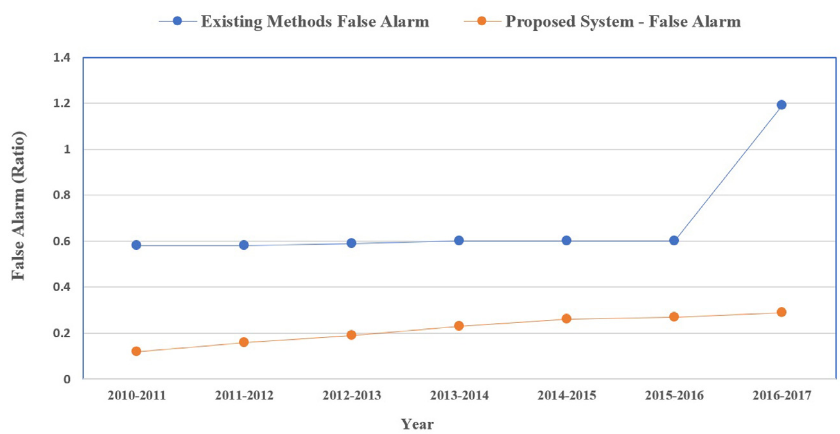

Fig. 5. Reason for fire loss ratio.

for video-1, video-2, and video-3 are given in Fig. 7(a), (b) and in (c). From the results, it is noticed that all the videos are quality video and the proposed approach has the ability to detect the fires from all the videos. The video files have more objects like humans, staircases, and trees. Though the method detects only the fire events occur in the video files, because of the efficiency.

The entire proposed method has various stages such as video divide into video-shots, shorts into frames, object detection from the frames, then object classification. Time complexity is calculated for various stages of the proposed approach. The overall complexity of the proposed approach is depending on each module involved. Hence this paper calculates the time complexity of each module separately, to focus on the particular module to concentrate more on to reduce the complexity. Fig. 8 shows the time complexity required for each module computation.

The number of frames extracted from video short is 95. Some of the frames sequentially obtained from the video shot is given in Fig. 8. Initially, all the images are considered as a normal image and the process started. In each frame, after object detection, the entropy is calculated from the pixel intensity values and compared with the threshold values already calculated and stored in a database from ground truth images. Ground truth images are suggested by programming experts. The abnormal fire event is identified from the sequence of input frames are shown in Fig. 7(a) to (c). The abnormal events are the fire events occurred in the video, which is shown in Fig. 7. The variation of the entropy and matching with the ground truth objects helps to classify the objects are normal or abnormal. The set of all normal and abnormal

Table 4
Performance analysis in terms of classification accuracy.

Data	Classification accuracy					Total	Accuracy (%)
Dataset (In Frames)	200	400	600	800	1000	3000	
Correctly classified	183	341	529	711	849	2613	87.1
Incorrectly classified	17	59	71	89	151	387	14.81056

Table 5
Computational time based on number of sensors.

Number of sensors	Time (s)
10	34
20	42
30	57
40	64
50	78

(Fire) events that are identified using the CNN model are shown in Figs. 6 and 7 respectively.

Also, the performance of the proposed model is evaluated by computing the computational time complexity and accuracy in classification. To do that, time taken for the video to segments, segment into frames, frames into objects and object classification is computed in the experiment and the obtained results are shown in Fig. 8. The average time taken for the entire system model is 74.25 ms including all the stages. In terms of classification, the accuracy is calculated and the obtained results are given in Tables 4 and 5.

Fig. 6. Video frame sequences.

Table 6
Data size based on number of sensors.

Number of sensors	Data size (GB)
10	3.4
20	5.8
30	8.3
40	12.3
50	15.6

Table 7
Performance comparison.

Optimization methods	Epochs	Accuracy
ADAM [30]	1000	0.9725
	3000	0.9836
	5000	0.9882
	10 000	0.9911
AdaGrad [30]	1000	0.8518
	3000	0.8998
	5000	0.9216
	10 000	0.9318
Proposed two-stage method	1000	0.982
	3000	0.987
	5000	0.9912
	10 000	0.991

Time taken for classifying the monitoring data is calculated and given in Tables 5 and 6. The number of IoT devices are increased and the computational time is calculated. From the result, it is identified that the computational time is directly proportional to the number of sensors.

The size of the data generated using sensors is calculated in the experiment and the results are given in Tables 6 and 7. From the obtained results, it is found that the data size is increased when the number of IoT devices is increasing. From the results, it is clear that the percentage of accuracy is 87.1%. The performance of the proposed approach is calculated and compared with the other existing approaches such as ADAM [30] and AdaGrad [30]. The accuracy comparison is given in Tables 2 and 7. From the comparison, it is noticed that the proposed approach obtained better accuracy than the existing approaches.

4. Conclusions

The main objective of this paper is to identify and detect fire accidents in forest areas using IoT. Most of the earlier research work detecting and managing natural disasters using IoT based disaster management system. Home automation, hospital management, and shopping zone are the main real-time applications are using a surveillance monitoring system for detecting abnormal events. Forest monitoring is one of the major research areas carried out in recent days because of maintaining the forest improves human health. Forests produce a major percentage of oxygen for humans. To manage the forest, this paper motivated to design and implement a two-stage method using IoT. In the first stage, it used sensor-based risk identification and the second stage process the surveillance data to identify the severity of the fire event. These two stages have experimented and the results are verified in MATLAB software with the Arduino based IoT devices and CNN. From the results and comparison, it is identified that the proposed approach outperforms the other existing approaches.

In future work, for identifying unusual happening, more exploration of deep learning algorithms-based attributes is predicted. Moreover, we would like to test this strategy on special kinds of scenes which do not only engage fire also human activity and objects that are kept moving. From the obtained results the proposed approach is considered a better approach for fire detection and recognition.

(a). Video-1

(b). Video-2

(c). Video -3

Fig. 7. Fire detection using proposed method.

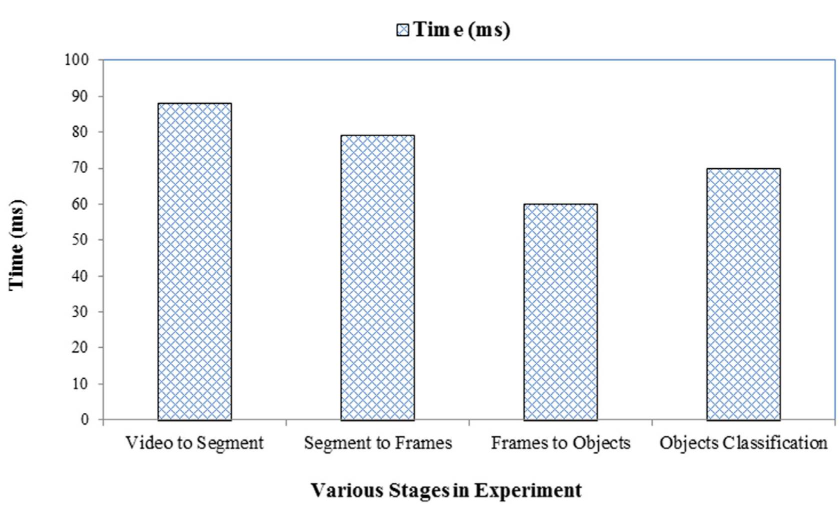

Fig. 8. Time complexity for various stages of the experiment.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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