Fog Enabled Forest Fire Management System using IoT and Machine Learning

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Abstract: ***Forest fires are one of the most serious natural disasters, caused mostly by global warming. Nature may exacerbate this danger by harming themselves and civilization as a result of pollution. Many issues, such as rehabilitating wild animals and animal migration to residential areas, are dealt with by the forest management and wild life departments. The tree's strength has severely dropped, resulting in an unhealthy forest environment. According to the annual report, wildfires are responsible for 85 percent of forest tragedies. Few studies on forest management employing wireless sensor networks have been conducted in recent years. However, forest management using wireless sensor networks is still plagued by data quality difficulties and delivery delays. Currently, a large wave of iot and fog computing is being used in a variety of smart applications to analyze data closer to the device for faster response rather than in the cloud. Edge/fog computing in iot also eliminates bandwidth, latency, and delay in data processing. As a result, we propose an iot-based forest fire monitoring system based on fog. The suggested iot fog-based forest fire control system is utilized for monitoring and warning in order to protect trees and wildlife.***

Keywords: Internet of Things

1.Introduction

Forest fires are a matter of concern because they cause extensive damage to environment, property and human life. Hence, it is crucial to detect the forest fire at an earlier stage. This can help in saving flora and fauna of the region along with the resources. Also, it may help to control the spread of fire at initial phase. The task of monitoring the forests is difficult because of the vast territory and dense forest.

The wide ranging adverse ecological, economic and social impacts of forest fires including forest degradation are:

- Loss of valuable wood resources
- Deterioration of catchment areas
- Loss of biodiversity and extermination of flora and fauna
- Loss of wildlife habitation and exhaustion of wildlife
- Global warming

The forest fire has become a threat to not only to the forest wealth but also flora and fauna and ecology of the environment of the region. The main cause of forest fires can be categorized under natural and man-made classes. High atmospheric temperature, lightening and dryness (low humidity) offer positive environment for a fire to start which are the natural causes for forest fire. The fire is also caused by Man-made sources like naked flame, cigarette, electric spark, etc [3].

Forest fire poses a great threat as they remain unnoticed for a long period till the effects comes to city. WSN is a technology which can be employed in real time to detect or predict such hazards. . A WSN generally consists of spatially disseminated autonomous sensors to keep watch on physical or environmental conditions such as temperature, sound, pressure, CO, CO2, smoke or pollutants etc. and transfer the data to base station. WSN consists of hundreds of nodes. Each sensor node is capable of sensing, computing and communicating. Each sensor node has several elements which are a) microcontroller, b) interfacing circuit of sensors, and c) battery (energy source). Through the intercommunication between these nodes and the base station, the message of event detection is reported.

Event detection by WSN can be used in various applications requiring spatially disseminated sensor nodes to transmit information about events to the base station at particular periods as the event is detected. The performance of event detection methodology will rely on the hardware and software capabilities of the small yet powerful nodes placed in robust environment [5]. In this paper we propose a decision tree machine learning approach for event detection. Various models have been generated. The performance of the proposed approach is determined in terms of complexity and accuracy [4].

2.Literature Review

The proposed research has been motivated by several earlier researches in the literature related to forest fire detection using spatial data and artificial intelligence techniques. A concise description of some of the recent researches is given in this section.

Armando et al. [1] have studied on the automatic recognition of smoke signatures in lidar signals attained from very small-scale experimental forest fires using neural-network algorithms. A scheme of multi-sensorial integrated systems for early detection of forest fires has been presented by Ollero et al. [2].

The system presented by the authors uses infrared images, visual images, and data from sensors, maps and models. To facilitate the minimization of perception errors and the improvement in reliability of the detection process, it is necessary for the integration of sensors, territory knowledge and expertise, according to their study. An improved fire detection algorithm which provides increased sensitivity to smaller, cooler fires as well as a significantly lower false alarm rate has been presented by Louis Giglio et al. [3].

The Theoretical simulation and high-resolution Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) scenes are employed to establish the performance of their algorithm.

Seng Chuan Tay et al. [4] have presented an approach to reduce the false alarms in the hotspots of forest fire regions which uses geographical coordinates of hot spots in forest fire regions for detection of likely fire points. The authors employ clustering and Hough transformation to determine regular patterns in the derived hotspots and classify them as false alarms on the assumption that fires generally do not spread in regular patterns such as straight lines. In this work demonstrate the application of spatial data mining for the reduction of false alarm from the set of hot spots is derived from NOAA images.

A graph based forest fire detection algorithm based on spatial outlier detection methods has been presented by Young Gi Byun et al. [5]. By using the spatial statistics the authors have achieved spatial variation in their algorithm. This algorithm illustrates higher user and producer accuracies, when compared with the MODIS fire product provided by the NASA MODIS science team. The ordinary scatter plot algorithm was proved to be inefficient by the authors because it is insensitive to small fires, while Moran's scatter plot was also weak because of the numerical criterion's absence for spatial variation which requires a more and less high commission error.

An approach to predict forest fires in Slovenia using different data mining techniques has been presented by Daniela Stojanova et al. [6].

The authors have employed the predictive models based on the data from a GIS (Geographical Information System) and the weather prediction model - Aladin and MODIS satellite data. The work examined three different datasets: one for the Kras region, one for Primorska region and one for continental Slovenia. The researchers demonstrated that Bagging and boosting of decision trees offers the best results in terms of accuracy for all three datasets.

Yasar Guneri Sahin [7] has proposed a mobile biological sensor system for prior detection of forest fires which utilizes animals as mobile biological sensors. This system is based on the existing animals tracking systems used for the zoological studies. The work illustrates that the combination of these fields may lead to instantaneous development of animal tracking as well as forest fire detection. A number of serious forest fires were detected by the system in the earliest, which reduced their effect and therefore contributes to the reduction of the speed of global warming.

A fully automated method of forest fire detection from TIR satellite images on the basis of random field theory has been presented by Florent Lafarge et al. [8]. The results of the system rely only on the confidence coefficient. The obtained values for the both detection rate and false alarm rate were convincing. The estimation of fire propagation direction presents interesting information associated to the evolution of the fires.

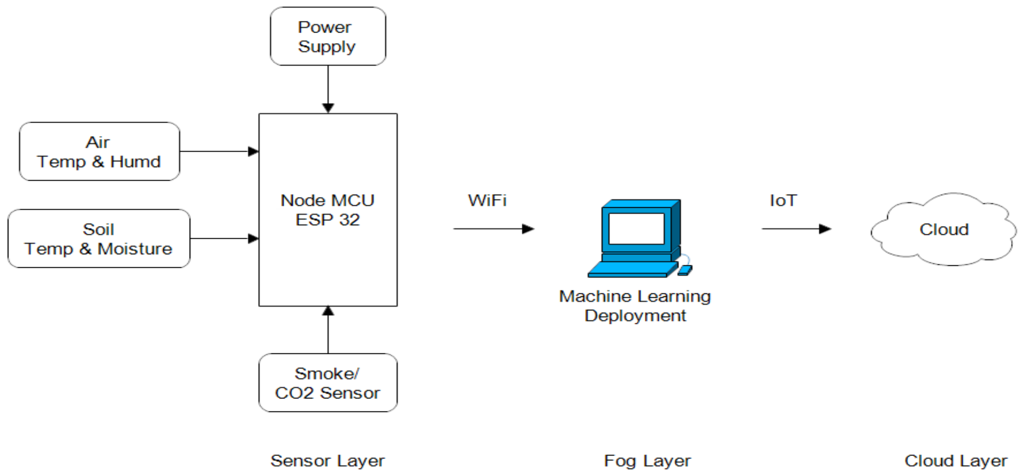
In Movaghati et al. [9], the capability of agents to be applied in processing of remote sensing imagery has been studied. An agent based approach for forest fire detection has been presented in this paper. The tests used in MODIS version 4 contextual fire detection algorithms were used by the agents to determine agent behavioral responses. The performance of their algorithm was compared against that of MODIS version 4 contextual fire detection algorithm and ground-based measurements. The results portray a good agreement between the algorithms and field data. George E. Sakr et al. (2010), an approach to the study of forest fire prediction methods based on artificial intelligence has been suggested. Forest fire risk forecast algorithm is built on help vector machines. Lebanon data were used for the application of the algorithm and has proven the ability to correctly estimate the risk of fire. Divya T L et al. (2015) in their paper have presented the by analysing a series of pixel values, an image mining technique can be used to predict the spread of a forest fire.

The proposed model uses the satellite images for forest fire prediction. Nizar HAMADEH LARIS EA et al. (2015), in this paper authors have considered an area called Lebanon to predict the occurrence of forest fire. Temperature, relative humidity, and wind speed are among the parameters. These parameters force Artificial Neural Networks to evolve in order to anticipate forest fires. Mukhammad Wildan Alauddin et al. (2018) For forest fire prediction, multiple linear regression has been proposed. Temperature, humidity, wind, and rain are among the factors involved. Different techniques such as gauss-jordan, gaussseidel, and least-squares are used to calculate various linear regression coefficients. Comparative analysis of the methods is done and the results are discussed. This Section discusses about the Literature survey.

3.Objectives

- To study the various aspect of forest fire management system using different platform.
- To design an embedded system this monitors the parameters in forest using IoT.
- To develop a fog enabled framework for intelligent forest fire management system using machine learning.
- To verify and analyze the proposed system performance.

4.Block Diagram

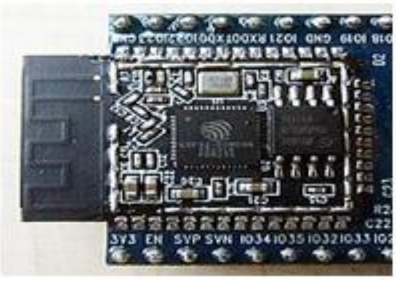


5.System Methodology

Components

NodeMCU ESP 32:

ESP32 is a series of low-cost, low-power system on chip microcontrollers with integrated Wi-Fi and dual-mode Bluetooth. The ESP32 series employs either a Tensilica Xtensa LX6 microprocessor in both dual-core and single-core variations, Xtensa LX7 dual-core microprocessor or a single-core RISC-V microprocessor and includes built-in antenna switches, RF balun, power amplifier, low-noise receive amplifier, filters, and power-management modules. ESP32 is created and developed by Espressif Systems, a Shanghai-based Chinese company, and is manufactured by TSMC using their 40 nm process.It is a successor to the ESP8266 microcontroller.



ESP WROOM-32 module with ESP32-D0WDQ6 chip

The proposed detection system focuses on two features: (1) detection early and (2) notify the appropriate authorities to rescue. Firstly, the detection unit comprises of smoke, heat, and detectors; moreover a camera is attached to verify the actual image. Secondly, according to the degree of the controller will perform a number of simultaneous operations; as it would sound a alarm to immediate notification, switch on the water sprinkler, turn on the electrical power supply, and notify the emergency service units as well as the owner by relaying a message including the address of the property

Sensor Layer

To monitor the parameters in Forest Fire scenario, which has used for climate sensitive environment air temperature and humidity sensors, soil temperature and humidity and Smoke/CO2 sensor deployed at sensor layer.

Fog Layer

This layer has main task of dealing decision making, controlling action to sensor layer and sending related data to cloud layer for forest department people. Decision making system will build by machine learning algorithm has several stages of processing.

- Data generation from sensors deployed at sensor layer
- Data collection by IoT devices and especially sensors, which can collect in real-time or small batches the data generated (temperature, humidity, etc).
- Aggregation of data collected in a target database.
- Filtration of data stored: In this phase algorithms can be launched to clean and accurate the data.
- Classification of data based on its field of use.
- Computing: In this phase calculations will be done (e.g., amount of water to pump) on the classified data.
- Decision-making form the predictions made and visualize the data in the form of reports or dashboards.

Cloud Layer

Data from sensor layer which further processed by fog layer will be visualize at cloud layer using an UI based application that help forest department person to monitor the status of forest environment

6.Simulation Results and Discussions

Data preprocessing

Among the fire features heat, smoke, and flame were selected, which provide the actual value to make a decision to detect the degree of fire according to the quantity. 300 cases of fire incident field parameters were selected to evaluate the model. It is found, the most commonly used sensors for fire detection are heat, flame, and smoke. A heat sensor ranges between 65C to 150C. The flame sensor's sensing wavelength is 185–260m, where the peak wavelength is 200m. The reasonable value of smoke in the smoke detector is greater than 50dB/m, and smoke more than 50dB/m could cause fire, see Refs. 12 and 51 for more details. From Refs. 12 and 51, the summary of sensitivity for physical phenomena of fire attributes is shown in Table 1.

In order to enhance the detection capability, reduce false alarm, and ensure significance in notification, according to the observed quantity of fire attributes (see Refs. 12 and 51) three fire status are classified as (1) normal, (2) potential, and (3) extreme. It is believed that, this three level fire status might provide suitable notification.

Experiment setup and tools

The experiments are set up to investigate the presence of fire. Heat, smoke, and °ame's physical phenomenon amount of environment (room) are used as input to classify the fire status. In testing the accuracy of the model two experimental methods are used (1) train-test, and (2) cross-validation. Firstly, for the train-test experiment, the dataset is divided into two parts: one for train and another for test, where 198 (66%) is used as train set, and remaining 102 (34%) is used as test set to verify the accuracy of the model. Secondly, for moderate-sized samples, cross validation (fold 10) is adapted. For comparing the proposed model, train-test and cross-validation results are compared. To run the experiment, WEKA and MATLAB machine learning tools were used.

Performance parameters

To provide a performance comparison among classification techniques, accuracy, precision, recall, f-factor, and ROC area evaluated.

Table 1: Estimated fire attributes indicating fire status.

	Fire status		
Fire elements	Normal(1)	Potential (2)	Extreme (3)
Heat(°c)	Less than 55	Between 55 and 65	Greater than 65
Flame	Less than 180	Between 180 and 190	Greater than 190
Smoke(dB/m)	Less than 50	Between 50 and 150	Greater than 150

Accuracy reflects the overall correctness of the classifier and the overall error rate is

(1 - accuracy). It is defined by Eq. (3).

Precision or confidence denotes the proportion of predicted positive cases that are correctly true positives. A higher precision means less false positives, whereas a lower precision means more false positives. Precision is defined in Eq. (4).

Conversely, recall or sensitivity is the proportion of true positive cases that are correctly predicted positive. It measures the completeness of a classifier. Higher recall means less false negatives, while lower recall means more false negatives. It is defined by Eq. (5).

F-measure or balanced f-score combines precision and recall in a harmonic mean of precision and recall calculated as Eq. (6).

$$\text{Accuracy} = \frac{to+tn}{tp+tn+fp+fn} \times 100\%;(3)$$

$$\text{Precision} = \text{Confidence} = \frac{tp}{tp+fp};(4)$$

$$\text{Recall} = \text{Sensitivity} = \frac{tp}{tp+fn}; (5)$$

$$F = 2\ (\text{Precision}\times\text{Precision} / \text{Recall}+\text{Recall}\ ); (6)$$

Where tp and fp are number of true and false positive, respectively; tn and fn are the number of true and false negative, respectively.

Receiver operator characteristic (ROC) curves are commonly used to present the result for binary decision problems in machine learning. A ROC curve shows true positive rate versus false positive rate for different thresholds of the classifier output. A useless test has an area under the ROC curve of 0.5, and a perfect test has an AUC of 1.0.

To evaluate the comparative prediction performance of the classifiers, mean absolute error (MAE) and relative absolute error (RAE) statistical metrics were used in this research. The result measures the discrepancy between the actual and predicted levels of fire.

7.Conclusions

This paper presents a smart fire detection system to notify the corresponding authorities in the early stages and even before the fire breakout. The initial aim of this study was to present a system that would secure the households to satisfy the demand of time. In order to fulfill the goal, a model has been proposed where a signal processing unit, an image processing unit, and a GSM module unit have been integrated. An integrated sensor system has also been proposed instead of using a single detector i.e., heat, smoke, flame.

A machine learning approach is adapted and compared with the output to get more accurate detection. The machine learning algorithm is required to make sure whether the outputs from the multi-sensor unit produce an appropriate result. An image processing unit has also been adapted to consolidate the prediction, and merge the output with result of the classifier.

The proposed smart fire detection system encompasses the entire safety and security of the property as well as reduces the expense and time while designing and securing modern properties in respect of fire danger. The adapted soft computing approach can open a scope for promoting further research work.

References

[1] Armando M. Fernandes, Andrei B. Utkin, Alexander V. Lavrov, Rui M. Vilar, “Neural Network Based Recognition of Smoke Signatures from Lidar Signals”, Neural Processing Letters, Vol. 19, No. 3, pp. 175-189, June 2004.
[2] Ollero, J.R. Martinez-De Dios and B.C. Arrúe, “Integrated systems for early forest-fire detection”, III International Conference on Forest Fire Research 14th Conference on Fire and Forest Meteorology VOL II, pp
[3] Louis Giglio, Jacques Descloitres, Christopher O. Justice, Yoram J. Kaufman, “An Enhanced Contextual Fire Detection Algorithm for MODIS”, Remote Sensing of Environment, vol. 87, pp. 273–282, 2003.
[4] Seng Chuan TAY, Wynne HSU, Kim Hwa LIM, “Spatial Data Mining: Clustering of Hot Spots and Pattern Recognition”, Proceedings. 2003 IEEE International Geoscience and Remote Sensing Symposium, Volume: 6, pp: 3685- 3687, 21-25 July 2003.
[5] Young Gi Byun, Yong Huh, Kiyun Yu, Yong Il Kim, “Evaluation of Graph-based Analysis for Forest Fire Detections”, Proceedings of world academy of science, engineering and technology, volume. 10, December 2005, ISSN 1307-6884.
[6] Daniela Stojanova, Panče Panov, Andrej Kobler, Sašo Džeroski, Katerina Taškova, “Learning to predict forest fires with different Data Mining techniques”, Conference on Data Mining and Data Warehouses (SiKDD 2006),Ljubljana, Slovenia, pp. 255-258, October 9, 2006.
[7] Yasar Guneri Sahin, “Animals as Mobile Biological Sensors for Forest Fire Detection”, Sensors, vol. 7, pp. 3084-3099, 2007.
[8] Florent Lafarge, Xavier Descombes, Josiane Zerubia, “Forest fire detection based on Gaussian field analysis”, In Proc. European Signal Processing Conference (EUSIPCO), Poznan, Poland, September 2007.
[9] S. Movaghati, F. Samadzadegan, A. Azizi, “An agent-based algorithm for forest fire detection”, The International Archives of The Photogrammetry, Remote Sensing and Spatial Information Sciences, ISPRS Congress Beijing 2008, Volume. XXXVII, Part. B7, Commission: VII/4, Advanced classification techniques, 2008. ISSN 1682-1750.
[10] T. Cheng and J. Wang, “Applications of spatio-temporal data mining and knowledge for forest fire,” in ISPRS Technical Commission VII Mid Term Symposium, Enschede, 2006, pp. 148–153.
[11] “Integrated Spatio-temporal Data Mining for Forest Fire Prediction,” Transactions in GIS, vol. 12, no. 5, pp. 591–611, 2008
[12] K. Clarke, J. Brass, and P. Riggan, “A cellular automaton model of wildfire propagation and extinction,” Photogrammetric Engineering and Remote Sensing, vol. 60, no. 11, pp. 1355–1367, 1994